On the Impact of Sustainability and Climate Change on Assets and Investors

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1 Introduction

This dissertation "On the Impact of Sustainability and Climate Change on Assets and Investors" discusses crucial sustainability and climate-related issues in finance. It provides insights on whether the intensifying climate change crisis will bring about a fundamental reshaping of finance (Fink, 2020). A thorough exploration of the topic provides grounds for motivation. This introduction is followed by a short description of the articles of the dissertation before they are presented in detail in separate chapters. The dissertation concludes with a discussion of the insights gained and describes unresolved questions and issues for future research in Sustainable and Climate Finance.

1.1 Motivation

This dissertation provides new insights into the impact of both sustainability and climate change on assets and investors. In this respect, it contributes with all six articles to the latest climate change and sustainability developments and challenges of our society.

The first four articles address capital market trends that arise from the agreement of the world to combat climate change and the ensuing transition process towards a green economy. The Paris Agreement, the outcome of the UN Climate Change Conference 2015 (Conference of the Parties (COP) 21), is groundbreaking in this context. Under this agreement, more than 195 nations agreed to limit global warming to well below 2°C – preferably below 1.5°C – above pre-industrial levels (United Nations, 2015). This emphasizes the need for a rethinking of present behavior with a consequent change in society, politics, and economy for the mitigation of climate change. The EU commission with its release of an EU action plan for financing sustainable growth makes a major contribution to this cause. Its purpose is to reorient capital flows towards sustainable investments in order to achieve sustainable and inclusive growth. This action plan also promotes the integration of sustainability into risk management and fosters transparency and long-termism in financial and economic activities. Central banks and supervisors are supporting these ambitions with their recently launched Network for Greening the Financial System (NGFS). Similarly, numerous representatives of the finance industry and stock exchanges organized in the Task Force on Climate-related Financial Disclosure (TCFD) are developing guidelines and a framework for comprehensive and efficient climate risk disclosure. Beyond the achievement of a global climate policy to successfully combat climate change, as expressed in the Paris Agreement, the world has agreed to adopt the Sustainable Development Goals (SDGs) outlined by the UN in 2015. Their adoption marks the challenging beginning of a global social and economic transition towards a sustainable future. An increasing number of asset managers consider SDGs to be an important investment opportunity and plan to integrate SDGs into their investment processes. Indeed, numerous investors are looking at how they can incorporate SDGs into their ESG frameworks. SDGs have thus become a highly relevant issue for capital market participants. For this reason, the last two articles in this dissertation contribute towards a better understanding of SDGs (and related sustainability frameworks) from a financial perspective.

This dissertation aims to add to our understanding of two societal developments. On the one hand, it analyzes how carbon risk, which arises from the transition process towards a green economy, is perceived in capital markets and by capital market participants. On the other hand, it examines a more holistic approach to sustainability, also taking into account SDGs and what implications they have for firms and investors. Chapter 1 will continue with an overview of all the articles of this dissertation. Chapter 2 examines carbon risk and the missing carbon risk premia in a factor-based capital markets approach. The focus of Chapter 3 is the integration of carbon risk into portfolio management and the associated impact on a portfolio's performance, risk profile and factor exposures. The following Chapter 4 looks into the perception of carbon risk during a crisis, also with a view to the current COVID-19 pandemic. The conclusion of the first part on carbon risks and climate change closes in Chapter 5 with an examination of the extent to which non-financial information, such as carbon emissions, can have an impact on the accuracy of firm valuations using multiples. The second part of the dissertation begins in Chapter 6 with an examination of how a firm's contribution to SDGs impacts its value. Chapter 7 discusses the last article investigating the sustainability and financial performance of the DAX 50 ESG. In the final Chapter 8, the results of this dissertation are outlined briefly and insights are provided on how these findings might be relevant for future research.

1.2 Overview over articles

The following Table 1 provides a brief overview of all six articles included in this dissertation. It contains the titles of the articles as well as information on the co-authors involved, whether they were published and if so, in which journal, and the date of the last version.

Table 1 – Overview

Title	Co-authors	Published	Journal	Date
Carbon Risk	Maximilian Görgen Andrea Jacob Ryan Riordan Martin Rohleder Marco Wilkens	No	WP, University of Augsburg	2020
Get green or die trying? Carbon risk integration into portfolio management	Maximilian Görgen Andrea Jacob	Yes	Journal of Portfolio Management	2021
Carbon Risk in times of COVID-19	Andrea Jacob	No	WP, University of Augsburg	2020
Enhancing the accuracy of firm valuation with multiples using carbon emissions	–	No	WP, University of Augsburg	2020
You never know the value of water before the well runs dry - The impact of Sustainable Development Goals on firm value	Marco Wilkens	No	WP, University of Augsburg	2020
Will the DAX 50 ESG establish the standard for German sustainable investments? A sustainability and financial performance analysis	–	Yes	Credit and Capital Markets	2020

The presentation of the articles at acknowledged conferences,[1] e.g., AEA Annual Meeting 2019, 31st NFA Annual Conference, EFA Annual Meeting 2018, or 24th Annual Meeting of the German Finance Association (DGF), as well as the prizes won, e.g., a Best Paper Award and a Highest Impact Award for the article "Carbon Risk", are shown on the respective title pages.

In addition to these scientific articles, related publications were also written especially for practitioners. First, the handbook "Carbon Risks and Financed Emissions of Financial Assets and Portfolios - Measurement, Management and Reporting based on Capital Market Data" should be mentioned here. This was developed within the CARIMA project and funded by the BMBF.[2] It sheds light on numerous aspects of the article "Carbon Risk" from the perspective of practitioners, such as portfolio managers, investors, regulators and politicians. It also describes an accompanying Excel tool with which carbon risks can be estimated using a simple asset pricing model approach.

In addition, an article titled "Carbon Footprints sind nicht gleich Carbon-Risiken" was published in the "Zeitschrift für das gesamte Kreditwesen" (VHB: D).[3] This article examines the relationships between carbon footprints and carbon risks and specifically looks at the differences in various sectors. It shows that carbon footprint and carbon risk, measured as carbon beta, can diverge. This means that assessing carbon footprints in isolation does not allow conclusions about carbon risk. It is therefore advisable to include both indicators in making a well-informed investment decision.

[1] By the time the dissertation was submitted, the listed articles had been presented or accepted for presentation at 18 acknowledged conferences and research seminars worldwide.

[2] Available on carima-project.de/en.

[3] Nerlinger, M., Wilkens, M., & Zink, J. (2020). Carbon footprints sind nicht gleich Carbon-Risiken. *Zeitschrift für das gesamte Kreditwesen* **73**, 13/2020, 32-35. https://www.kreditwesen.de/kreditwesen/themenschwerpunkte/aufsaetze/carbon-footprints-gleich-carbon-risiken-id65391.html.

The six articles of this dissertation are now briefly described in the following sections starting with the articles on carbon risk, carbon emissions and climate change in relation to asset pricing and firm valuation and ending with the articles on sustainability, SDGs and firm value.

1.2.1 Carbon Risk

The first article of this dissertation focuses on the investigation of carbon risk in global equity prices. Generally, carbon 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. There are major challenges in quantifying carbon risk, such as the limited availability of carbon risk-related information, which is only available for a short and volatile time series, and the isolation of carbon risks from the rest of the uncertain transition process.

As a first step towards tackling this problem, we use an extensive, unique data set consisting of four major ESG databases to address data issues as best as possible.To extract carbon risk, we develop a capital market-based approach. First, we classify green and brown firms using a brown-green score (BGS). Our BGS is a fundamental measure of the greenness or brownness of individual firms. Second, we examine the carbon risk in stock prices through the lens of a factor-based asset pricing model by constructing a Brown-Minus-Green (BMG) portfolio based on BGS in line with the well-known approach of Fama and French (1993, 2015). Third, we show that carbon risk is not yet being priced. We show that this may be the case: (1) because of the opposing price movements of brown firms versus firms becoming greener, and (2) because carbon risk is associated with unpriced cash-flow changes rather than priced discount-rate changes.

Our paper is related to a nascent but growing literature on the relationship between climate change and asset prices. In a subsequent paper, Bolton and Kacperczyk (2020) document a similar relationship between carbon emissions, carbon risk and asset prices. Our results are in line with the theoretical model of Pástor, Stambaugh, and Taylor (2020) and add to the understanding of the functioning of carbon risk. Krüger, Sautner, and Starks (2019) underline the results of our study by also stating that climate concerns are an important factor in the investment decision process. The results and methodology of our article can be used by investors, regulators, and academia to better understand the role carbon risk and climate change play in a global asset pricing context.

1.2.2 Get green or die trying? Carbon risk integration into portfolio management

The second article discusses the integration of carbon risk into portfolio management and provides recommendations on how investors can manage the carbon risk exposure in their portfolios. The idea of considering aspects such as the performance and risk of sustainability in portfolio management is by no means new (e.g., Sauer (1997), Madhavan and Sobczyk (2020)). While here we focus on climate change-related portfolio management, there are, for example, studies analyzing carbon emissions (e.g. Bender et al. (2020)). We are taking a further significant step in demonstrating how to measure and manage carbon risk in portfolio management based on a capital markets-based approach.

We analyze implications for portfolio management by constructing quintile portfolios based on the carbon beta. Portfolios with low carbon beta (green) have lower average returns than portfolios with high carbon beta (brown). Moreover, we show that the margin portfolios, i.e. mainly green and mainly brown portfolios, have a higher risk than the middle portfolios. We find that this pattern is not only driven by higher beta exposures. Moreover, the risk-adjusted performance of the margin portfolios is lower, suggesting that the additional carbon risk is only disproportionately remunerated in capital markets. To better understand the impact of integrating carbon risk into common investment strategies, we apply traditional screening and best-in-class strategies based on sectors and countries. The results of this variety of portfolio strategy can be used to achieve a desired level of carbon risk exposure, taking into account the associated risk and return profile. Based on this, we recommend that portfolio managers conduct due diligence when integrating carbon risk and refrain from simple screening strategies.

1.2.3 Carbon Risk in times of COVID-19

The third article analyzes the extent to which the COVID-19 pandemic has caused damage to stocks with differing exposure to climate change risk. In particular, we focus on carbon risk, i.e. the risk stemming from unexpected changes in the transition process from a carbon-intensive to a low-carbon economy. We show that a stock's degree of greenness or brownness, has had a significant performance impact within the COVID-19 market downturn. Shifts towards neutral stocks from either the green or brown direction improved return patterns. In line with our reasoning, risk was highest for extremely green and extremely brown stocks. The effect of a stock's carbon risk exposures on its volatility was stronger for brown than green stocks. From our results, we conclude that green and brown business models are not sufficient to mitigate crisis periods successfully. However, being on the forefront of sustainability, i.e. being green, turned out to be more beneficial than being brown.

Related literature on the intersection of firm characteristics and crisis periods has surged during the pandemic. Ramelli and Wagner (2020) investigate cross-sectional stock price responses to the emergence of COVID-19. They find that firms with low cash holdings as well as firms with high leverage have suffered the most. Albuquerque et al. (2020) study the causal link between ESG exposures of stocks and financial performance. They find that stocks rated high on environmental and social issues have so far been more resilient during the COVID-19 downturn. We add to the literature by focusing on one of the most prevalent long-term risks of humankind − carbon risk − and its interrelations with sudden and severe short-term risk shocks. In future, as the transition process towards a low-carbon world accelerates, we expect green stocks to build on their advantage compared to brown stocks and even outpace neutral stocks.

1.2.4 Enhancing the accuracy of firm valuation with multiples using carbon emissions

The fourth article addresses a related topic in the field of Climate Finance besides carbon risk. It is the first to analyze the potential of carbon emissions data in enhancing the accuracy of firm valuations using the similar public company methodology with multiples. Motivated by the concerns of investors, asset managers, regulators and those analyzing the risk to firm value of accelerating climate change, we are evaluating possible applications of carbon emission data to improve the accuracy of firm valuations.

In two ways, the use of carbon emissions can help to construct more accurate multipliers for firm valuation. First, we construct carbon emission-based multipliers (carbon emission multiples, CEM) and assess their accuracy in firm valuation. Second, we identify and create a more appropriate Carbon Emissions Peer Group (CEPG) for firm valuation using carbon emissions as a classification criterion. Based on the results of our numerous analyses, we find that estimating firm values with CEM has a limited potential. However, we can suggest the use of CEPG in most cases. The inclusion of carbon emissions to compose peer groups increases the accuracy of firm valuation in more than three quarters of our analyses.

This article contributes to a fast-growing strand of literature analyzing the impact of carbon emissions on firm value. For example, carbon emissions and carbon disclosure have a significant positive effect on the value of a firm (Matsumura, Prakash, & Vera-Muñoz, 2014) and are relevant to investors (Griffin, Lont, & Sun, 2017). In our analysis, we follow best practices in applying multiples for firm valuation purposes (Plenborg & Pimentel, 2016). Furthermore, we use several error measures to obtain detailed knowledge of distortions within our results (Chullen, Kaltenbrunner, & Schwetzler, 2015). Overall, based on our results, we recommend that carbon emissions be included in the composition of peer groups. Our approach leads to consistent, efficient and accurate firm valuations for asset managers and investors to improve their investment decisions. It also increases the accuracy of analysts' firm valuation estimates, especially for firms that are heavily affected by carbon emissions, e.g., fossil fuel or cement firms. Finally, it helps capital market participants, regulators and analysts to better understand how information on carbon emissions is incorporated into a firm's valuation process.

1.2.5 You never know the value of water before the well runs dry - The impact of Sustainable Development Goals on firm value

In addition to articles analyzing the impact of climate change on capital markets, this dissertation also examines a more holistic perspective to sustainability and its impact on firms. In the fifth article, we are the first to study the impact of a firm's contribution to the 17 Sustainable Development Goals (SDGs) on its value. To provide new insights, we are using unique data on SDG-aligned products and services from more than 5,800 global firms from ISS-oekom.

Our analyses are threefold. First, we conduct two mean comparison tests to compare firms that have disclosed SDG data with firms that have not, and firms with high versus low SDG performance. We identify the differences between these groups and take them into account in our second analysis. Hence, in addition to the usual pooled and panel regressions, we apply a Heckman correction by estimating both a disclosure-choice and a firm-value model. The disclosure-choice model reveals what underlies the decision of firms to disclose SDG data in their reporting (e.g., García-Sánchez et al., 2020). The firm-value model shows that aggregated SDG measures have no clear and constant impact on firm value but we identify specific SDG objectives, such as "combating hunger", "attaining gender equality", and "optimizing material use" that have a significantly negative impact on firm value – as well as goals such as "ensuring health" and "mitigating climate change" that have a significantly positive impact on firm value.

These results contribute to a better understanding of the impact of sustainability on a firms' value as related to early studies (e.g. Hussain et al., 2018). In addition, we analyze the relationship between ESG and SDGs and provide insights on the difference between the product and the conduct dimension of sustainability. We find that while a firm’s ESG value still has a significant impact on its value, it has little impact on the relationship between a firm's SDG performance and its value. We can therefore draw the conclusion that sustainability has an impact on the value of a firm in both dimensions.

Our results contribute to a growing body of related finance literature on corporate social responsibility (CSR), environmental, social und governance (ESG) behavior, and impact investing (e.g. Fatemi et al., 2015, Friede et al., 2015, Barber et al. 2019). We provide investors, asset managers and firms with insights into how to incorporate a firm’s contribution to the SDGs in their investment decisions. This not only can lead to a more holistic approach to understand sustainability, but to a better financial performance.

1.2.6 Will the DAX 50 ESG establish the standard for German sustainable investments? A sustainability and financial performance analysis

The sixth article deals with the sustainability and financial performance of the DAX 50 ESG. It discusses the non-financial and financial performance of both the index and its constituens. Therefore, we compare the sustainability performance of the DAX 50 ESG to major German and global indices. Furthermore, we examine the sustainability performance using both ESG criteria and the alignment of products and services with the Sustainable Development Goals. Using comprehensive ESG and SDG data from all German and MSCI-ESG indices, we aim to take a holistic view of sustainability.

Our results show that the DAX 50 ESG has a relatively high sustainability performance, however, its constituents are not significantly more sustainable compared to, e.g., the DAX constituents. The results of the financial analysis show that the DAX 50 ESG has a relatively poor performance paired with an average risk profile. This poor performance cannot be explained by factor exposures, as they are very similar across all indices. Even in times of the

COVID-19 crisis, an investment in the DAX 50 ESG does not offer any additional risk protection through its sustainability. In an additional event study, we show that firms are currently penalized for their inclusion in the DAX 50 ESG. This may be an explanation for the relatively poor performance of the index currenlty. Our results are relevant for capital market participants as we observe a growing demand from investors for sustainable financing opportunities in Germany (FNG, 2019) and worldwide (PRI, 2019).

Our paper contributes to both the emerging literature on sustainability measurement in finance and on the relationship between sustainability and financial performance (e.g., Carolina Rezende de Carvalho Ferrei, Amorim Sobreiro, Kimura, & Luiz de Moraes Barboza, 2016). We also add to related studies that analyze the characteristics of different sustainability indices (Bianchi & Drew, 2012; López, Garcia, & Rodriguez, 2007). Our analysis of the DAX 50 ESG increases investors' attention to sustainability, helps to better understand the sustainability performance of an index and enables better investment decisions.

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2 Carbon Risk

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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 explain 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. We extend our analysis to different geographic regions and time periods to confirm the missing risk premium.

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

JEL Classification: G12, G15, Q51, Q54

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Seminar 2019, The Sydney University Research Seminar 2019 and the Macquarie University Research Seminar 2019 in Sydney, two CARIMA Workshops 2018 in Frankfurt, the seminar with the EU Commission, and a German Bundesbank workshop. The paper received the Best Paper Award at the 2018 SWFA Annual Meeting in Albuquerque and the Highest Impact Award at the 2017 Green Summit in Vaduz. We are responsible for all errors.

2.1 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.[4] Simultaneously, institutional investors have committed to divesting $11 trillion USD in assets of fossil fuel firms.[5] 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, 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 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.

[4] World Bank Group (2019) - https://carbonpricingdashboard.worldbank.org.

[5] https://350.org/11-trillion-divested/

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 et al. (2019) 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., 2019) 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 tests 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. (2019), 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., 2019) making understanding them central to the pricing of assets. Barnett et al. (2019) demonstrate theoretically how climate uncertainty, including physical risks, can be priced in a dynamic stochastic equilibrium model. Bolton and Kacperczyk (2019) provide insights if and how investors do care about carbon risk measured by different carbon emission intensity scopes. Choi et al. (2019) show that high-carbon firms underperform low-carbon firms during extreme heat events. In addition, Hong et al. (2019) demonstrate that food firms exposed to physical risks underperform in the long-run. 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. (2019) 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. Several papers report a link between climate change and property values, e.g., Bakkensen and Barrage (2018), Baldauf et al. (2019), Bernstein et al. (2019), Giglio et al. (2018), Ortega and Taspinar (2018), and Rehse et al. (2019). From an investor’s perspective, Krüger et al. (2019) suggest that climate concerns are important factors in the investment decisions of large institutional investors, while Monasterolo and De Angelis (2020) explore investors’ demand for a risk premium for carbon-intensive assets and Alok et al. (2019) 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., 2019), firm-value effects of carbon disclosure (Matsumara 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 (Chava, 2014; El Ghoul et al., 2011).

2.2 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. We minimize a potential self-reporting bias by using four ESG databases with different approaches in collecting data including estimations by analysts.

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 2.1). 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.

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., 2019). 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 IPPC 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.

2.3 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.

2.3.1 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). 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 (Krüger, 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). 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., 2019). 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.[6] 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).

$$BGS_{i,t} = 0.70 \text{ Value Chain}_{i,t} + 0.15 \text{ Public Perception}_{i,t} + 0.15 \text{ Adaptability}_{i,t} \qquad (1)$$

The value chain subscore has a weight of 70% in the BGS to reflect its relative importance.[7] The public perception and adaptability subscore carries each 15% weight in the BGS.[8] As a

[6] For a full list of variables see Internet Appendix Table A.2.

[7] 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.

[8] 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.

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 is 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.

2.3.2 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. 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. (2019). 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 on stock returns, thus confounding clear-cut effects on stock returns. 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.]

2.4 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).[9] 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.

2.4.1 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 (2). 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.

$$BMG_t = 0.5\ (SH_t + BH_t) - 0.5\ (SL_t + BL_t) \quad (2)$$

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.

[9] For a comprehensive overview of the discussion about past factors, we suggest reading Harvey et al. (2019) and Feng et al. (2019).

Following the reasoning of Pástor et al. (2019), 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 factors of a Carhart (1997) four-factor model in Panel A and the 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.[10] This suggests that the BMG factor possesses unique return-influencing characteristics that are able to enhance the explanatory power of common factor models.[11]

[Insert Table 4 here.]

2.4.2 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-

[10] 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.

[11] Nevertheless, to completely exclude a potential influence of other risk factors, we conduct an analysis with democratically orthogonalized factors in Internet Appendix A.3.

series regressions of the quintiles' equal-weighted monthly excess returns on the Carhart model and on the Carhart + BMG model (see Equation 3).[12]

$$er_{i,t} = \alpha_i + \beta_i^{mkt} er_{M,t} + \beta_i^{smb}\, SMB_t + \beta_i^{hml}\, HML_t + \beta_i^{wml}\, WML_t + \beta_i^{BMG}\, BMG_t + \varepsilon_{i,t} \qquad (3)$$

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 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.

2.4.3 Comparison of common factor models

To reinforce the results of the previous section on a larger basis, we compare the results of 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

[12] Value-weighted quintile portfolios show the same patterns, therefore our results remain robust.

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.

2.4.4 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.

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 α. 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 Π (excess returns of all assets) and f (all factors of a model) and the one with only the latter, as the following Equation (4) displays.

$$\alpha'\Sigma^{-1}\alpha = Sh^2(\Pi) - Sh^2(f) \tag{4}$$

They show that differences in the vector of intercepts (α) from the regression of Π on f and the residual covariance matrix (Σ^{-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.]

[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.

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, 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 this test asset portfolio. 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]

2.5 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.

2.5.1 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

[14] We also conducted further asset pricing tests like, e.g., excluded factor regressions in the Internet Appendix (Table A.4).

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 as dependent variable.[15] First, each year in June, we sort all stocks based on their market capitalization into deciles. Second, within each size quintile, 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.]

[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, 2019; 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.

2.5.2 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 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

[16] Technical details can be found in Internet Appendix A.4.

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. (2019) 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 kind 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

[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.

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.

2.6 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 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 backcast 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]

2.7 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

[18] When considering non-EIV-corrected cross-sectional regressions, the carbon risk premium remains unverified.

[19] We provide results upon request.

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-rate changes. These results are in line with the theoretical model of Pástor et al. (2019) 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.

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Figures and Tables

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 the Table A.2.

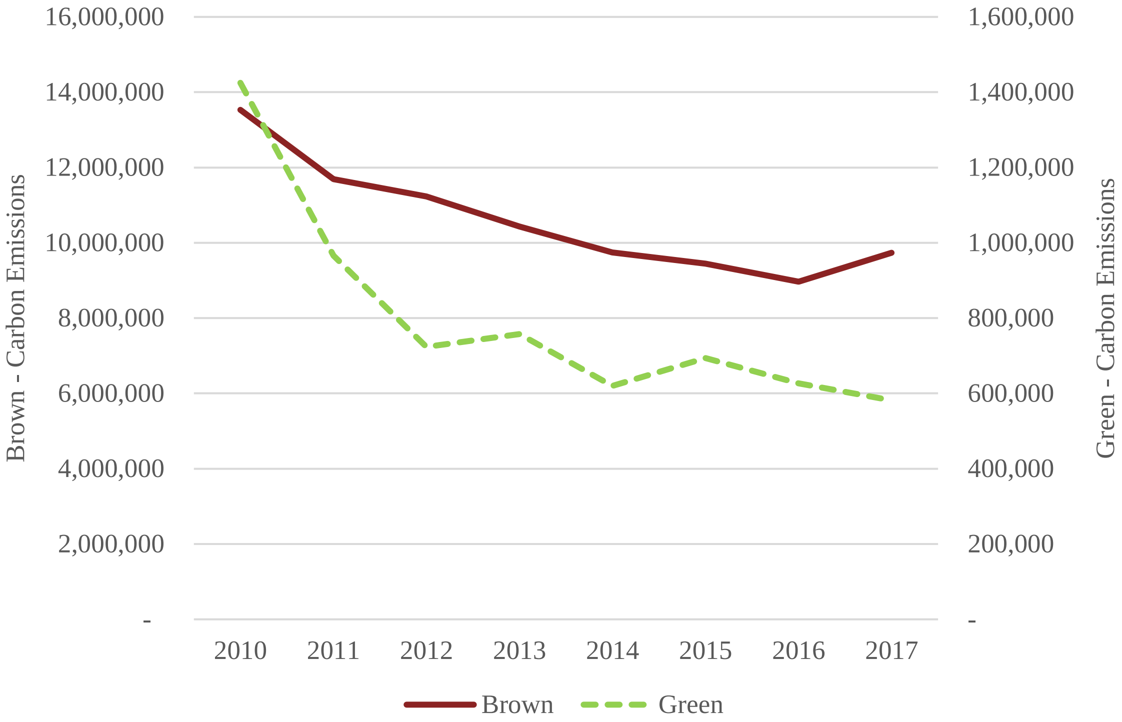
Table 2
Panel regressions

	(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

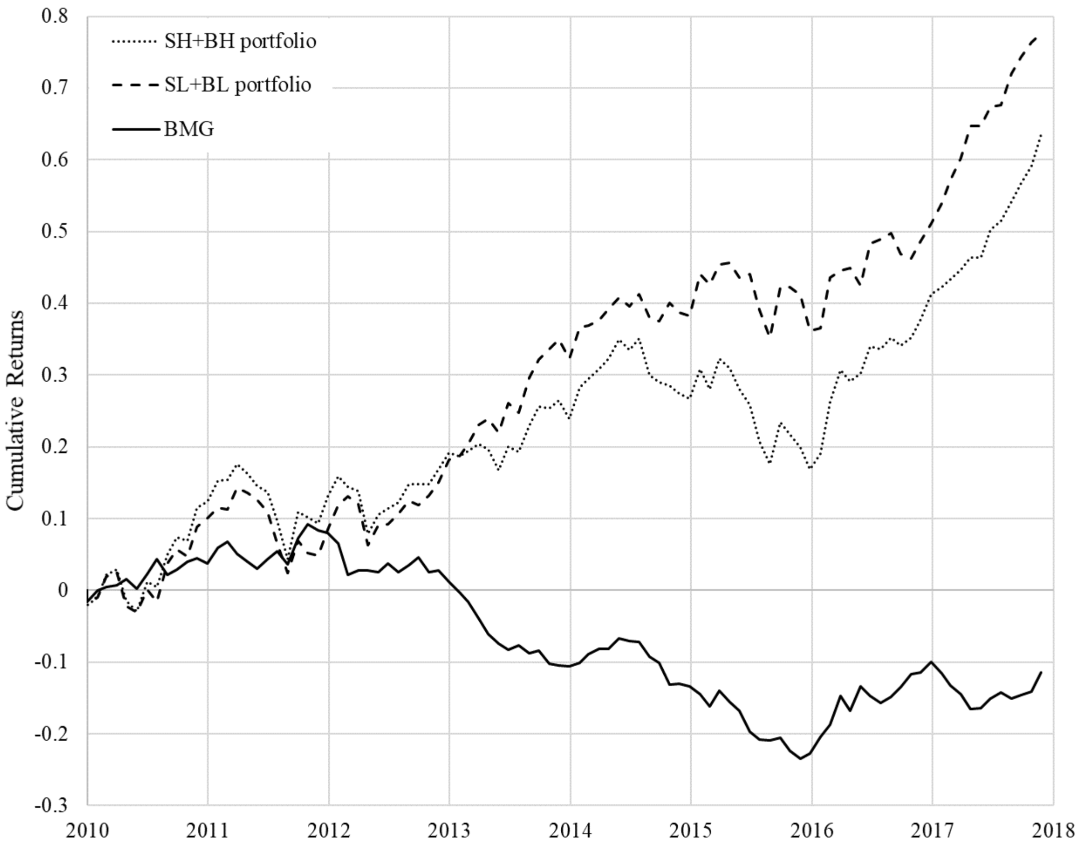


Panel B. Development of carbon and transition-related variables of brown and green firms

Variable	Mean: Brown	Mean: Green	Difference	Mean ann. change in %: Brown	Mean ann. change in %: 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. Fama/French 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 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						Adj. R^2 (%)	Δ Coefficient					Δ Adj. R^2 (%)
		Alpha	er_M	SMB	HML	WML	BMG		Δ Alpha	Δ er_M	Δ SMB	Δ HML	Δ WML	
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 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 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

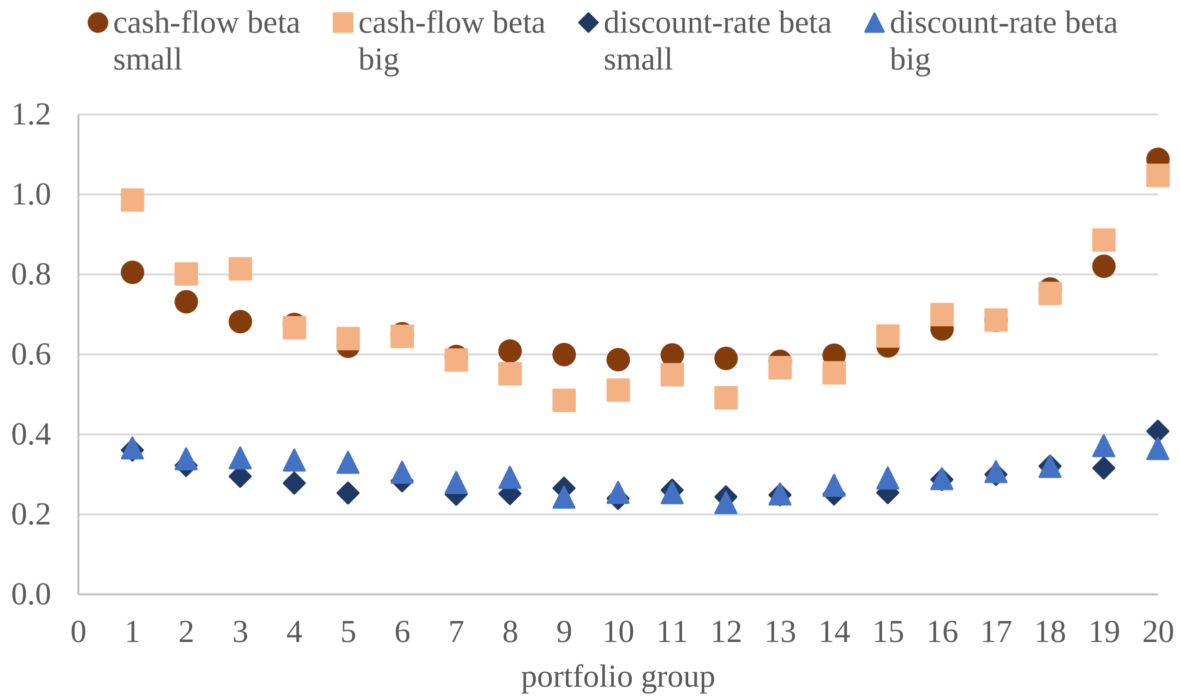
This table shows results of cross-sectional Fama and MacBeth (1973) regressions. We follow the implementation of Pukthuanthong et al. (2019) and use two different methodologies. First, we simply conduct single-stock cross-sectional regressions (no EIV correction). Second, we us double sorted portfolios 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.

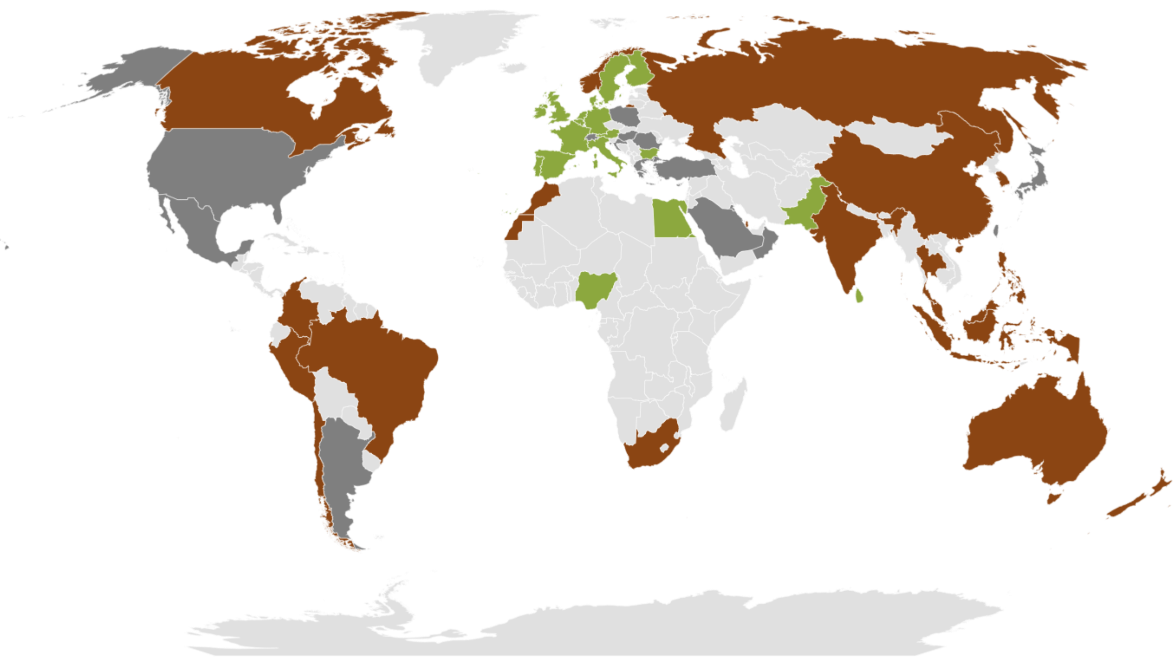
Table 10
Pricing cash-flow and discount-rate betas

	Factor model		Two-beta ICAPM	
	Unrestricted	α=0	Unrestricted	α=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)	
$\widehat{\beta}_{CF}$ 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)
$\widehat{\beta}_{DR}$ 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 (α=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
UK	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 9 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.1 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	100.00	Total		1,657	100.00

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.
PAdaptability	
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
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-1}	94.30%	1.93%	0.19%	3.44%	0.11%	0.02%
SN_{t-1}	1.96%	92.67%	1.91%	0.12%	3.13%	0.20%
SH_{t-1}	0.16%	1.70%	95.05%	0.01%	0.10%	2.98%
BL_{t-1}	1.64%	0.05%	0.01%	96.82%	1.31%	0.18%
BN_{t-1}	0.07%	1.98%	0.08%	1.93%	93.63%	2.31%
BH_{t-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-5}	81.93%	7.08%	0.98%	9.03%	0.88%	0.10%
SN_{t-5}	7.42%	73.84%	7.96%	1.00%	8.48%	1.29%
SH_{t-5}	0.70%	6.89%	82.51%	0.07%	0.88%	8.95%
BL_{t-5}	3.33%	0.24%	0.04%	90.07%	5.52%	0.81%
BN_{t-5}	0.35%	3.97%	0.46%	8.61%	77.48%	9.13%
BH_{t-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 A.2 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 A.4 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 A.4 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. Overall other panels, this analysis clearly favors including the BMG factor into common factor models.

Table A.4
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	-0.000967	-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	0.0000499	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 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 4.1.

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, that 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 6 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 6 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 A.5 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 A.5

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 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 backcasted sample period from January 2002 to December 2017.

[Insert Table A.6 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 A.5). 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 A.6

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 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 A.3 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 A.7 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 factors, er_M, SMB, HML, and WML, respectively.

[Insert Table A.7 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 A.8). 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 A.8 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 A.9 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 A.9 here.]

Additionally, Table A.10 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 A.10 here.]

Next, we again assess the importance of our factor related to the significance of its coefficient in single stock regressions. Table A.11 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 A.11 here.]

Table A.7
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 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 factors er_M, SMB, HML, and WML are provided by Kenneth French.

Table A.8
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 A.9
Decomposition of R^2

Quintile	Decomposed-R^2					Systematic R^2 (%)	Idiosyncratic Variance $(1-R^2)$ (%)
	$er_M^{\perp}$	$SMB^{\perp}$	$HML^{\perp}$	$WML^{\perp}$	$BMG^{\perp}$		
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 factors er_M, SMB, HML, and WML are provided by Kenneth French.

Table A.10
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 A.11
Significance tests for factor betas for the Carhart + BMG model

	Avg. coefficient	T-test of significance of coefficients					
		10% level		5% 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 A.4 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:

$$z_{t+1}=a+\Gamma z_t+u_{t+1} \tag{A.1}$$

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

$$N_{DR,t+1}=e1'\lambda u_{t+1} \tag{A.2}$$

$$N_{CF,t+1}=(e1'+e1'\lambda)u_{t+1} \tag{A.3}$$

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

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[21] We set ρ 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):

$$Var(BMG_t-E_{t-1}BMG_t)=Var(N_{CF})+Var(N_{DR})-2Cov(N_{CF},N_{DR}) \quad (A.4)$$

$$1=\frac{Var(N_{CF})}{Var(BMG_t-E_{t-1}BMG_t)}+\frac{Var(N_{DR})}{Var(BMG_t-E_{t-1}BMG_t)}-2\frac{Cov(N_{CF},N_{DR})}{Var(BMG_t-E_{t-1}BMG_t)} \quad (A.5)$$

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):

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

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

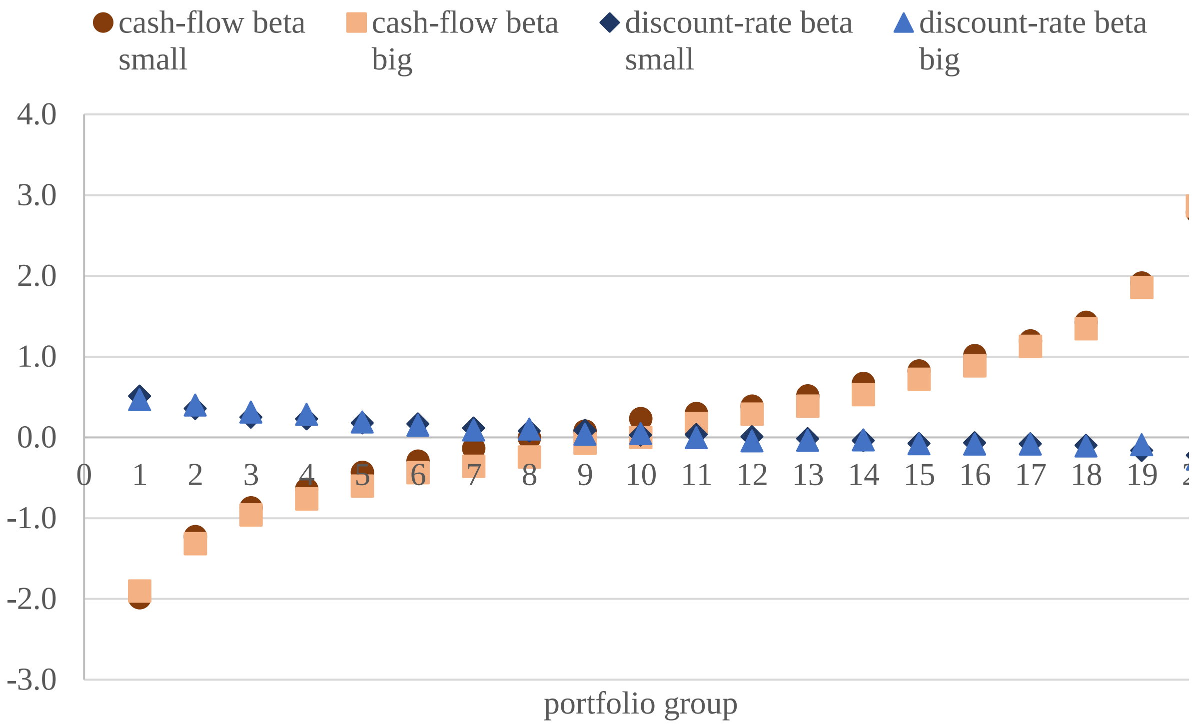
where $r_{i,t}$ is the return of a specific test asset.

In addition, Figure A.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 –

[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.

solely with an opposite sign, i.e., negatively for green and positively for brown portfolios, respectively.

Figure A.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.

3 Get green or die trying? Carbon risk integration into portfolio management

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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 markets. 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.

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

JEL Classification: G11, Q54

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4 Carbon Risk in times of COVID-19

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Abstract. Climate-change induced long-term risk and pandemic short-term risk both have remarkable impacts on financial markets. What happens if these risk sources coincide? We find that a stock's degree of greenness and brownness, respectively, significantly determined a stock's susceptibility towards the COVID-19 crash. Both green and brown business models were not sufficient to mitigate this unforeseeable shock. However, green stocks fared better from a risk perspective than brown stocks pointing to a slight advantage of being adapted to climate change impacts.

Keywords: Carbon risk, COVID-19, asset returns, risk management, climate change

JEL Classification: G12, G11, Q54

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We are responsible for all errors. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors. Declarations of interest: none.

4.1 Introduction

Extreme weather, natural disasters, climate action failure, and biodiversity loss – these are terminologies, we know well since the world finally has recognized the far-reaching impacts of climate change. There is good reason to list these topics as the predominant risks by likelihood and impact in the World Economic Forum's Global Risks Report 2020. In this ranking, infectious diseases appear on rank 10 by impact – with a negligible likelihood. However, with the COVID-19 pandemic, we had to learn that infectious diseases could lead to unforeseen and far-reaching challenges worldwide. Climate change and the pandemic thus have become two interwoven human challenges. This paper analyzes in how far the pandemic caused damage for stocks with differing risk exposure arising from climate change. In specific, we focus on carbon risk, the risk stemming from unexpected changes in the transition process from a carbon-intensive to a low-carbon economy. Apart from common perception, carbon risk has effects in both directions; since the definite outcome and pace of the transition process are unknown, both "green" and "brown" firms are confronted with this climate change-related risk source.

In times of the pandemic, all financial markets experienced an unforeseeable downturn with rising risk levels (see, e.g., Zhang et al., 2020 and Shehzad et al., 2020). Thus, no matter how brown or green stocks have been characterized, they all had to suffer from the COVID-19 market downturn. However, we show that a stock's degree of greenness or brownness, respectively, significantly influenced the potential severity with which it was hit. More specifically, extremely green and extremely brown stocks had the lowest returns during the first quarter of 2020 and within the COVID-19 period, respectively. Moving towards neutral stocks from both the green and brown direction improved return patterns. In line with our reasoning, risk was highest for extremely green and extremely brown stocks. The effect of a stock's carbon risk exposures on its volatility was stronger for brown than green stocks. From our results, we conclude that green and brown business models are not sufficient to mitigate crisis periods successfully. However, being on the forefront of sustainability, i.e. being green, turned out to be more beneficial than being brown.

Literature on the intersection of firm characteristics, sustainability performance and crisis periods has surged during the pandemic. Ramelli and Wagner (2020) investigate cross-sectional stock price responses to the emergence of COVID-19. They find that firms with low cash holdings as well as firms with high leverage suffered the most. Albuquerque et al. (2020) study the causal link from ESG exposures of stocks to financial performance. They find that stocks rated high on environmental and social issues were more resilient during the COVID-19 downturn. Mirza et al. (2020) find that social entrepreneurship funds displayed positive risk-adjusted performance for different stages of the COVID-19 pandemic. Ferriani and Natoli (2020) analyze fund flows during the COVID-19 period and find that investors preferred low ESG risk funds, whereas the environmental risk factor was the main driver of investors' sustainability preferences. Studies on different market crash periods, such as the financial crisis in 2008, point to the same results (e.g., Lins et al., 2017 and Nofsinger and Varma, 2014). We add to the literature by focusing on one of the most prevalent long-term risks of humankind, carbon risk, and its interrelations with sudden and severe short-term risk shocks like COVID-19.

The remainder of the paper is organized as follows. In section 2, we present our data and approach for measuring carbon risk on stock level. Section 3 contains our empirical results and their discussion, while section 4 concludes.

4.2 Data and measurement of carbon risk

For our analyses, we use a global stock sample based on stocks of the MSCI All Countries World Investable Market Index (ACWI IMI). In order to determine a stock's greenness and brownness, respectively, we apply the methodology of Görgen et al. (2020a). They present a capital markets-based approach for measuring carbon risk on stock level. In specific, we use their "Brown-Minus-Green" (BMG) zero-cost portfolio to estimate the measure for carbon risk, the carbon beta, for each stock. The BMG portfolio invests in brown stocks while short selling green stocks and thus captures the systematic return difference between green and brown stock returns.

We estimate a constant carbon beta based on daily return data for 2019 following equation (1).

$$er_{i,t} = \alpha_i + \beta_i^{MKT} er_{M,t} + \beta_i^{SMB}\, SMB_t + \beta_i^{HML}\, HML_t + \beta_i^{WML}\, WML_t + \beta_i^{BMG}\, BMG_t + \varepsilon_{i,t} \qquad (1)$$

with $er_{i,t}$ being the excess return at time t of stock i, $er_{M,t}$, SMB_t, HML_t, and WML_t being the global market risk factor as well as the size, value, and momentum factors at time t from Kenneth R. French's data library, and BMG_t being the return time series of the carbon risk mimicking portfolio at time t. The carbon beta, β_i^{BMG}, measures a stock's exposure towards carbon risk. Stocks with a negative carbon beta (green stocks) are likely to be positively affected by unanticipated changes of the transition process towards a low-carbon economy. Positive carbon betas are rather associated with brown stocks, i.e. stocks that are possibly negatively affected by unforeseen changes in the transition process towards a greener economy.

We use the carbon beta to form three distinct stock groups: stocks with a carbon beta of less than –0.05 are labelled as green stocks, stocks with a carbon beta of greater than 0.05 are brown, and all stocks with carbon betas between those two thresholds are neutral towards carbon risk.[24] We obtain financial data from Refinitiv Datastream for the first quarter of 2020 to cover the relevant COVID-19 period since the outbreak in China. We extract daily returns and December 2019 accounting data known to influence returns such as Tobin's Q, size measured by the logarithm of market capitalization, cash holdings over total assets, the leverage ratio, return on

[24] To ensure that each group has distinct carbon risk characteristics, we choose absolute thresholds and do not rely on sample distribution breakpoints.

equity, expenses for selling, general and administrative functions (SGAE), and the dividends ratio. 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). Table 1 provides summary statistics of all variables used in this study.

[Insert Table 1 here.]

In total, we work with a global sample of 14,381 stocks, which is restricted only by the availability of financial data. The overall sample displays on average a slightly negative carbon beta of –0.0161. Cumulative daily returns for both the first quarter and the COVID-19 period are highly negative with mean values of –28.06% and –26.07%, respectively. Volatility of daily returns was higher during the COVID-19 phase than for the whole quarter with 5.95% compared to 4.35%. For comparison, the average daily historical volatility for 2019 was 2.21%, i.e. less than half of the COVID-19 period volatility.

4.3 Empirical results and discussion

4.3.1 Descriptive comparison of stocks

We compare return and risk characteristics of green, neutral, and brown stocks. Green stocks have an average carbon beta of –0.1684, whereas brown stocks display a carbon beta of 0.1940 during the first quarter of 2020 (see Table 2). Hence, the carbon risk sensitivities of green and brown stocks are substantial different. The neutral stock group has a carbon beta near zero.

[Insert Table 2 here.]

We find that mean daily returns differ between the three stock groups. Neutral stocks performed best (but still negative during the first quarter), followed by brown and then green stocks. For median returns, green stocks slightly outperformed brown stocks in the first quarter.[25]

Volatility measures point to the fact that carbon beta neutral stocks are less risky than green and brown stocks during the first quarter of 2020 (columns (1) to (3)).[26] In turn, brown stocks are the most risky ones. For example, the Value at Risk at 1% is -13.86% for green and -15.55% for brown stocks. The maximum drawdown is around 1% higher for brown than for green stocks. Last, systematic risk measured by the market beta is near unity for brown stocks, but lower for green (0.9136) and neutral stocks (0.8736). These results confirm that both green and brown stocks are riskier than neutral stocks. In addition, brown stocks turn out to be even riskier than green stocks.

These patterns remain stable when focusing on the COVID-19 period (columns (4) to (6)). Nevertheless, returns are even lower and risk measures higher compared to the whole quarter. Neutral stocks are the most resilient during the pandemic period.

4.3.2 Interrelation between carbon risk exposure and return

This section focuses on the interplay between a stock's sensitivity towards carbon risk and its return pattern. We use cross-sectional regressions on different stocks groups to determine the impact of carbon beta on returns. The cross-section comprises over 10,000 stocks, thus allowing to inferring reliable conclusions. Table 3 summarizes the results for all groups based on the first quarter of 2020 and the COVID-19 period. We use cumulative daily returns as dependent

[25] Görgen et al. (2020b) find in a portfolio analysis, that extremely green and brown portfolios, respectively, are prone to different common factor exposures, which partly drive their return patterns. Controlling for common risk exposures, however, leads to the same return patterns.

[26] This finding is consistent with the portfolio analysis of Görgen et al. (2020b). They find that green and brown portfolios are riskier than neutral portfolios in different analyses, even though the sorting approach on the carbon beta risk measure implies higher volatility.

variable and control for further variables known to significantly influence stock return patterns (in line with Albuquerque et al., 2020).

[Insert Table 3 here.]

When taking into account all stocks, the carbon beta does not have a significant influence on returns during the first quarter of 2020 (see column (1)). Obviously, there does not exist a linear relationship between carbon beta and returns. To unravel effects for distinct stock groups, we analyze green, neutral, and brown stocks separately in columns (2) to (4). In the first quarter of 2020, the carbon beta had a significantly positive influence of 0.109 on the returns of green stocks. In contrast, the influence of carbon beta on the cumulative return of brown stocks was –0.179. Neutral stocks' returns were not significantly exposed to carbon beta. These results deliver important insights on the interrelation between a stock's carbon risk exposure and return patterns. Since green stocks have a negative carbon beta, extremely green stocks lose return compared to green stocks with higher carbon beta (i.e. green stocks that are browner). Brown stocks with a positive carbon beta also lost during the first quarter of 2020 and being extremely brown was even worse. In fact, we observe that moving towards the zero point of greenness/brownness from both directions led to more resilience. This relation is not symmetrical though, since the influence of carbon beta on returns was more pronounced for brown than for green stocks.

We repeat the same analysis for the COVID-19 period in columns (5) to (8) of Table 3. In essence, we find the same results. The effect of carbon beta on the green stock group turns out to be stronger than for the whole first quarter period. Thus, in the COVID-19 period the influence of carbon beta on stock return was more prominent for green stocks (beta value of 0.155) than for brown stocks (–0.149). As a robustness check, we redo our analysis with industry fixed effects to account for industry-specific crisis responses. Our results remain stable (see Table A.1 of the supplementary material).

In summary, during the crisis period and in the heat of COVID-19, investors were better off by relying on neutral stocks. Stocks with absolute high carbon risk sensitivity (either green or brown), proved to be less resilient. A difference-in-differences estimation based on daily returns confirms this result, as during the COVID-19 period green and brown stocks (the treatment group) significantly performed worse than the neutral (control) group. Furthermore, the difference-in-differences estimator (DID) is significantly negative, i.e. green and brown stocks lost more during the COVID-19 period than neutral stocks (see Table A.2 of the supplementary material).

4.3.3 Interrelation between carbon risk exposure and volatility

Besides returns, we investigate the role of carbon risk sensitivity for return volatilities. For this purpose, we repeat the cross-sectional regressions and use the daily return volatility over the first quarter of 2020 and the COVID-19 period, respectively, as dependent variables.

[Insert Table 4 here.]

Table 4 summarizes all model results. Taking into account all stocks, the carbon beta has a significantly positive influence on return volatility, irrespective of the considered time period (columns (1) and (5)). This might suggest a linear relationship between carbon beta and volatility. However, based on our results of Table 2, we expect the relationship to show a U-shaped pattern, since both ends of carbon beta, i.e. green and brown stocks, displayed higher volatilities than neutral stocks. This hypothesis is confirmed with the results of the green, neutral, and brown subgroups. The volatility during the first quarter of 2020 for green stocks is negatively influenced by the carbon beta (–0.00946). Since the carbon beta is negative for green stocks, extremely green stocks display higher volatilities than green stocks with an absolute lower carbon beta. Besides, extremely brown stocks have higher volatilities than less brown stocks. The volatility of neutral stocks is not significantly related to carbon beta, which in summary leads to a U-shaped relationship between carbon beta and volatility.

The influence of carbon beta on volatility rises for all groups when focusing on the COVID-19 period (columns (5) to (8)). This is in line with expectations, since stock volatility is higher during crisis periods. Overall, the effect of carbon beta on brown stocks is strongest, i.e. extremely brown stocks are the most volatile, more so than extremely green stocks.[27] Investors trying to avoid risk exposure were better off investing in neutral stocks.

4.4 Conclusion

With this paper, we shed light on the intersection between two of the most recent challenges of humankind: carbon risk as long-term risk and the COVID-19 pandemic as short-term risk source. We highlight in how far a stock's exposure towards carbon risk influenced its resilience in times of COVID-19. We find that investors were better off by avoiding extreme risk exposures. This means that both extremely green and extremely brown stocks lost more in terms of cumulative return than stocks neutral towards carbon risk exposure. From a risk perspective, both green and brown stocks displayed higher volatilities in the first quarter of 2020 as well as in the COVID-19 period. However, brown stocks were even riskier than green stocks. Thus, we conclude that pure green and brown business models are not sufficient to mitigate crisis periods. However, being on the forefront of sustainability, i.e. being green, was more beneficial than being brown during the COVID-19 pandemic. Our findings may provide new insights into the development of green stimulus packages for a post-pandemic economy. In future, as the transition process towards a low-carbon world accelerates, we expect green stocks to build on their advantage compared to brown stocks and even outpace neutral stocks.

[27] These results remain robust when including industry fixed effects. Results can be found in Table A.3 of the supplementary material.

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Tables

Table 1
Descriptive statistics

Variable	N	Mean	SD	P25	Median	P75
Carbon Beta	14,381	-0.0161	0.2197	-0.1189	-0.0246	0.0712
Cum. Returns Q1	13,944	-28.0618	19.9987	-41.1213	-27.8373	-15.2255
Cum. Returns COVID-19	13,558	-26.0666	17.7339	-37.2890	-25.1496	-13.9752
Volatility Q1	13,940	4.3492	1.8087	3.0858	4.0166	5.2335
Volatility COVID-19	13,860	5.9575	2.6763	4.0736	5.4427	7.3195
Tobin's Q	11,892	1.6573	1.4747	0.9329	1.1374	1.7350
Size	12,358	13.7929	1.8868	12.4724	13.7187	15.1066
Cash	11,330	0.1247	0.1316	0.0324	0.0822	0.1704
Leverage	11,943	0.2478	0.1875	0.0771	0.2312	0.3851
Return on Equity	11,673	0.0438	0.2536	0.0171	0.0760	0.1374
SGAE	14,373	0.1161	0.1637	0.0000	0.0539	0.1584
Historical Volatility	14,354	2.2075	1.0130	1.5139	1.9952	2.6828
Dividends	14,283	1.1397	2.2889	0.0000	0.0585	1.1964

This table provides descriptive statistics of all variables used in this study. Carbon beta measures the carbon risk exposure following Görgen et al. (2020a). Return and volatility measures are given in percent. The cum. return Q1 shows the performance of a stock over the first quarter of 2020, while cum. returns COVID-19 is measured for the period from 02/24/2020 to 03/31/2020. Volatility Q1 is the daily return volatility of a stock during the first quarter of 2020 and volatility COVID-19 is the volatility during the period from 02/24/2020 and 03/31/2020, respectively. Tobin’s Q is defined as the sum of the equity market value and the liabilities market value over the sum of the equity book value and the liabilities book value. Size is measured as the natural logarithm of the market capitalization. Cash represents cash holdings over total assets. Leverage equals total debt over total assets. Return on equity is defined as net income less preferred dividend requirements over the average of last year's and current year’s common equity. SGAE represents the expenses for selling, general and administrative functions. The historical volatility is the daily return volatility of a firm during 2019. Dividends are measured as the ratio to the stock price.

Table 2
Descriptive comparison of stock groups

	First Quarter 2020			COVID-19 period		
	(1) Green	(2) Neutral	(3) Brown	(4) Green	(5) Neutral	(6) Brown
Carbon Beta	-0.1684	-0.0019	0.1940	-0.1683	-0.0020	0.1937
Mean Daily Return	-0.5388	-0.4370	-0.5186	-1.1545	-0.9163	-1.0668
Median Daily Return	-0.3531	-0.2830	-0.3909	-1.2447	-1.0651	-1.2170
Volatility	4.3042	3.9872	4.7834	5.8621	5.5171	6.5585
VaR 25%	-2.2049	-1.9569	-2.4518	-4.4743	-4.0658	-4.8211
VaR 10%	-5.1380	-4.6371	-5.4829	-8.4621	-7.7463	-9.0860
VaR 5%	-7.6947	-6.9804	-8.1366	-10.3635	-9.5613	-11.2427
VaR 1%	-13.8603	-13.0915	-15.5486	-13.6141	-12.8084	-15.3187
Maximum Drawdown	45.4036	41.3326	46.4210	38.7097	35.0578	39.4352
Market Beta	0.9136	0.8736	1.0207	0.9138	0.8745	1.0224

This table provides average return and risk characteristics for green, neutral, and brown stock groups, respectively. Columns (1) to (3) refer to the first quarter of 2020, whereas columns (4) to (6) are restricted to the COVID-19 period from 02/24/2020 to 03/31/2020. Return, volatility, VaR, and maximum drawdown are given as a percentage.

Table 3
Cross-sectional regressions for cumulative returns

	First Quarter 2020				COVID-19 period			
	(1) All	(2) Green	(3) Neutral	(4) Brown	(5) All	(6) Green	(7) Neutral	(8) Brown
Carbon Beta	0.0143	0.109***	0.0400	-0.179***	0.0378***	0.155***	0.0165	-0.149***
	(1.24)	(3.43)	(0.36)	(-5.85)	(3.70)	(6.23)	(0.16)	(-5.67)
Tobin's Q	0.0232***	0.0223***	0.0148***	0.0315***	0.00995***	0.00721***	0.00369	0.0197***
	(14.29)	(8.95)	(5.43)	(9.91)	(7.78)	(3.96)	(1.62)	(7.46)
Size	0.000310	0.000896	0.00456*	-0.00436	-0.00319***	-0.00424**	0.00105	-0.00521**
	(0.28)	(0.53)	(2.55)	(-1.87)	(-3.33)	(-2.97)	(0.65)	(-2.59)
Cash	0.151***	0.152***	0.189***	0.103***	0.179***	0.178***	0.194***	0.146***
	(9.55)	(6.21)	(6.33)	(3.61)	(13.48)	(8.99)	(7.38)	(6.03)
Leverage	-0.151***	-0.199***	-0.148***	-0.0903***	-0.150***	-0.187***	-0.151***	-0.0983***
	(-14.25)	(-12.45)	(-8.02)	(-4.31)	(-15.72)	(-12.77)	(-8.87)	(-5.46)
Return On Equity	0.0317***	0.0361**	0.0161	0.0410*	0.0193*	0.0252*	-0.00899	0.0306*
	(3.47)	(2.63)	(0.85)	(2.56)	(2.47)	(2.13)	(-0.52)	(2.34)
SGAE	0.00331	-0.0297	0.0142	0.0184	0.0326**	0.00340	0.0600**	0.0273
	(0.26)	(-1.58)	(0.63)	(0.70)	(2.88)	(0.20)	(2.94)	(1.22)
Historical Volatility	-4.928***	-3.250***	-6.189***	-3.536***	-5.247***	-3.698***	-6.234***	-3.727***
	(-18.86)	(-7.59)	(-12.89)	(-6.23)	(-23.04)	(-9.90)	(-14.37)	(-7.67)
Dividends	-0.000895	-0.00353**	-0.00316**	0.00260*	0.00526***	0.00323**	0.00423***	0.00767***
	(-1.29)	(-2.87)	(-2.69)	(2.25)	(8.34)	(2.82)	(3.88)	(7.62)
Constant	-0.188***	-0.207***	-0.200***	-0.149***	-0.104***	-0.0928***	-0.125***	-0.106**
	(-10.98)	(-8.00)	(-7.19)	(-4.01)	(-7.07)	(-4.27)	(-5.06)	(-3.28)
Observations	10,763	4,529	3,053	3,181	10,586	4,465	3,018	3,103
Adjusted R^2	0.131	0.139	0.136	0.143	0.139	0.147	0.145	0.151

This table provides the results of cross-sectional regressions for different stock groups. The dependent variable in columns (1) to (4) is the cumulative return of the first quarter of 2020, and in columns (5) to (8) the cumulative return during the COVID-19 period (02/24/2020 to 03/31/2020). Control variables are defined as in Table 1. ***, **, and * indicate significance at the 0.1%, 1%, and 5% level, respectively.

Table 4
Cross-sectional regressions for volatilities

	First Quarter 2020				COVID-19 period			
	(1) All	(2) Green	(3) Neutral	(4) Brown	(5) All	(6) Green	(7) Neutral	(8) Brown
Carbon Beta	0.00676***	-0.00946***	0.00838	0.0205***	0.0134***	-0.0121**	0.0189	0.0350***
	(6.80)	(-3.65)	(0.97)	(7.98)	(8.90)	(-2.62)	(1.37)	(8.83)
Tobin's Q	0.000217*	0.000186	0.000394*	0.000141	0.000139	0.0000628	0.000424	0.0000771
	(2.07)	(1.25)	(1.99)	(0.71)	(0.83)	(0.26)	(1.36)	(0.23)
Size	0.000730***	0.000867***	0.000535***	0.000650***	0.00145***	0.00162***	0.00122***	0.00135***
	(8.50)	(6.83)	(3.68)	(3.57)	(10.53)	(7.90)	(5.34)	(4.60)
Cash	-0.0158***	-0.0114***	-0.0185***	-0.0175***	-0.0269***	-0.0191***	-0.0312***	-0.0308***
	(-13.96)	(-7.09)	(-8.72)	(-8.06)	(-14.88)	(-7.24)	(-9.19)	(-9.03)
Leverage	0.0110***	0.0148***	0.0113***	0.00561**	0.0170***	0.0236***	0.0177***	0.00757**
	(12.24)	(11.06)	(6.91)	(3.29)	(11.98)	(10.90)	(6.82)	(2.87)
Return On Equity	-0.00498***	-0.00600***	-0.00184	-0.00590***	-0.00699***	-0.00848***	-0.00232	-0.00834***
	(-6.64)	(-5.33)	(-1.24)	(-4.51)	(-5.98)	(-4.61)	(-1.01)	(-4.25)
SGAE	0.00380***	0.00604***	0.00296	0.00240	0.00982***	0.0130***	0.00943***	0.00744*
	(4.05)	(4.56)	(1.77)	(1.21)	(6.60)	(6.04)	(3.57)	(2.39)
Historical Volatility	0.929***	0.801***	0.988***	0.756***	1.091***	0.865***	1.155***	0.863***
	(40.78)	(22.30)	(24.30)	(14.72)	(32.03)	(15.31)	(18.17)	(11.59)
Dividends	-0.000202***	-0.0000240	-0.0000390	-0.000481***	-0.000142	0.000198	0.000129	-0.000618***
	(-3.40)	(-0.24)	(-0.39)	(-4.65)	(-1.60)	(1.32)	(0.83)	(-4.05)
Constant	0.0111***	0.00774***	0.0115***	0.0165***	0.0124***	0.00823**	0.0120***	0.0198***
	(8.34)	(4.10)	(5.08)	(5.46)	(5.89)	(2.73)	(3.40)	(4.13)
Observations	10,761	4,528	3,053	3,180	10,739	4,526	3,049	3,164
Adjusted R^2	0.295	0.291	0.252	0.299	0.206	0.187	0.171	0.229

This table provides the results of cross-sectional regressions for different stock groups. The dependent variable in columns (1) to (4) is the return volatility of the first quarter of 2020 and in columns (5) to (8) the return volatility during the COVID-19 period (02/24/2020 to 03/31/2020). Control variables are defined as in Table 1. ***, **, and * indicate significance at the 0.1%, 1%, and 5% level, respectively.

Supplementary material

Table A.1
Cross-sectional regressions for cumulative returns with industry fixed effects

	First Quarter 2020				COVID-19 period			
	(1) All	(2) Green	(3) Neutral	(4) Brown	(5) All	(6) Green	(7) Neutral	(8) Brown
Carbon Beta	0.0417***	0.0987**	0.0403	-0.0815**	0.0572***	0.137***	0.0183	-0.0583*
	(3.79)	(3.18)	(0.38)	(-2.85)	(5.82)	(5.50)	(0.19)	(-2.27)
Tobin's Q	0.0153***	0.0159***	0.00932***	0.0197***	0.00334**	0.00155	-0.000408	0.00976***
	(9.56)	(6.24)	(3.38)	(6.58)	(2.67)	(0.84)	(-0.17)	(4.01)
Size	0.000324	0.000435	0.00153	0.000103	-0.00298**	-0.00390**	-0.00109	-0.00232
	(0.30)	(0.26)	(0.85)	(0.05)	(-3.17)	(-2.74)	(-0.68)	(-1.19)
Cash	0.138***	0.138***	0.195***	0.0854**	0.176***	0.173***	0.210***	0.139***
	(8.65)	(5.55)	(6.45)	(3.03)	(13.30)	(8.70)	(7.94)	(5.82)
Leverage	-0.143***	-0.188***	-0.137***	-0.0892***	-0.140***	-0.177***	-0.140***	-0.0895***
	(-13.73)	(-11.93)	(-7.50)	(-4.40)	(-14.90)	(-12.28)	(-8.26)	(-5.07)
Return On Equity	0.0412***	0.0442**	0.0347	0.0441**	0.0272***	0.0298*	0.00263	0.0380**
	(4.54)	(3.14)	(1.84)	(2.86)	(3.54)	(2.48)	(0.16)	(3.03)
SGAE	-0.0351**	-0.0458*	-0.00607	-0.0594*	-0.0114	-0.0231	0.0274	-0.0418
	(-2.68)	(-2.39)	(-0.25)	(-2.26)	(-1.00)	(-1.37)	(1.32)	(-1.87)
Historical Volatility	-4.515***	-3.283***	-6.241***	-3.225***	-4.970***	-3.854***	-6.297***	-3.671***
	(-17.23)	(-7.48)	(-13.07)	(-5.77)	(-21.79)	(-10.13)	(-14.30)	(-7.83)
Dividends	-0.00198**	-0.00363**	-0.00388***	-0.000122	0.00397***	0.00266*	0.00303**	0.00526***
	(-2.91)	(-2.91)	(-3.34)	(-0.11)	(6.39)	(2.27)	(2.83)	(5.51)
Observations	10,763	4,529	3,053	3,181	10,586	4,465	3,018	3,103
Adjusted R^2	0.205	0.182	0.199	0.253	0.208	0.192	0.207	0.249

This table provides the results of cross-sectional regressions for different stock groups. The dependent variable in columns (1) to (4) is the cumulative return of the first quarter of 2020, and in columns (5) to (8) the cumulative return during the COVID-19 period (02/24/2020 to 03/31/2020). Control variables are defined as in Table 1. Industry fixed effects are included. ***, **, and * indicate significance at the 0.1%, 1%, and 5% level, respectively.

Table A.2

Difference-in-differences regressions for daily returns

	Before COVID-19 period	COVID-19 period
Neutral (Control)	-0.00096	-0.00830
Green & Brown (Treatment)	-0.00123	-0.00985
Difference (Treatment – Control)	-0.00027*	-0.00155***
DID	-0.00128***	

This table displays results for a difference-in-differences regression. The neutral stock group serves as the control group, whereas both the green and brown stock group are subsumed to the treatment group. The difference-in-differences estimator (DID) is provided in the last row. ***, **, and * indicate significance at the 0.1%, 1%, and 5% level, respectively.

Table A.3
Cross-sectional regressions for volatilities with industry fixed effects

	First Quarter 2020				COVID-19 period			
	(1) All	(2) Green	(3) Neutral	(4) Brown	(5) All	(6) Green	(7) Neutral	(8) Brown
Carbon Beta	0.00472***	-0.00832**	0.00884	0.0141***	0.00994***	-0.0104*	0.0201	0.0242***
	(4.77)	(-3.19)	(1.05)	(5.61)	(6.58)	(-2.20)	(1.49)	(6.42)
Tobin's Q	0.000421***	0.000353*	0.000555**	0.000376	0.000486**	0.000348	0.000728*	0.000466
	(3.98)	(2.23)	(2.86)	(1.89)	(2.87)	(1.39)	(2.40)	(1.39)
Size	0.000596***	0.000799***	0.000576***	0.000207	0.00121***	0.00149***	0.00126***	0.000634*
	(6.98)	(6.19)	(3.92)	(1.15)	(8.86)	(7.15)	(5.39)	(2.22)
Cash	-0.0159***	-0.0115***	-0.0197***	-0.0180***	-0.0267***	-0.0186***	-0.0326***	-0.0312***
	(-14.10)	(-7.12)	(-9.19)	(-8.42)	(-14.77)	(-7.03)	(-9.55)	(-9.33)
Leverage	0.0106***	0.0146***	0.0101***	0.00560***	0.0161***	0.0231***	0.0156***	0.00753**
	(11.84)	(11.02)	(6.17)	(3.32)	(11.35)	(10.69)	(5.97)	(2.89)
Return On Equity	-0.00424***	-0.00541***	-0.00181	-0.00416***	-0.00576***	-0.00738***	-0.00240	-0.00565**
	(-5.72)	(-4.76)	(-1.25)	(-3.30)	(-4.97)	(-3.98)	(-1.07)	(-2.97)
SGAE	0.00757***	0.00862***	0.00692***	0.00678***	0.0162***	0.0174***	0.0164***	0.0147***
	(7.91)	(6.45)	(3.99)	(3.38)	(10.69)	(7.99)	(6.03)	(4.69)
Historical Volatility	0.905***	0.815***	1.005***	0.728***	1.059***	0.893***	1.194***	0.823***
	(39.88)	(22.81)	(24.73)	(14.53)	(31.33)	(15.88)	(18.67)	(11.43)
Dividends	-0.0000757	0.0000498	0.0000950	-0.000321**	0.0000567	0.000321*	0.000351*	-0.000379*
	(-1.27)	(0.48)	(0.95)	(-3.15)	(0.63)	(2.05)	(2.26)	(-2.49)
Observations	10,761	4,528	3,053	3,180	10,739	4,526	3,049	3,164
Adjusted R^2	0.333	0.313	0.292	0.356	0.249	0.212	0.217	0.292

This table provides the results of cross-sectional regressions for different stock groups. The dependent variable in columns (1) to (4) is the return volatility of the first quarter of 2020 and in columns (5) to (8) the return volatility during the COVID-19 period (02/24/2020 to 03/31/2020). Control variables are defined as in Table 1. Industry fixed effects are included. ***, **, and * indicate significance at the 0.1%, 1%, and 5% level, respectively.

5 Enhancing the accuracy of firm valuation with multiples using carbon emissions

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Abstract. Carbon emissions are nowadays an important driver of the value of a firm. We are the first to analyze the potential of carbon emissions data in enhancing the accuracy of firm valuations using the similar public company methodology with multiples. Using carbon emissions has a potential to improve firm valuation accuracy in two separate ways. First, we construct multiples based on carbon emissions (CEM) which are able to estimate firm values. And second, we create more precise peer groups by including carbon emissions (CEPG) in the composition process. To gain deeper insights, we are conducting further analyses, e.g. by measuring the accuracy of carbon emissions peer groups and carbon emissions multiples at valuing carbon intensive or carbon inefficient firms. We extend our study by looking at firms in countries with carbon pricing or by taking ESG and SDGs concerns into account. Overall, we find that CEPG improves the accuracy of firm valuations in more than three quarters of all cases whereas CEM have limited use. Therefore, we recommend analysts, asset managers and investors to include carbon emissions data into their peer group composition.

Keywords: Corporate finance, Firm valuation, Multiples, Climate finance, Carbon emissions, Similar public companies method, Peer group composition

JEL Classification: G14, G32, Q54

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5.1 Introduction

In the latest global risks perception survey the failure of climate change mitigation and adaption is ranked first by its impact (World Economic Forum, 2020). The awareness of these climate-related financial risks has grown in recent years especially since the Paris COP 21 (International Monetary Fund, 2019). In addition, most countries have committed to emission mitigation and are introducing respective policies, e.g. carbon pricing or carbon taxes (World Bank Group, 2019). These recent developments impact firms depending on their amount of carbon emissions and can lead to a significant change in their firm value. Motivated by the concerns of investors, asset managers, regulators and standard setters about the risk of an accelerating climate change on firm value, we assess possible applications of carbon emissions data to improve the accuracy of firm valuation.

We are the first to analyze the valuation potential of carbon emissions data using one of the most used firm-valuation approaches: multiples based on the similar public company method. Using carbon emissions can help constructing more accurate multiples for firm valuation in two ways. First, we construct carbon emissions-based multiples (carbon emissions multiples, CEM) and evaluate their firm valuation accuracy. And second, we identify and compose a more suitable peer group (carbon emissions peer group, CEPG) for firm valuations using carbon emissions as a classification criteria. Our results can be used by practitioners, e.g. analysts, asset managers and investors, to improve the accuracy of their firm valuation approaches.

Our basic multiples approach is as follows. First of all, we construct multiples based on different financial and non-financial indicators. Next, we compose peer groups of similar firms based on their characteristics. Now, we can form a self-excluding average multiple within each peer group for each firm. We use the average multiple of a peer group to estimate a firm’s value. Afterwards, we can compare the valuation error by subtracting the estimated from the observed firm value. Subsequently, we are evaluating the valuation accuracy of a multiple by computing four different error measures: logarithmic error, absolute logarithmic error, overvaluation percentage, and absolute logarithmic error percentage. We aggregate these error measures in four different ways across all firms and peer groups using either the arithmetic mean, the median, the geometric mean or the harmonic mean. After this procedure, we are able to evaluate the firm valuation accuracy of each financial and non-financial multiple as well as of each peer group composing.

Throughout all our analyses, we use common financial and accounting data from Refinitiv Datastream and Worldscope[28] to compile a global firm data sample of more than 27,000 firms on a yearly basis. We add carbon emissions data from three major data providers, Refinitiv ESG, CDP and Sustainalytics, to broaden our coverage and address known biases within the data collection approaches.

In our first analyses, we use carbon emissions to construct CEM and evaluate their firm valuation accuracy. For this purpose, we use Scope 1 and Scope 2 carbon emissions in relation to either the equity or the entity value of a firm. We find that CEM have on average higher absolute logarithmic errors as well as a lower percentage of absolute logarithmic error below 15%. In contrast, in most cases they have lower logarithmic errors which points to significantly higher percentage of undervaluations. This observation is reinforced by a higher percentage of undervaluations in all cases.

In our second analyses, we examine the valuation potential of carbon emissions data by including them into the peer group composition procedure. Firms with similar carbon emissions are affected to a similar extent by investor behavior, e.g. divestment, as well as additional risks from climate policies, e.g. carbon tax. We find that we can increase the accuracy of a firm

[28] Formerly known as Thomson Reuters Datastream and Worldscope.

valuation significantly using CEPG. We measure a higher accuracy of the estimated firm value using the logarithmic error and especially the absolute logarithmic error as our error measure. Our results hold across all four error aggregation methods as well as for both equity and entity multiples. Measured by the percentage of overvaluation, we receive a mixed picture, but more precise valuations are achieved in half of the cases. However, the percentage of absolute logarithmic error of multiples below 15% is slightly higher if we include carbon emissions.

If we combine our analyses by constructing CEM using CEPG, we observe only a limited improvement in the firm valuation accuracy in comparison with financial multiples in all cases across all aggregation measures as well as for both equity and entity multiples. We find that our results are mostly driven by a more suitable composition of peer groups rather than the use of CEM.

To gain further insights, we carry out numerous analyses. Our main findings even hold for important subgroups. We find that we were able to increase the accuracy of firm valuations, especially for firms with reported carbon emissions data available. A similar picture emerges if we look at carbon intensive industries. Here, the inclusion of carbon emissions into the composition of peer groups leads to more precise firm valuations. However, we cannot find similar results when considering carbon intensive firms.

In order to include the current climate policy development, we also carried out two analyses in which we look at firms that are located in countries with a carbon pricing initiative. In the first case, we cover countries with a national carbon pricing initiative. In the second case, we also take regional carbon pricing initiatives into account. We show that an improvement in the accuracy of firm valuations can be achieved in both CEM and CEPG cases.

If, on the other hand, we take into consideration the recent increasing relevance of the climate topic for asset management, we conclude that more precise firm valuations are obtained for relatively fewer firms even before and for relatively more firms since 2010. Considering the differences between various geographical regions, we observe only minor differences. The highest CEM and CEPG firm valuation accuracy is achieved in Asia, but if we combine the two approaches, the best results are achieved in Oceania. Overall, 16 out of 18 geographical cases show a 50% or higher firm valuation accuracy.

In a further analyses, we are taking ESG and SDGs issues into account. We find that the firm valuation accuracy increases especially for firms with low ESG ratings. This is due to the fact that ESG ratings also include many carbon-related components such as carbon efficiency or carbon emissions. But beyond that, ESG ratings are also expressing the general adaptability to ESG issues, which is particularly weak at low ratings and thus affecting firm value in particular. We find similar effects for firms that are located in countries with a high SDG 13 (Climate Action) performance. In this case, the country's SDGs performance indicates that it is actively involved in combatting climate change and therefore have, for example, reduced its carbon emissions to meet its NDCs.

Overall, our study shows that it is worthwhile to use carbon emissions for the composition of suitable peer groups (CEPG) and in certain cases also for the construction of multiples (CEM). Analysts, asset managers and investors can improve their firm valuation accuracy by using CEPG. Our paper contributes to studies that analyze the impact of carbon emissions on firm value and to studies on the valuation of firms, especially those that use multiples.

A fast growing strand of literature is analyzing the impact of carbon emissions on firm value. Carbon emissions and carbon disclosure have a significant positive effect on the value of a firm (Matsumura, Prakash, & Vera-Muñoz, 2014). Especially, mandatory carbon disclosure has a significant impact on the market valuation of a firm and the overall market efficiency. It increases market liquidity (higher trading volume) and lowers information asymmetries (lower bid-ask spreads) for carbon-intensive firms (Krueger, 2015; Liesen, Figge, Hoepner, & Patten, 2017). Furthermore, investors and firms do care about carbon emission disclosures (Brammer & Pavelin, 2006; Griffin, Lont, & Sun, 2017).

From a risk perspective, high carbon emissions add additional risk on a firm, thereby impacting its value. Environmental friendliness and environmental risks, of which carbon emissions are a huge part of, have a significant impact on firm value (Fernando, Sharfman, & Uysal, 2017). The risk of emitting carbon as a firm can also be measured by analyzing, e.g. extreme weather events, which show a lowering firm value effect for carbon intensive firms (Berkman, Jona, & Soderstrom, 2019). Moreover, carbon emissions increase a firm's tail risk (Ilhan, Sautner, & Vilkov, 2019). In addition, firms with high carbon emissions intensity and high carbon risk have lower stock returns (Bolton & Kacperczyk, 2019; Görgen et al., 2020). However, if firms receive free carbon certificates, they profit from this 'free lunch' and have comparable higher returns (Oestreich & Tsiakas, 2015).

Firm valuation can be conducted via various equity and entity approaches that are mainly divided into being market-based or fundamental-based. One of the most used firm valuation market-based approaches in practice is the similar public company method (Asquith, Mikhail, & Au, 2005; Koller, Goedhart, & Wessels, 2005; Pinto, Robinson, & Stowe, 2019). This method is grounded in the belief of Jevon's law of one price (Jevons, 1879), so that no identical good can be traded at different prices in efficient markets. Due to the large number of different ways to apply multiples for firm valuation, we follow best practices in applying multiples for firm valuation purposes (Plenborg & Pimentel, 2016).

The literature focuses on the valuation accuracy of multiples as a main criterion to prove their usefulness. Most studies analyze either the composition of suitable peer groups, the aggregation of multiples within a peer group, or the most useful variables to compose multiples. Studies focusing on a suitable peer group composition (Eberhart, 2001, 2004) should control for differences within peer groups (Henschke & Homburg, 2009) to identify similar firms. Early studies advise to compose peer groups using a firm's industry classification (Alford, 1992), and its characteristics (Bhojraj & Lee, 2002). New studies propose to integrate insights about similar internet searched firms (Lee, Ma, & Wang, 2015) to compile optimal peer groups.

To aggregate multiples within a peer group, several authors have suggested to correct for related biases using different aggregation methods, e.g. mean, median, geometric mean or harmonic mean (Cooper & Lambertides, 2014; Dittmann & Maug, 2008). Furthermore, we use several error measures to obtain detailed knowledge of distortions within our results: logarithmic error, absolute logarithmic error, overvaluation percentage, and absolute logarithmic error percentage (Chullen, Kaltenbrunner, & Schwetzler, 2015). To additionally improve the accuracy of a multiple-based firm valuation, a study suggest to use a combination of multiples (Yoo, 2006).

The selection of financial indicators for multiples is part of some studies. Many multiples are based on either cash flows or earnings (Chen, Folsom, Paek, & Sami, 2014), which contain different valuation information (Liu, Nissim, & Thomas, 2007). Other studies construct valid multiples based on historical balance sheet key indicators, e.g., asset, sales and earning values (Lie & Lie, 2002; Yin, Peasnell, & Hunt, 2018), analyst forecasts, e.g., forward earnings (Liu, Nissim, & Thomas, 2002), or different cash flow measures, e.g. operating cash flow (Koller, Goedhart, & Wessels, 2015; Liu et al., 2007).

The range of applications with multiples is large. Multiples are used, e.g. for the assessment of the value of initial public offerings (IPOs) (Deloof, Maeseneire, & Inghelbrecht, 2009; Kim & Ritter, 1999). Different studies focus on the valuation accuracy of multiples in specific geographical areas, e.g., European or Asian countries (Herrmann & Richter, 2003; Schreiner & Spremann, 2007; Sehgal & Pandey, 2010) or sector-specific areas, e.g. internet firms (Trueman, Wong, & Zhang, 2000). Furthermore, multiples are used to predict future returns (An, Bhojraj, & Ng, 2010) or to test the value impact of majority or minority ownership (Graham & Lefanowicz, 1999).

The remainder of our analysis is structured as follows: Section 1 presents the used carbon and financial data, Section 2 explains the applied construction methodology to obtain suitable peer groups and multiples. Section 3 provides the results using CEM to determine firm value. Section 4 presents the findings about the usefulness of CEPG. Section 5 combines both CEM and CEPG. Section 6 provides further insights based on additional robustness analyses. Section 7 concludes.

5.2 Data

Following common global sample construction approaches of papers like Schmidt, Arx, Schrimpf, Wagner, and Ziegler (2019), Hou, Karolyi, and Kho (2011), and Ince and Porter (2006), we compile yearly global financial data from Refinitiv Datastream. We apply common screening techniques introduced in Ince and Porter (2006) and exclude all firms that are not identified as equity (e.g. ADRs) or which are not primary listed. Moreover, we include only firms that account for approximately 99.5% of a country's market capitalization to reduce liquidity biases. This leaves us a global firm data sample of 27,667 unique firms for our sample period from 2002 to 2019[29].

To avoid common data biases related to carbon data, e.g., self-reporting bias, we also take three different carbon data providers with differing data collection and quality approaches into account (Busch, Johnson, Pioch, & Kopp, 2018). Furthermore, this merge enables us to lengthen our analysis in time as well as broaden our coverage of global firms.

[29] A descriptive statistics of the used variables can be found in the appendix Table A.1 and a geographic and sectoral breakdown in Table A.2.

5.2.1 Carbon data

With respect to latest literature dealing with data issues (Busch et al., 2018), e.g. data collection processes and self-reporting biases in carbon data, we merge three major data providers: CDP, Refinitiv ESG, and Sustainalytics. Each database is used in many publications covering environmental, carbon and climate topics, e.g. CDP: (Görgen et al., 2020; Ilhan et al., 2019; Ioannou, Li, & Serafeim, 2016); Refinitiv Asset 4/ESG: (Dyck, Lins, Roth, & Wagner, 2019; Gibson, Krueger, Riand, & Schmidt, 2019; Görgen et al., 2020); and Sustainalytics: (Engle, Giglio, Lee, Kelly, & Stroebel, 2020; Gibson et al., 2019; Verheyden, Eccles, & Feiner, 2016).

Our data comprises two dimensions of reported carbon emissions: Scope 1 (direct emissions) and Scope 2 (indirect emissions). Due to the lack of high quality data of Scope 3 (indirect emissions within the value chain of a firm), we leave them out of our analysis. Furthermore, we extend our analysis beyond pure carbon emissions towards carbon intensity by dividing all carbon emissions by net sales.

5.2.2 Financial data

We use common financial data from Refinitiv Datastream and Worldscope. From the P&L we use net sales and revenues, earnings, net and gross income, EBIT and EBITDA to construct respective multiples. We build balance sheet multiples using the following variables: common equity, total assets and total capital. The third group of multiples uses cash flow data including net cash flow from operating activities and cash dividends paid. We extend our dataset using estimates from I/B/E/S, e.g. 1 and 2 year analyst forecasts for earnings, net sales, and EBITDA to compile forward-looking multiples. Equity value is measured by price and entity value by its respective value. To sort firms according to their size, we use market values. We identify the sector of a firm using the Thomson Reuters Business Classification (TRBC).

5.3 Multiple construction methodology

To determine the value of a firm using multiples, we start by identifying similar firms and composing peer groups. Subsequently, we construct multiples and calculate the self-excluding average multiple for each peer group firm. Afterwards, we are able to determine a value for a firm using these multiples and the respective reported variable of the firm. Therefore, we can determine the firm valuation accuracy by comparing the reported value of a firm with its estimated multiple-based value.

Figure 1 shows all financial and carbon multiples used within this analysis. We assume that carbon emissions data can be used to construct either equity or entity-based multiples. Therefore, we use them in both cases.

[Insert Figure 1 here.]

5.3.1 Identifying and composing suitable peer group

We are using several firm characteristics to identify a similar public firm, which is suitable for a respective peer group. First, we use the business classification of a firm as the main peer group criteria. In untabulated results, we extend our peer group composition adding further common fundamental characteristics, e.g. size or profitability (Lie & Lie, 2002). We include carbon emissions in our second analyses to compose CEPG. Within each peer group there must be at least ten different firms, so that we obtain meaningful results that are less driven by extreme values of individual firms.

5.3.2 Constructing and aggregating multiples

The used multiples are commonly formed as follows in our analyses:

$$m_p = \frac{\mathrm{fv}_p}{rv_p} \tag{1}$$

A multiple m of a peer group firm p is a fraction with the numerator fv as the firm value and the denominator rv as the reference value.

$$m_p\, rv_t \; = \widehat{fv}_t \tag{2}$$

By multiplying the multiple of the peer group $m_p$with the reference value rv_t of the target firm, we receive an estimated firm value $\widehat{fv}_t$.

Following Chullen, Kaltenbrunner, and Schwetzler (2015), we use four different aggregation measures to improve the valuation accuracy of our peer group multiples: arithmetic mean $\left(\bar{m}_p{}^A\right)$, median $\left(\bar{m}_p{}^M\right)$, harmonic mean $\left(\bar{m}_p{}^H\right)$ and geometric mean $\left(\bar{m}_p{}^G\right)$. These measures are defined as:

$$\bar{m}_p{}^A = \sum_{i=1}^{n}\left[\frac{fv_i}{rv_i}\right]\frac{1}{n} \tag{3}$$

$$\bar{m}_p{}^M = inf\left\{\frac{fv_i}{rv_i}: F\left(\frac{fv_i}{rv_i}\right) \geq \frac{1}{2}\right\} \tag{4}$$

$$\bar{m}_p{}^H = \frac{1}{\left[\sum_{i=1}^{n}\left[\frac{1}{\frac{fv_i}{rv_i}}\right]\right] \div n} \tag{5}$$

$$\bar{m}_p{}^G = exp\left\{\frac{1}{n}\sum_{i=1}^{n} ln\left[\frac{fv_i}{rv_i}\right]\right\} \tag{6}$$

In practice, analysts widely use the average of the peers' multiples as the simplest approach to calculate the aggregated multiple. But this approach lacks robustness towards outliers. Peer group multiples based on mean values suffer from the impact of extreme observations. Both the harmonic mean and median values avoid the impact of extreme values, and empirical evidence documents that both averaging processes perform significantly better than mean values (and geometric means).

In the literature, most studies use the median or the harmonic mean as an aggregate multiple approach (Baker & Ruback, 1999; Henschke & Homburg, 2009; Liu et al., 2002; Schreiner & Spremann, 2007). Only some studies include the geometric mean (Herrmann & Richter, 2003). Overall, it is documented in the literature that the harmonic mean is less biased than the arithmetic mean, the geometric mean, or the median if percentage errors are used as the error measure for firm valuation accuracy. Using logarithmic errors, however, the harmonic mean is biased downward as much as the arithmetic mean is biased upward, whereas the geometric mean and the median are unbiased. Therefore, we use each aggregation method in its most proven field of application and briefly describe how the others are performing.

5.3.3 Determining firm valuation errors

Several error measures are used to judge the accuracy of a firm valuation approach, which all have their benefits and shortcomings (Chullen et al., 2015). Therefore, we use several measures capturing different accuracy dimensions, e.g. the percentage of over- or undervaluations, logarithmic-scaled and the absolute logarithmic-scaled errors. These accuracy measures are defined as follows:

$$e_{per} = \frac{\widehat{fv}_t - fv_p}{fv_p} \tag{7}$$

$$e_{log} = ln\left(\frac{\widehat{fv}_t}{fv_p}\right) \tag{8}$$

$$e_{alog} = \left| ln\left(\frac{\widehat{fv}_t}{fv_p}\right) \right| \tag{9}$$

In our analyses, we generally report the logarithmic error, the absolute logarithmic error, the overvaluation percentage, and the absolute logarithmic error percentage below 15%.

5.4 Constructing new multiples using carbon data

First, we want to study if non-financial but valuation relevant multiples of comparable firms can be used in a similar manner to common financial ones. According to the aforementioned literature, high carbon emissions and carbon footprints have an impact on the value of a firm. Therefore, we use carbon emissions to construct new multiples and analyze their firm valuation accuracy.

We construct carbon emissions multiples (CEM) based on Scope 1 (CE I), Scope 2 (CE II) and the sum of both scopes (CE I & II) emissions for both estimating equity and entity values. As mentioned in the methodology chapter, we are using four different aggregation methods and four different error measures to evaluate the firm valuation accuracy of multiples.

[Insert Table 1 here.]

Table 1 provides us with the results displaying the logarithmic error for 25 different multiples. The multiples based on both carbon emission scopes leads to the least logarithmic error and is comparable towards some financial-based multiples. But if we consider the higher average logarithmic error of our carbon emissions equity and entity multiples, we can only note a limited use of CEM. This is in line with our expectations, since carbon emissions have an influence, but not the most important impact, on the value of a firm.

[Insert Table 2 here.]

In the next Table 2 we find these results confirmed for the next error measure. Regarding the absolute logarithmic error, we find significantly higher firm valuation errors both for each single carbon emissions multiple as wells as for the average across them.

[Insert Table 3 here.]

In contrast, when looking at the percentage of overvaluations in Table 3, we find a significantly lower value for all CEM. With only 47.7% of overvalued firms, the carbon emissions Scope 1 multiples has the lowest value across all 25 constructed multiples. This can also be confirmed in the following Table 4, where we present the percentage of absolute logarithmic errors above

15%. On average, we get four percentage points lower errors. This is particularly important, as CEM-based estimated firm values are thus only in a few cases far from the true observed firm value.

[Insert Table 4 here.]

Overall, we can therefore conclude that CEMs are suitable for a firm valuation to only a limited extent. However, its valuation error is usually caused by an undervaluation and may therefore compensate the potential overvaluation of financial multiples.

5.5 Constructing peer groups using carbon data

To determine the potential of carbon emissions data in enhancing multiples, we first analyze if the inclusion of carbon emissions into the peer group composition can improve the accuracy of firm valuations. Therefore, we apply the described methodology to construct different equity and entity value-based multiples. Following this, we annually divide all firms into deciles according to their carbon emissions. This classification is now also incorporated into the composition of peer groups towards carbon emissions peer groups (CEPG). As a result, within one year and one industry there are now firms in a peer group that have similar carbon emissions.[30]

[Insert Table 5 here.]

Table 5 presents firm valuation accuracy evaluated by the logarithmic error of the estimated firm value using 19 different financial multiples in comparison to the observed firm value. Each multiple is classified as either equity or entity value-based. The table also presents all four possible aggregation methods of firm valuations errors across all firms and years. As an example, the first multiple P / SA, which is based on net sales or revenues and aggregated across

[30] We also include several other common characteristics to compose peer groups, e.g., size or profitability. Our results remain robust.

peer group firms with the average mean, has a logarithmic error across all firm year observations within our sample of 0.324. In comparison with the corresponding value 0.971 of Table 1, which is just using normal peer groups, we observe a firm valuation logarithmic error reduced by two-thirds. For the average mean aggregation of multiples, this helps reducing the logarithmic error of overvaluation in all cases. We achieve similar results for both the median and the geometric mean, but the harmonic mean results in an increased occurrence of significant undervaluation percentages.

[Insert Table 6 here.]

In Table 6, we now compare the results for the absolute logarithmic error. Taking a look, e.g., at the earnings based multiple (P / EBT), we observe an absolute logarithmic error with a value of 0.826. By enhancing the peer group using carbon emissions, this error value is halved to 0.462. This improved firm valuation accuracy can be assessed across all four aggregation methods.

[Insert Table 7 here.]

To provide further insides on the ratio of over- and undervaluations, we measure the percentage of overvaluations in Table 7. For all financial multiples, we get around 6% less overvaluations for the carbon emissions peer groups. This supports the result of Table 5 that the use of carbon emissions to compose peer groups helps improving the firm valuation accuracy.

[Insert Table 8 here.]

In our last analysis within this chapter, we have a look at the percentage of absolute logarithmic errors below 15% in Table 8. In line with the results of Table 6, we have an increased percentage across all aggregation methods and multiples. Therefore, the use of CEPG leads to less accurate firm valuations according to this error measure.

Overall, we can conclude that two of the error measures lead to improvements in the firm valuation accuracy, one too mixed and one to a worsening of the results. Furthermore, it can be stated that the use of CEPG leads to significantly fewer overvaluations. The possible undervaluation is therefore the biggest problem and must be taken into account.

5.6 Combining carbon emission multiples and carbon emission enhanced peer groups

In the following analyzes, we now look at the results when we combine both approaches, CEM and CEPG. Therefore, we construct carbon emissions-based multiples and use carbon emissions-enhanced peer groups. Our evaluation considers again the four different aggregation methods for multiples and the four alternative firm valuation error measures.

[Insert Table 9 here.]

Table 9 provides first the results of the logarithmic error analysis. Compared to the CEM from Table 1 without using CEPG, we now obtain significantly lower valuation errors. If we now compare these new CEM with the different multiples from Table 5, they are more precise, but still not the most accurate firm valuation multiple.

[Insert Table 10 here.]

This finding is also continued in Table 10. We can see that we now have significantly fewer absolute logarithmic errors than before, but they are still higher compared to financial multiples. These results do not vary if we use different aggregation methods.

[Insert Table 11 here.]

In a next step, we again consider the share of overvaluations in Table 11. We observe only a little difference, which, in the context of the previous results, suggests that the combination of the two approaches has a low effect on reducing the percentage of undervaluations.

[Insert Table 12 here.]

Table 12 provides the results for the fourth error measure. In comparison with earlier results we get slightly higher error values across all aggregation measures.

Overall, it can be concluded that the combination of the two approaches is definitely useful for improving the firm valuation accuracy of CEM. However, CEM are still not able to estimate firm values to the same precision as many financial multiples. For this reason, we continue to view it as particularly worthwhile to use carbon emissions mainly for the composition of the peer groups of financial multiples (CEPG).

5.7 Robustness

In order to increase the significance of our results regarding the usefulness of CEM and CEPG, we carry out numerous further analyses, which we briefly outline in the following. Table 13 presents the results of all different cases.[31]

[Insert Table 13 here.]

Each case is evaluated whether it increases the valuation accuracy either using CEPG, CEM or both. Both equity and entity multiples as well as the four aggregation measures and the four error measures are used for the evaluation. Therefore, a total of 32 values per procedure are considered for the evaluation of the firm valuation accuracy. We indicate in the table the percentage of the 32 values in which an improvement of the firm valuation accuracy is found.

In a first step, we provide the results of our last analyses (Case 1). In the second step (Case 2), we consider only those firms that have carbon emissions available in at least 50% of our sample period. This ensures that the selected firms regularly report their carbon emissions. As a result, it can be assumed that the quality of these emissions data is significantly higher.

[31] A detailed presentation of the results for each case can be found in the appendix tables: Table A.3 to Table A.12.

We get slightly better results using CEPG than in our evaluation of all firms (Case 1), while the results for CEM and the combination of both remains basically the same.

In the next case, we look at firms that are either part of carbon intensive industries (Case 3) or are emitting high carbon emissions (Case 4). Carbon intensive industries include firms from the following business sectors according to the Thomson Reuters Business Classification (TRBC): Energy - Fossil Fuels, Mineral Resources, Transportation, Automobiles & Auto Parts, and Utilities. Carbon intensive firms are defined as those firms which are during a year among the 25% largest carbon emitters. Overall, the firms of carbon intensive industries can be valued accurate and their firm valuation accuracy is improved to a similar extent by our two approaches CEM and CEPG. If we look at the carbon-intensive firms, we can see that they can also be valued accurate overall, i.e. we observe low valuation errors. However, both CEM and CEPG lead to a more precise firm value accuracy in only one-third of the used aggregation methods and error measures, which is lower than in most other cases.

Usually, not only the absolute amount of carbon emissions plays a role in the valuation of a firm. The carbon efficiency, measured as carbon intensity, is also considered in two cases for carbon efficient and carbon inefficient firms (Case 5 and 6). Our results remain very consistent for both firm groups, so that we assume that both indicators can be considered in a similar manner when valuing firms based on their carbon intensity.

In a further case, we assume that the existence of carbon pricing initiatives (CPI) within a country leads to an increased impact of carbon emissions on a firm value. For example, the introduction of a carbon emissions certificate system leads to increased costs for firms. Therefore, we use in one case (Case 7) only firms of countries with a national CPI. And in another case (Case 8), we loosen this condition by including all countries with either a national or a regional CPI. We are referring to the carbon pricing dashboard of the World Bank to detect currently active CPIs (Dolphin, Pollitt, & Newbery, 2016; World Bank Group, 2019). The accuracy of firm valuations increases, in particular if we use CEPG.

Next, we consider whether our results depend on the topicality of the climate crisis debate (Case 9 and 10). It can be assumed that only in recent years the interest in carbon emissions has increased by a huge amount. This leads to the assumption that carbon emissions have become more relevant in terms of value impact nowadays (Engle et al., 2020). Therefore, we split our sample into two separate time periods: before and since 2010. The choice of the year 2010 was chosen because, e.g. we observe a huge increase of available carbon emissions data within all three of our data providers. In line with our expectations, we are getting better firm valuation results since 2010, but the use of our methods is also useful before 2010.

Afterwards, we examine our results for differences across geographical regions. We analyze the following regions individually: USA (Case 11), Europe (Case 12), Americas (Case 13), Asia (Case 14), Oceania (Case 15) and Africa (Case 16).[32] However, we cannot see any major differences between the different regions and in all cases CEPG is worth using to improve the firm valuation accuracy.

In addition to the previous analyses, we are now including ESG information about individual firms (Case 17 and 18). We assume that the quality of the non-financial reporting and thus also of the carbon emissions is higher for ESG firms, but also that the influence of emissions on the firm value is strongly moderated by the ESG rating. For our analysis we use the Refinitiv ESG score. Overall, we find that for firms with high ESG ratings, CEPG is the most useful approach to improve firm value accuracy. In contrast, low ESG firm values are much less accurately assessed.

[32] We have very few firms from Africa and Oceania as well as from low SDG countries or with low ESG ratings, so only half of all firms are required for the composition of a peer group.

In our last analysis, we want to analyze whether the SDG 13 (Climate Action) performance of a country has an influence on the carbon emissions and firm value relationship. Such an influence should be reflected by more accurate firm value estimations (Case 19 and 20). We are using data from the Sustainable Development Report (Sachs et al., 2019) to analyze the top 25 and the worst 50 SDG 13 performing countries separately. We find only slight improvements for the top 25 countries.

Overall, we can state on the results of the twenty different cases that the use of CEPG can be recommended in all cases to improve the accuracy of firm valuations using multiples.

5.8 Recommendation for using carbon emissions for multiples and further research

Based on the results of our numerous analyses, we find a limited potential of estimating firm values with CEM. However, we can suggest the use of CEPG in most cases. The inclusion of carbon emissions to compose peer groups, leads to an increase in the firm valuation accuracy in more than three quarters of our cases.

In order to further improve the composition of peer groups, a propensity score matching can be useful. Beyond common financial indicators, carbon emissions can be included to identify similar firms for valuation purposes. Further studies may focus on including the illiquidity discount (Damodaran, 2005; Officer, 2007; Pratt & Niculita, 2008) or the control premium (Betton, Eckbo, & Thorburn Karin S., 2009; Petersen, Plenborg, & Scholer, 2006; Pratt & Niculita, 2008) into the valuation approach. It may also be promising to study the valuation potential of multiples comprising of ESG ratings or scores, even if the ratings of different providers differ considerably (Gibson et al., 2019).

Overall, we recommend including carbon emissions into the composition of peer groups based on our results. Our approach yields consistent, efficient, and accurate firm valuations for asset managers and investors to improve their investment decision making. It also increases the accuracy of analysts' firm valuation estimations, especially for carbon emissions impacted firms. Finally, it helps capital market participants, regulators, and firms to better understand the inclusion of carbon emissions information into the valuation process of a firm.

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Figures and Tables

Figure 1

Overview of the main calculated multiples

	(1) Non-financial	(2) P&L	(3) Balance sheet	(4) Cash flow	(5) Forward-looking
Equity value	*P / CE I*	*P / SA*	*P / CEQ*	*P / OCF*	*P / E 1*
	P / CE II	*P / EBT*		*P / D*	*P / E 2*
	P / CE I + II	*P / E*			
Entity value	*EV / CE I*	*EV / SA*	*EV / TA*	*EV / OCF*	*EV / SA 1*
	EV / CE II	*EV / GI*	*EV / TC*		*EV / SA 2*
	EV / CE I + II	*EV / EBIT*			*EV / EBITDA 1*
		EV / EBITDA			*EV / EBITDA 2*

This figure provides an overview of the main calculated multiples. They are either equity or entity value-based and can be classified into five categories: (1) Carbon emissions multiples (CEM) are based on carbon emissions scope 1 (CE I), scope 2 (CE II), and scope 1 and 2 combined (CE I + II). (2) Multiples using key figures from the profit & loss statement are consisting of net sales or revenues (SA), pre-tax income (EBT), net income (E), gross income (GI), earnings before interest and taxes (EBIT), and earnings before interest, taxes, depreciation and amortization (EBITDA). (3) Balance sheet multiples are composed of common equity (CEQ), total assets (TA), or total capital (TC). (4) Net cash flow from operating activities (OCF) and paid cash dividends (D) are used to compile cash flow multiples. (5) Forward-looking multiples are made of analyst one and two year forecasts of earnings (E 1 and E 2), net sales or revenues (SA 1 and SA 2) and earnings before interest, taxes, depreciation and amortization (EBITDA 1 and EBITDA 2).

Table 1
Carbon emissions multiples (CEM) firm valuation accuracy as per logarithmic error

	Multiples	AM	ME	HM	GM
Equity Value Multiples	*P / CE I*	1.029	0.027	-0.917	0.055
	P / CE II	0.752	0.033	-0.568	0.080
	P / CE I & II	0.752	0.030	-0.691	0.068
	P / SA	0.971	0.081	-0.524	0.120
	P / EBT	0.701	0.087	-0.191	0.183
	P / E	0.709	0.083	-0.200	0.170
	P / CEQ	0.546	0.084	-0.268	0.128
	P / OCF	0.753	0.072	-0.322	0.134
	P / D	0.889	0.086	-0.274	0.171
	P / E 1	0.354	0.072	-0.168	0.088
	P / E 2	0.270	0.056	-0.177	0.046
Entity Value Multiples	*EV / CE I*	1.270	0.198	-0.507	0.294
	EV / CE II	1.045	0.254	-0.370	0.265
	EV / CE I & II	0.980	0.197	-0.395	0.264
	EV / SA	1.021	0.187	-0.371	0.243
	EV / GI	0.862	0.186	-0.290	0.233
	EV / EBITDA	0.632	0.136	-0.175	0.193
	EV / EBIT	0.705	0.169	-0.167	0.237
	EV / TA	0.588	0.106	-0.411	0.136
	EV / TC	0.616	0.128	-0.339	0.171
	EV / OCF	0.887	0.188	-0.215	0.269
	EV / SA 1	0.588	0.160	-0.304	0.147
	EV / SA 2	0.529	0.135	-0.327	0.124
	EV / EBITDA 1	0.360	0.080	-0.130	0.095
	EV / EBITDA 2	0.294	0.070	-0.172	0.065
ø Overall		0.724	0.116	-0.339	0.159
ø carbon EQ Multiples		0.844	0.030	-0.725	0.067
ø fin. EQ Multiples		0.649	0.078	-0.265	0.130
ø carbon EV Multiples		1.099	0.216	-0.424	0.274
ø fin. EV Multiples		0.644	0.140	-0.264	0.174

This table presents 25 multiples constructed. They are either equity or entity value-based and can be classified into five categories: (1) Carbon emissions multiples (CEM) are based on carbon emissions scope 1 (CE I), scope 2 (CE II), and scope 1 and 2 combined (CE I + II). Please check previous tables for the definitions of the other four categories. Each logarithmic error of each multiple is a measure for the multiples valuation accuracy and represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table 2
Carbon emissions multiples (CEM) firm valuation accuracy as per absolute logarithmic error

	Multiples	**AM**	**ME**	**HM**	**GM**
Equity Value Multiples	*P / CE I*	1.256	0.849	1.151	0.917
	P / CE II	0.951	0.722	0.848	0.728
	P / CE I & II	1.017	0.749	0.939	0.757
	P / SA	1.101	0.703	0.810	0.716
	P / EBT	0.813	0.500	0.482	0.523
	P / E	0.826	0.494	0.471	0.529
	P / CEQ	0.692	0.534	0.553	0.537
	P / OCF	0.878	0.544	0.592	0.557
	P / D	1.000	0.564	0.571	0.583
	P / E 1	0.471	0.360	0.357	0.366
	P / E 2	0.401	0.329	0.345	0.332
Entity Value Multiples	*EV / CE I*	1.416	0.865	0.955	0.966
	EV / CE II	1.148	0.833	0.802	0.794
	EV / CE I & II	1.166	0.776	0.825	0.834
	EV / SA	1.127	0.721	0.741	0.733
	EV / GI	0.974	0.665	0.675	0.678
	EV / EBITDA	0.727	0.513	0.500	0.528
	EV / EBIT	0.793	0.531	0.502	0.555
	EV / TA	0.713	0.560	0.642	0.565
	EV / TC	0.737	0.560	0.593	0.572
	EV / OCF	0.984	0.572	0.564	0.604
	EV / SA 1	0.764	0.614	0.651	0.618
	EV / SA 2	0.714	0.588	0.635	0.595
	EV / EBITDA 1	0.495	0.399	0.397	0.415
	EV / EBITDA 2	0.449	0.374	0.389	0.381
ø Overall		0.864	0.597	0.640	0.615
ø carbon EQ Multiples		1.075	0.773	0.980	0.801
ø fin. EQ Multiples		0.773	0.503	0.523	0.518
ø carbon EV Multiples		1.243	0.825	0.861	0.865
ø fin. EV Multiples		0.771	0.554	0.572	0.568

This table presents 25 multiples constructed. They are either equity or entity value-based and can be classified into five categories: (1) Carbon emissions multiples (CEM) are based on carbon emissions scope 1 (CE I), scope 2 (CE II), and scope 1 and 2 combined (CE I + II). Please check previous tables for the definitions of the other four categories. Each absolute logarithmic error of each multiple is a measure for the multiples valuation accuracy and represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table 3

Carbon emissions multiples (CEM) firm valuation accuracy as per overvaluation percentage

	Multiples	AM	ME	HM	GM
Equity Value Multiples	*P / CE I*	47.7%	49.7%	23.8%	51.0%
	P / CE II	48.0%	50.9%	29.0%	52.0%
	P / CE I & II	47.9%	50.4%	26.6%	51.1%
	P / SA	80.7%	53.2%	30.8%	54.9%
	P / EBT	80.9%	56.2%	40.5%	61.3%
	P / E	81.2%	56.2%	40.0%	61.2%
	P / CEQ	75.7%	54.7%	37.0%	56.3%
	P / OCF	80.6%	54.4%	34.4%	57.6%
	P / D	83.1%	54.7%	36.8%	58.8%
	P / E 1	73.8%	55.6%	39.5%	57.3%
	P / E 2	71.1%	55.6%	37.7%	55.2%
Entity Value Multiples	*EV / CE I*	61.2%	56.5%	33.3%	59.2%
	EV / CE II	60.3%	56.2%	36.6%	58.2%
	EV / CE I & II	60.6%	56.1%	34.7%	57.9%
	EV / SA	82.1%	57.4%	35.7%	59.3%
	EV / GI	80.1%	57.8%	38.3%	59.8%
	EV / EBITDA	78.8%	58.8%	42.2%	61.7%
	EV / EBIT	80.2%	60.0%	43.0%	63.2%
	EV / TA	75.8%	56.0%	33.8%	57.0%
	EV / TC	76.8%	57.0%	36.5%	58.7%
	EV / OCF	83.2%	58.8%	40.2%	62.8%
	EV / SA 1	74.6%	56.0%	36.3%	56.4%
	EV / SA 2	73.1%	55.7%	36.0%	55.5%
	EV / EBITDA 1	73.3%	57.2%	41.6%	58.5%
	EV / EBITDA 2	71.5%	56.9%	39.9%	56.9%
ø Overall		72.1%	55.7%	36.2%	57.7%
ø carbon EQ Multiples		47.8%	50.4%	26.5%	51.4%
ø fin. EQ Multiples		78.4%	55.1%	37.1%	57.8%
ø carbon EV Multiples		60.7%	56.3%	34.9%	58.4%
ø fin. EV Multiples		77.2%	57.4%	38.5%	59.1%

This table presents 25 multiples constructed. They are either equity or entity value-based and can be classified into five categories: (1) Carbon emissions multiples (CEM) are based on carbon emissions scope 1 (CE I), scope 2 (CE II), and scope 1 and 2 combined (CE I + II). Please check previous tables for the definitions of the other four categories. Each overvaluation percentage of each multiple is a measure for the multiples valuation accuracy and represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table 4
Carbon emissions multiples (CEM) firm valuation accuracy as per absolute log. error percentage

	Multiples	AM	ME	HM	GM
Equity Value Multiples	*P / CE I*	6.0%	9.7%	6.9%	9.4%
	P / CE II	6.6%	11.2%	9.4%	11.1%
	P / CE I & II	6.6%	10.9%	8.2%	10.7%
	P / SA	7.1%	11.8%	10.2%	11.5%
	P / EBT	8.4%	16.9%	17.6%	15.3%
	P / E	8.3%	17.0%	17.7%	15.5%
	P / CEQ	11.5%	15.3%	14.9%	15.0%
	P / OCF	8.2%	15.6%	14.1%	14.9%
	P / D	6.9%	14.6%	14.4%	13.8%
	P / E 1	16.4%	22.9%	22.5%	22.2%
	P / E 2	19.8%	24.8%	23.7%	24.3%
Entity Value Multiples	*EV / CE I*	6.2%	9.8%	8.6%	9.1%
	EV / CE II	6.9%	10.4%	10.3%	10.2%
	EV / CE I & II	6.4%	10.5%	9.5%	10.0%
	EV / SA	6.7%	11.6%	11.1%	11.2%
	EV / GI	7.6%	12.2%	12.5%	11.7%
	EV / EBITDA	10.0%	15.9%	16.7%	15.1%
	EV / EBIT	8.6%	15.3%	16.5%	14.3%
	EV / TA	10.9%	14.4%	13.1%	14.2%
	EV / TC	10.5%	14.5%	14.0%	14.2%
	EV / OCF	6.8%	14.3%	14.7%	13.4%
	EV / SA 1	10.5%	13.4%	12.8%	13.3%
	EV / SA 2	11.3%	13.9%	13.0%	13.7%
	EV / EBITDA 1	15.9%	20.7%	20.5%	20.2%
	EV / EBITDA 2	17.9%	22.1%	21.2%	21.7%
ø Overall		9.7%	14.8%	14.2%	14.2%
ø carbon EQ Multiples		6.4%	10.6%	8.2%	10.4%
ø fin. EQ Multiples		10.8%	17.3%	16.9%	16.6%
ø carbon EV Multiples		6.5%	10.2%	9.5%	9.8%
ø fin. EV Multiples		10.6%	15.3%	15.1%	14.8%

This table presents 25 multiples constructed. They are either equity or entity value-based and can be classified into five categories: (1) Carbon emissions multiples (CEM) are based on carbon emissions scope 1 (CE I), scope 2 (CE II), and scope 1 and 2 combined (CE I + II). Please check previous tables for the definitions of the other four categories. Each absolute logarithmic error percentage above 15% of each multiple is a measure for the multiples valuation accuracy and represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table 5
Carbon emissions peer groups (CEPG) firm valuation accuracy as per logarithmic error

	Multiples	AM	ME	HM	GM
Equity Value Multiples	*P / SA*	0.324	0.050	-0.303	0.068
	P / EBT	0.362	0.062	-0.123	0.098
	P / E	0.321	0.052	-0.131	0.088
	P / CEQ	0.322	0.090	-0.077	0.123
	P / OCF	0.341	0.063	-0.175	0.046
	P / D	0.536	0.106	-0.068	0.161
	P / E 1	0.204	0.049	-0.084	0.057
	P / E 2	0.159	0.050	-0.087	0.048
Entity Value Multiples	*EV / SA*	0.417	0.157	-0.137	0.145
	EV / GI	0.418	0.159	-0.042	0.174
	EV / EBITDA	0.319	0.125	-0.038	0.161
	EV / EBIT	0.423	0.171	-0.015	0.190
	EV / TA	0.337	0.153	-0.053	0.160
	EV / TC	0.375	0.139	-0.019	0.186
	EV / OCF	0.466	0.136	-0.031	0.180
	EV / SA 1	0.358	0.143	-0.084	0.115
	EV / SA 2	0.341	0.160	-0.128	0.095
	EV / EBITDA 1	0.215	0.091	-0.059	0.073
	EV / EBITDA 2	0.173	0.074	-0.072	0.062
ø Overall		0.337	0.107	-0.091	0.117
ø fin. EQ Multiples		0.321	0.065	-0.131	0.086
ø fin. EV Multiples		0.349	0.137	-0.062	0.140

This table presents 19 multiples, which are either equity or entity value-based and can be classified into five categories: (1) Multiples using key figures from the profit & loss statement are consisting of net sales or revenues (SA), pre-tax income (EBT), net income (E), gross income (GI), earnings before interest and taxes (EBIT), and earnings before interest, taxes, depreciation and amortization (EBITDA). (2) Balance sheet multiples are composed of common equity (CEQ), total assets (TA), or total capital (TC). (3) Net cash flow from operating activities (OCF) and paid cash dividends (D) are used to compile cash flow multiples. (4) Forward-looking multiples are made of analyst one and two year forecasts of earnings (E 1 and E 2), net sales or revenues (SA 1 and SA 2) and earnings before interest, taxes, depreciation and amortization (EBITDA 1 and EBITDA 2). Each logarithmic error of each multiple is a measure for the multiples valuation accuracy and represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups are compiled using carbon emissions in addition. Therefore, they are called carbon emissions peer groups (CEPG). The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table 6
Carbon emissions peer groups (CEPG) firm valuation accuracy as per absolute logarithmic error

	Multiples	AM	ME	HM	GM
Equity Value Multiples	*P / SA*	0.554	0.505	0.590	0.510
	P / EBT	0.436	0.360	0.378	0.366
	P / E	0.462	0.347	0.366	0.353
	P / CEQ	0.455	0.402	0.409	0.386
	P / OCF	0.488	0.408	0.440	0.401
	P / D	0.641	0.450	0.438	0.464
	P / E 1	0.345	0.288	0.308	0.296
	P / E 2	0.306	0.263	0.286	0.266
Entity Value Multiples	*EV / SA*	0.657	0.588	0.592	0.586
	EV / GI	0.629	0.539	0.524	0.531
	EV / EBITDA	0.484	0.405	0.414	0.410
	EV / EBIT	0.570	0.445	0.436	0.457
	EV / TA	0.512	0.447	0.450	0.460
	EV / TC	0.513	0.429	0.418	0.458
	EV / OCF	0.593	0.455	0.438	0.457
	EV / SA 1	0.619	0.556	0.558	0.563
	EV / SA 2	0.601	0.538	0.546	0.538
	EV / EBITDA 1	0.394	0.364	0.361	0.351
	EV / EBITDA 2	0.354	0.325	0.331	0.322
ø Overall		0.506	0.427	0.436	0.430
ø fin. EQ Multiples		0.461	0.378	0.402	0.380
ø fin. EV Multiples		0.539	0.463	0.461	0.467

This table presents 19 multiples, which are either equity or entity value-based and can be classified into five categories: (1) Multiples using key figures from the profit & loss statement are consisting of net sales or revenues (SA), pre-tax income (EBT), net income (E), gross income (GI), earnings before interest and taxes (EBIT), and earnings before interest, taxes, depreciation and amortization (EBITDA). (2) Balance sheet multiples are composed of common equity (CEQ), total assets (TA), or total capital (TC). (3) Net cash flow from operating activities (OCF) and paid cash dividends (D) are used to compile cash flow multiples. (4) Forward-looking multiples are made of analyst one and two year forecasts of earnings (E 1 and E 2), net sales or revenues (SA 1 and SA 2) and earnings before interest, taxes, depreciation and amortization (EBITDA 1 and EBITDA 2). Each absolute logarithmic error of each multiple is a measure for the multiples valuation accuracy and represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups are compiled using carbon emissions in addition. Therefore, they are called carbon emissions peer groups (CEPG). The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table 7
Carbon emissions peer groups (CEPG) firm valuation accuracy as per overvaluation percentage

	Multiples	**AM**	**ME**	**HM**	**GM**
Equity Value Multiples	*P / SA*	67.6%	52.7%	34.0%	51.0%
	P / EBT	73.9%	56.1%	41.9%	58.4%
	P / E	74.3%	56.2%	41.4%	58.5%
	P / CEQ	70.3%	54.8%	40.8%	55.8%
	P / OCF	71.1%	53.8%	37.0%	53.9%
	P / D	76.5%	54.3%	41.1%	59.1%
	P / E 1	69.7%	56.6%	42.6%	56.9%
	P / E 2	67.2%	56.7%	42.2%	55.2%
Entity Value Multiples	*EV / SA*	70.7%	56.5%	41.4%	56.6%
	EV / GI	71.9%	56.9%	42.3%	57.2%
	EV / EBITDA	73.3%	59.1%	47.9%	60.8%
	EV / EBIT	76.0%	60.5%	49.0%	63.2%
	EV / TA	69.6%	56.8%	43.2%	57.0%
	EV / TC	71.2%	57.2%	45.4%	58.7%
	EV / OCF	76.0%	58.4%	45.5%	60.8%
	EV / SA 1	69.2%	56.5%	42.8%	56.4%
	EV / SA 2	68.3%	56.3%	42.7%	55.8%
	EV / EBITDA 1	68.2%	57.6%	46.9%	57.8%
	EV / EBITDA 2	66.4%	56.8%	45.9%	56.4%
ø Overall		71.1%	56.5%	42.8%	57.3%
ø fin. EQ Multiples		71.3%	55.2%	40.1%	56.1%
ø fin. EV Multiples		71.0%	57.5%	44.8%	58.2%

This table presents 19 multiples, which are either equity or entity value-based and can be classified into five categories: (1) Multiples using key figures from the profit & loss statement are consisting of net sales or revenues (SA), pre-tax income (EBT), net income (E), gross income (GI), earnings before interest and taxes (EBIT), and earnings before interest, taxes, depreciation and amortization (EBITDA). (2) Balance sheet multiples are composed of common equity (CEQ), total assets (TA), or total capital (TC). (3) Net cash flow from operating activities (OCF) and paid cash dividends (D) are used to compile cash flow multiples. (4) Forward-looking multiples are made of analyst one and two year forecasts of earnings (E 1 and E 2), net sales or revenues (SA 1 and SA 2) and earnings before interest, taxes, depreciation and amortization (EBITDA 1 and EBITDA 2). Each overvaluation percentage of each multiple is a measure for the multiples valuation accuracy and represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups are compiled using carbon emissions in addition. Therefore, they are called carbon emissions peer groups (CEPG). The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table 8

Carbon emissions peer groups (CEPG) firm valuation accuracy as per absolute log. error percentage

	Multiples	AM	ME	HM	GM
Equity Value Multiples	*P / SA*	13.9%	14.9%	12.7%	14.7%
	P / EBT	15.4%	21.9%	21.5%	21.2%
	P / E	15.5%	22.5%	21.9%	21.3%
	P / CEQ	15.4%	18.6%	18.3%	18.3%
	P / OCF	15.5%	19.4%	17.1%	19.0%
	P / D	10.2%	17.7%	18.0%	16.6%
	P / E 1	22.0%	27.5%	26.2%	26.7%
	P / E 2	25.4%	29.4%	27.4%	28.2%
Entity Value Multiples	*EV / SA*	11.9%	13.7%	13.6%	13.7%
	EV / GI	12.3%	15.0%	15.0%	15.0%
	EV / EBITDA	15.2%	19.2%	19.2%	18.5%
	EV / EBIT	12.5%	18.4%	19.1%	17.7%
	EV / TA	14.3%	16.9%	16.1%	16.3%
	EV / TC	14.6%	17.0%	16.7%	16.9%
	EV / OCF	12.2%	17.7%	17.4%	16.8%
	EV / SA 1	12.7%	14.4%	13.7%	14.3%
	EV / SA 2	13.3%	14.5%	14.1%	14.6%
	EV / EBITDA 1	19.9%	22.2%	21.8%	22.1%
	EV / EBITDA 2	21.5%	23.5%	23.3%	23.4%
ø Overall		15.5%	19.2%	18.6%	18.7%
ø fin. EQ Multiples		16.7%	21.5%	20.4%	20.8%
ø fin. EV Multiples		14.6%	17.5%	17.3%	17.2%

This table presents 19 multiples, which are either equity or entity value-based and can be classified into five categories: (1) Multiples using key figures from the profit & loss statement are consisting of net sales or revenues (SA), pre-tax income (EBT), net income (E), gross income (GI), earnings before interest and taxes (EBIT), and earnings before interest, taxes, depreciation and amortization (EBITDA). (2) Balance sheet multiples are composed of common equity (CEQ), total assets (TA), or total capital (TC). (3) Net cash flow from operating activities (OCF) and paid cash dividends (D) are used to compile cash flow multiples. (4) Forward-looking multiples are made of analyst one and two year forecasts of earnings (E 1 and E 2), net sales or revenues (SA 1 and SA 2) and earnings before interest, taxes, depreciation and amortization (EBITDA 1 and EBITDA 2). Each absolute logarithmic error percentage above 15% of each multiple is a measure for the multiples valuation accuracy and represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups are compiled using carbon emissions in addition. Therefore, they are called carbon emissions peer groups (CEPG). The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table 9
Carbon emissions multiples (CEM) with carbon emissions peer groups (CEPG) firm valuation accuracy as per logarithmic error

	Multiples	AM	ME	HM	GM
Equity Value Multiples	*P / CE I*	0.677	0.031	-0.591	0.027
	P / CE II	0.551	0.013	-0.463	0.031
	P / CE I & II	0.478	0.022	-0.409	0.033
Entity Value Multiples	*EV / CE I*	0.855	0.215	-0.253	0.251
	EV / CE II	0.777	0.216	-0.142	0.273
	EV / CE I & II	0.657	0.158	-0.244	0.171
ø Overall		0.666	0.109	-0.350	0.131
ø carbon EQ Multiples		0.569	0.022	-0.487	0.030
ø carbon EV Multiples		0.763	0.196	-0.213	0.232

This table presents 6 carbon emissions multiples (CEM) constructed. They are either equity or entity value-based and can be classified into one category: (1) Carbon emissions multiples (CEM) are based on carbon emissions scope 1 (CE I), scope 2 (CE II), and scope 1 and 2 combined (CE I + II). Each logarithmic error of each multiple is a measure for the multiples valuation accuracy and represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups are compiled using carbon emissions in addition. Therefore, they are called carbon emissions peer groups (CEPG). The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table 10
Carbon emissions multiples (CEM) with carbon emissions peer groups (CEPG) firm valuation accuracy as per absolute logarithmic error

	Multiples	**AM**	**ME**	**HM**	**GM**
Equity Value Multiples	*P / CE I*	0.964	0.766	0.906	0.752
	P / CE II	0.817	0.679	0.758	0.679
	P / CE I & II	0.756	0.663	0.737	0.668
Entity Value Multiples	*EV / CE I*	1.105	0.779	0.827	0.801
	EV / CE II	0.972	0.730	0.745	0.754
	EV / CE I & II	0.904	0.729	0.745	0.734
ø Overall		0.920	0.724	0.786	0.731
ø carbon EQ Multiples		0.846	0.703	0.800	0.700
ø carbon EV Multiples		0.994	0.746	0.772	0.763

This table presents 6 carbon emissions multiples (CEM) constructed. They are either equity or entity value-based and can be classified into one category: (1) Carbon emissions multiples (CEM) are based on carbon emissions scope 1 (CE I), scope 2 (CE II), and scope 1 and 2 combined (CE I + II). Each absolute logarithmic error of each multiple is a measure for the multiples valuation accuracy and represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups are compiled using carbon emissions in addition. Therefore, they are called carbon emissions peer groups (CEPG). The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table 11
Carbon emissions multiples (CEM) with carbon emissions peer groups (CEPG) firm valuation accuracy as per overvaluation percentage

	Multiples	**AM**	**ME**	**HM**	**GM**
Equity Value Multiples	*P / CE I*	48.6%	50.2%	29.7%	50.6%
	P / CE II	49.5%	51.5%	32.5%	51.8%
	P / CE I & II	49.3%	50.8%	31.5%	50.6%
Entity Value Multiples	*EV / CE I*	58.8%	57.0%	39.2%	58.5%
	EV / CE II	58.7%	57.0%	41.0%	58.8%
	EV / CE I & II	59.1%	56.2%	39.2%	56.8%
ø Overall		54.0%	53.8%	35.5%	54.5%
ø carbon EQ Multiples		49.1%	50.8%	31.2%	51.0%
ø carbon EV Multiples		58.9%	56.7%	39.8%	58.0%

This table presents 6 carbon emissions multiples (CEM) constructed. They are either equity or entity value-based and can be classified into one category: (1) Carbon emissions multiples (CEM) are based on carbon emissions scope 1 (CE I), scope 2 (CE II), and scope 1 and 2 combined (CE I + II). Each overvaluation percentage of each multiple is a measure for the multiples valuation accuracy and represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups are compiled using carbon emissions in addition. Therefore, they are called carbon emissions peer groups (CEPG). The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table 12
Carbon emissions multiples (CEM) with carbon emissions peer groups (CEPG) firm valuation accuracy as per absolute log. error percentage

	Multiples	**AM**	**ME**	**HM**	**GM**
Equity Value Multiples	*P / CE I*	7.9%	10.8%	9.1%	11.0%
	P / CE II	8.6%	12.3%	10.4%	12.1%
	P / CE I & II	8.3%	12.7%	10.3%	12.3%
Entity Value Multiples	*EV / CE I*	7.8%	10.4%	9.8%	10.2%
	EV / CE II	8.2%	11.1%	11.1%	10.8%
	EV / CE I & II	8.1%	11.4%	10.8%	11.0%
ø Overall		8.2%	11.5%	10.2%	11.2%
ø carbon EQ Multiples		8.3%	11.9%	9.9%	11.8%
ø carbon EV Multiples		8.1%	11.0%	10.6%	10.7%

This table presents 6 carbon emissions multiples (CEM) constructed. They are either equity or entity value-based and can be classified into one category: (1) Carbon emissions multiples (CEM) are based on carbon emissions scope 1 (CE I), scope 2 (CE II), and scope 1 and 2 combined (CE I + II). Each absolute logarithmic error percentage above 15% of each multiple is a measure for the multiples valuation accuracy and represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups are compiled using carbon emissions in addition. Therefore, they are called carbon emissions peer groups (CEPG). The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table 13
Overview of all cases and their firm valuations accuracy results

Case	Peer group	Multiples	Peer group & Multiples	Case	Peer group	Multiples	Peer group & Multiples
(1) All firms	*81.3%*	*37.5%*	*37.5%*	*(11) USA*	*75.0%*	*37.5%*	*37.5%*
(2) Carbon data available	*87.5%*	*37.5%*	*37.5%*	*(12) Europe*	*65.6%*	*37.5%*	*25.0%*
(3) Carbon intensive industries	*87.5%*	*28.1%*	*31.3%*	*(13) Americas*	*75.0%*	*37.5%*	*37.5%*
(4) Carbon intensive firms	*37.5%*	*31.3%*	*31.3%*	*(14) Asia*	*81.3%*	*40.6%*	*37.5%*
(5) Carbon efficient firms	*78.1%*	*34.4%*	*31.3%*	*(15) Oceania*	*68.8%*	*31.3%*	*43.8%*
(6) Carbon inefficient firms	*34.4%*	*34.4%*	*31.3%*	*(16) Africa*	*53.1%*	*37.5%*	*37.5%*
(7) National carbon pricing	*75.0%*	*34.4%*	*31.3%*	*(17) High ESG firms*	*43.8%*	*28.1%*	*15.6%*
(8) Any carbon pricing	*81.3%*	*37.5%*	*37.5%*	*(18) Low ESG firms*	*65.6%*	*25.0%*	*34.4%*
(9) Since 2010	*71.9%*	*31.3%*	*31.3%*	*(19) High SDG 13 countries*	*81.3%*	*34.4%*	*31.3%*
(10) Before 2010	*87.5%*	*25.0%*	*37.5%*	*(20) Low SDG 13 countries*	*75.0%*	*31.3%*	*12.5%*

This table provides an overview of all firm valuations accuracy results. Each case is evaluated whether it increases the valuation accuracy either using CEPG, CEM or both. Both equity and entity multiples as well as the four aggregation measures and the four valuation accuracy measures are used for the evaluation. Therefore, a total of 32 values per procedure are considered for the evaluation of the firm valuation accuracy. The table indicates the percentage of these 32 cases in which an improvement of the firm valuation accuracy is found.

Appendix

Table A.1
Descriptive statistics

Variable	N	Mean	SD	P25	Median	P75
Panel A. Non-Financials						
Carbon emissions scope 1 & 2	67,738	22,122	116,830	143	821	4,851
Carbon emissions scope 1	64,604	18,024	172,485	29	236	2,136
Carbon emissions scope 2	63,762	3,623	42,964	68	330	1,491
Panel B. Financials						
Market Value	437,594	2,354.00	11,986.37	94.46	307.73	1,090.54
Total Assets	400,787	7,634.06	73,562.04	126.44	419.03	1,668.14
Common Equity	400,637	1,218.49	6,358.33	56.18	176.29	587.58
Total Capital	400,215	2,496.86	22,467.67	76.11	247.60	937.25
Net Sales Or Revenues	402,123	2,106.06	10,266.52	64.04	242.32	928.45
Gross Income	359,471	529.69	2,782.27	15.53	59.14	226.17
EBITDA	379,399	349.57	1,982.91	7.69	33.96	140.32
EBIT	387,452	244.25	1,668.37	3.41	21.77	94.32
EBT	401,916	180.53	1,344.52	1.09	16.00	71.87
Net Income	402,188	126.00	1,051.09	0.70	11.60	52.58
Net Cash Flow Op. Activities	392,539	257.40	2,035.53	1.29	19.29	93.64
Cash Dividends Paid	380,255	61.90	408.84	0.00	2.49	17.31
Sales 1 Year Forecast	211,541	7.01	170.02	0.18	0.58	2.06
Sales 2 Year Forecast	215,562	7.36	178.94	0.20	0.62	2.18
EBITDA 1 Year Forecast	170,320	1.81	107.92	0.04	0.11	0.39
EBITDA 2 Year Forecast	177,900	2.20	188.10	0.04	0.13	0.43
Net Income 1 Year Forecast	204,033	0.67	42.62	0.01	0.04	0.15
Net Income 2 Year Forecast	209,452	0.84	62.97	0.02	0.05	0.17

This table provides descriptive statistics for all variables used. All variables are shown on a yearly basis for all firms within the data sample from 2002 to 2019. All financials are from Refinitiv Datastream and Worldscope.

Table A.2
Geographic and sectoral breakdown

Panel A. Geographic			Panel B. Sectoral		
Country	#	%	Sector	#	%
USA	5,839	21.1	Financials	5,276	19.1
China	3,490	12.6	Industrials	4,575	16.5
Japan	2,781	10.1	Cyclical Cons. Goods & Services	4,245	15.3
Hong Kong	1,240	4.5	Technology	3,406	12.3
Canada	1,237	4.5	Basic Materials	2,990	10.8
United Kingdom	1,180	4.3	Healthcare	2,252	8.1
India	1,171	4.2	Non-Cyclical Cons. Goods & Services	1,982	7.2
Korea	1,122	4.1	Energy	1,730	6.3
Taiwan	1,019	3.7	Utilities	785	2.8
Australia	854	3.1	Telecommunications Services	426	1.5
Other Europe	3,681	13.3			
Other Asia	2,750	9.9			
Other Americas	743	2.7			
Other Africa	462	1.7			
Other Oceania	98	0.4			
Total	27,667	100	Total	27,667	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 2002 to 2019. The sectoral breakdown is based on the Thomson Reuters Business Classification (TRBC).

Table A.3
Overview of all results

			(1) All firms				(2) Carbon data firms			
			AM	ME	HM	GM	AM	ME	HM	GM
Panel A. Peer Group	log error	ø carbon EQ Multiples	*0.569*	*0.022*	*-0.487*	*0.030*	*0.569*	*0.022*	*-0.487*	*0.030*
		ø fin EQ Multiples	*0.321*	*0.065*	*-0.131*	*0.086*	*0.306*	*0.064*	*-0.116*	*0.086*
		ø carbon EV Multiples	*0.763*	*0.196*	*-0.213*	*0.232*	*0.763*	*0.196*	*-0.213*	*0.232*
		ø fin. EV Multiples	*0.349*	*0.137*	*-0.062*	*0.140*	*0.337*	*0.136*	*-0.053*	*0.140*
	alog error	ø carbon EQ Multiples	*0.846*	*0.703*	*0.800*	*0.700*	*0.846*	*0.703*	*0.800*	*0.700*
		ø fin EQ Multiples	*0.461*	*0.378*	*0.402*	*0.380*	*0.449*	*0.374*	*0.395*	*0.376*
		ø carbon EV Multiples	*0.994*	*0.746*	*0.772*	*0.763*	*0.994*	*0.746*	*0.772*	*0.763*
		ø fin. EV Multiples	*0.539*	*0.463*	*0.461*	*0.467*	*0.534*	*0.462*	*0.454*	*0.465*
	overval.	ø carbon EQ Multiples	*49.1%*	*50.8%*	*31.2%*	*51.0%*	*49.1%*	*50.8%*	*31.2%*	*51.0%*
		ø fin EQ Multiples	*71.3%*	*55.2%*	*40.1%*	*56.1%*	*70.7%*	*55.2%*	*40.8%*	*56.1%*
		ø carbon EV Multiples	*58.9%*	*56.7%*	*39.8%*	*58.0%*	*58.9%*	*56.7%*	*39.8%*	*58.0%*
		ø fin. EV Multiples	*71.0%*	*57.5%*	*44.8%*	*58.2%*	*70.6%*	*57.5%*	*45.4%*	*58.3%*
	alog over.	ø carbon EQ Multiples	*8.3%*	*11.9%*	*9.9%*	*11.8%*	*8.3%*	*11.9%*	*9.9%*	*11.8%*
		ø fin EQ Multiples	*16.7%*	*21.5%*	*20.4%*	*20.8%*	*17.1%*	*21.6%*	*20.8%*	*20.9%*
		ø carbon EV Multiples	*8.1%*	*11.0%*	*10.6%*	*10.7%*	*8.1%*	*11.0%*	*10.6%*	*10.7%*
		ø fin. EV Multiples	*14.6%*	*17.5%*	*17.3%*	*17.2%*	*14.8%*	*17.6%*	*17.5%*	*17.3%*
Panel B. Multiples	log error	ø carbon EQ Multiples	*0.844*	*0.030*	*-0.725*	*0.067*	*0.844*	*0.030*	*-0.725*	*0.067*
		ø fin EQ Multiples	*0.649*	*0.078*	*-0.265*	*0.130*	*0.456*	*0.078*	*-0.190*	*0.105*
		ø carbon EV Multiples	*1.099*	*0.216*	*-0.424*	*0.274*	*1.099*	*0.216*	*-0.424*	*0.272*
		ø fin. EV Multiples	*0.644*	*0.140*	*-0.264*	*0.174*	*0.479*	*0.136*	*-0.127*	*0.163*
	alog error	ø carbon EQ Multiples	*1.075*	*0.773*	*0.980*	*0.801*	*1.075*	*0.773*	*0.980*	*0.801*
		ø fin EQ Multiples	*0.773*	*0.503*	*0.523*	*0.518*	*0.583*	*0.430*	*0.445*	*0.441*
		ø carbon EV Multiples	*1.243*	*0.825*	*0.861*	*0.865*	*1.243*	*0.825*	*0.861*	*0.865*
		ø fin. EV Multiples	*0.771*	*0.554*	*0.572*	*0.568*	*0.622*	*0.485*	*0.489*	*0.497*
	overval.	ø carbon EQ Multiples	*47.8%*	*50.4%*	*26.5%*	*51.4%*	*47.8%*	*50.4%*	*26.5%*	*51.4%*
		ø fin EQ Multiples	*78.4%*	*55.1%*	*37.1%*	*57.8%*	*75.2%*	*56.1%*	*40.1%*	*57.8%*
		ø carbon EV Multiples	*60.7%*	*56.3%*	*34.9%*	*58.4%*	*60.7%*	*56.3%*	*34.9%*	*58.4%*
		ø fin. EV Multiples	*77.2%*	*57.4%*	*38.5%*	*59.1%*	*74.6%*	*58.1%*	*43.5%*	*59.5%*
	alog over.	ø carbon EQ Multiples	*6.4%*	*10.6%*	*8.2%*	*10.4%*	*6.4%*	*10.6%*	*8.2%*	*10.4%*
		ø fin EQ Multiples	*10.8%*	*17.3%*	*16.9%*	*16.6%*	*14.3%*	*20.1%*	*19.5%*	*19.4%*
		ø carbon EV Multiples	*6.5%*	*10.2%*	*9.5%*	*9.8%*	*6.5%*	*10.2%*	*9.5%*	*9.8%*
		ø fin. EV Multiples	*10.6%*	*15.3%*	*15.1%*	*14.8%*	*13.2%*	*17.3%*	*17.3%*	*16.8%*

This table presents the overview of the results for case (1) and (2). Each measure (logarithmic error, absolute logarithmic error, overvaluation percentage, and absolute log. error percentage) represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups in Panel A. are compiled using carbon emissions. The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table A.4
Overview of all results

			(3) Carbon intensive industries				(4) Carbon intensive firms			
			AM	**ME**	**HM**	**GM**	**AM**	**ME**	**HM**	**GM**
Panel A. Peer Group	**log error**	ø carbon EQ Multiples	*0.657*	*0.022*	*-0.432*	*0.060*	*0.500*	*0.021*	*-0.415*	*0.042*
		ø fin EQ Multiples	*0.310*	*0.056*	*-0.112*	*0.077*	*0.234*	*0.056*	*-0.115*	*0.058*
		ø carbon EV Multiples	*0.832*	*0.222*	*-0.190*	*0.268*	*0.660*	*0.195*	*-0.155*	*0.222*
		ø fin. EV Multiples	*0.335*	*0.136*	*-0.060*	*0.137*	*0.277*	*0.124*	*-0.021*	*0.122*
	alog error	ø carbon EQ Multiples	*0.882*	*0.669*	*0.739*	*0.670*	*0.774*	*0.644*	*0.733*	*0.654*
		ø fin EQ Multiples	*0.481*	*0.385*	*0.408*	*0.387*	*0.424*	*0.363*	*0.391*	*0.371*
		ø carbon EV Multiples	*1.001*	*0.727*	*0.729*	*0.728*	*0.905*	*0.716*	*0.734*	*0.722*
		ø fin. EV Multiples	*0.544*	*0.471*	*0.465*	*0.476*	*0.496*	*0.457*	*0.450*	*0.455*
	overval.	ø carbon EQ Multiples	*50.5%*	*51.3%*	*33.2%*	*52.4%*	*50.0%*	*51.0%*	*33.4%*	*51.2%*
		ø fin EQ Multiples	*69.6%*	*53.7%*	*38.7%*	*54.3%*	*66.1%*	*52.9%*	*39.4%*	*53.1%*
		ø carbon EV Multiples	*62.4%*	*57.7%*	*42.6%*	*59.6%*	*63.1%*	*57.4%*	*42.9%*	*58.4%*
		ø fin. EV Multiples	*69.6%*	*56.9%*	*45.0%*	*57.4%*	*66.2%*	*55.7%*	*46.1%*	*56.2%*
	alog over.	ø carbon EQ Multiples	*8.6%*	*12.2%*	*10.8%*	*12.2%*	*8.8%*	*12.5%*	*10.6%*	*12.4%*
		ø fin EQ Multiples	*16.7%*	*21.4%*	*19.6%*	*20.3%*	*19.8%*	*23.3%*	*21.4%*	*22.1%*
		ø carbon EV Multiples	*7.2%*	*11.4%*	*11.3%*	*10.8%*	*7.7%*	*11.7%*	*11.5%*	*11.4%*
		ø fin. EV Multiples	*14.7%*	*17.2%*	*16.9%*	*16.9%*	*16.7%*	*18.3%*	*18.1%*	*18.1%*
Panel B. Multiples	**log error**	ø carbon EQ Multiples	*1.184*	*0.017*	*-0.593*	*0.143*	*0.571*	*0.023*	*-0.513*	*0.020*
		ø fin EQ Multiples	*0.769*	*0.100*	*-0.300*	*0.156*	*0.246*	*0.043*	*-0.134*	*0.047*
		ø carbon EV Multiples	*1.396*	*0.239*	*-0.224*	*0.412*	*0.751*	*0.209*	*-0.230*	*0.204*
		ø fin. EV Multiples	*0.761*	*0.196*	*-0.233*	*0.236*	*0.282*	*0.098*	*-0.056*	*0.103*
	alog error	ø carbon EQ Multiples	*1.356*	*0.787*	*0.891*	*0.814*	*0.873*	*0.713*	*0.829*	*0.718*
		ø fin EQ Multiples	*0.889*	*0.529*	*0.565*	*0.550*	*0.432*	*0.366*	*0.392*	*0.375*
		ø carbon EV Multiples	*1.499*	*0.778*	*0.804*	*0.862*	*1.015*	*0.757*	*0.796*	*0.783*
		ø fin. EV Multiples	*0.891*	*0.597*	*0.619*	*0.612*	*0.489*	*0.444*	*0.453*	*0.450*
	overval.	ø carbon EQ Multiples	*48.6%*	*50.8%*	*29.4%*	*54.5%*	*49.7%*	*50.8%*	*31.2%*	*50.8%*
		ø fin EQ Multiples	*79.5%*	*55.1%*	*35.7%*	*57.7%*	*66.9%*	*52.8%*	*38.9%*	*53.0%*
		ø carbon EV Multiples	*63.6%*	*58.5%*	*40.9%*	*63.3%*	*63.6%*	*56.9%*	*42.2%*	*57.7%*
		ø fin. EV Multiples	*78.7%*	*58.8%*	*39.7%*	*60.3%*	*66.1%*	*55.2%*	*44.9%*	*55.7%*
	alog over.	ø carbon EQ Multiples	*6.8%*	*10.4%*	*9.4%*	*9.8%*	*7.8%*	*11.2%*	*10.1%*	*11.3%*
		ø fin EQ Multiples	*9.8%*	*16.4%*	*15.4%*	*15.6%*	*19.5%*	*23.2%*	*21.2%*	*22.4%*
		ø carbon EV Multiples	*6.7%*	*10.5%*	*10.7%*	*9.5%*	*7.0%*	*10.8%*	*10.5%*	*10.6%*
		ø fin. EV Multiples	*9.5%*	*14.2%*	*13.6%*	*13.6%*	*16.7%*	*18.6%*	*18.3%*	*18.4%*

This table presents the overview of the results for case (3) and (4). Each measure (logarithmic error, absolute logarithmic error, overvaluation percentage, and absolute log. error percentage) represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups in Panel A. are compiled using carbon emissions. The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table A.5
Overview of all results

			(5) High carbon footprint firms				(6) Low carbon footprint firms			
			AM	**ME**	**HM**	**GM**	**AM**	**ME**	**HM**	**GM**
Panel A. Peer Group	**log error**	ø carbon EQ Multiples	*0.558*	*0.024*	*-0.413*	*0.027*	*0.451*	*0.017*	*-0.437*	*0.007*
		ø fin EQ Multiples	*0.282*	*0.056*	*-0.117*	*0.069*	*0.317*	*0.076*	*-0.141*	*0.072*
		ø carbon EV Multiples	*0.741*	*0.209*	*-0.165*	*0.210*	*1.223*	*0.476*	*0.026*	*0.543*
		ø fin. EV Multiples	*0.339*	*0.130*	*-0.018*	*0.147*	*0.632*	*0.320*	*0.050*	*0.328*
	alog error	ø carbon EQ Multiples	*0.801*	*0.637*	*0.712*	*0.637*	*0.762*	*0.667*	*0.789*	*0.675*
		ø fin EQ Multiples	*0.454*	*0.364*	*0.390*	*0.371*	*0.470*	*0.383*	*0.407*	*0.386*
		ø carbon EV Multiples	*0.913*	*0.718*	*0.725*	*0.724*	*1.299*	*0.911*	*0.870*	*0.945*
		ø fin. EV Multiples	*0.531*	*0.463*	*0.459*	*0.459*	*0.770*	*0.619*	*0.589*	*0.625*
	overval.	ø carbon EQ Multiples	*49.9%*	*51.2%*	*33.1%*	*51.5%*	*48.6%*	*50.2%*	*31.9%*	*50.5%*
		ø fin EQ Multiples	*68.0%*	*52.6%*	*38.3%*	*53.2%*	*70.3%*	*55.8%*	*40.5%*	*55.5%*
		ø carbon EV Multiples	*61.7%*	*57.0%*	*42.8%*	*57.9%*	*65.2%*	*62.8%*	*47.9%*	*64.9%*
		ø fin. EV Multiples	*68.0%*	*55.9%*	*45.7%*	*56.9%*	*74.5%*	*62.2%*	*49.3%*	*62.5%*
	alog over.	ø carbon EQ Multiples	*9.7%*	*13.1%*	*10.9%*	*13.2%*	*8.8%*	*13.1%*	*10.9%*	*12.9%*
		ø fin EQ Multiples	*18.4%*	*22.8%*	*20.5%*	*21.5%*	*18.5%*	*22.9%*	*21.5%*	*22.4%*
		ø carbon EV Multiples	*7.8%*	*12.2%*	*11.4%*	*12.0%*	*8.0%*	*9.9%*	*10.5%*	*9.0%*
		ø fin. EV Multiples	*15.7%*	*18.1%*	*17.8%*	*17.8%*	*11.9%*	*14.8%*	*15.9%*	*15.1%*
Panel B. Multiples	**log error**	ø carbon EQ Multiples	*0.733*	*0.036*	*-0.503*	*0.042*	*0.653*	*0.022*	*-0.446*	*0.073*
		ø fin EQ Multiples	*0.336*	*0.065*	*-0.118*	*0.086*	*0.330*	*0.070*	*-0.128*	*0.093*
		ø carbon EV Multiples	*0.807*	*0.195*	*-0.250*	*0.207*	*1.199*	*0.356*	*-0.127*	*0.407*
		ø fin. EV Multiples	*0.372*	*0.116*	*-0.042*	*0.145*	*0.485*	*0.212*	*0.022*	*0.223*
	alog error	ø carbon EQ Multiples	*0.933*	*0.683*	*0.794*	*0.695*	*0.871*	*0.694*	*0.759*	*0.691*
		ø fin EQ Multiples	*0.513*	*0.394*	*0.410*	*0.403*	*0.472*	*0.382*	*0.394*	*0.393*
		ø carbon EV Multiples	*1.038*	*0.739*	*0.775*	*0.732*	*1.300*	*0.833*	*0.803*	*0.874*
		ø fin. EV Multiples	*0.554*	*0.460*	*0.464*	*0.469*	*0.636*	*0.514*	*0.505*	*0.525*
	overval.	ø carbon EQ Multiples	*49.7%*	*51.8%*	*30.2%*	*51.8%*	*48.9%*	*50.5%*	*31.4%*	*51.4%*
		ø fin EQ Multiples	*71.4%*	*53.3%*	*38.0%*	*54.3%*	*72.0%*	*55.2%*	*40.8%*	*56.5%*
		ø carbon EV Multiples	*64.5%*	*57.0%*	*40.1%*	*57.6%*	*63.6%*	*59.0%*	*42.9%*	*61.2%*
		ø fin. EV Multiples	*70.8%*	*56.1%*	*44.7%*	*57.7%*	*73.6%*	*59.3%*	*45.5%*	*60.1%*
	alog over.	ø carbon EQ Multiples	*7.3%*	*12.1%*	*10.3%*	*11.7%*	*6.8%*	*11.9%*	*10.6%*	*11.7%*
		ø fin EQ Multiples	*16.2%*	*21.1%*	*19.2%*	*20.4%*	*17.7%*	*22.8%*	*21.9%*	*22.2%*
		ø carbon EV Multiples	*6.7%*	*11.4%*	*10.8%*	*11.2%*	*6.4%*	*10.6%*	*10.9%*	*9.9%*
		ø fin. EV Multiples	*14.6%*	*17.7%*	*17.4%*	*17.2%*	*14.0%*	*17.8%*	*18.0%*	*17.4%*

This table presents the overview of the results for case (5) and (6). Each measure (logarithmic error, absolute logarithmic error, overvaluation percentage, and absolute log. error percentage) represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups in Panel A. are compiled using carbon emissions. The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table A.6
Overview of all results

			(7) National carbon pricing				(8) Any carbon pricing			
			AM	**ME**	**HM**	**GM**	**AM**	**ME**	**HM**	**GM**
Panel A. Peer Group	**log error**	ø carbon EQ Multiples	*0.511*	*0.008*	*-0.381*	*0.029*	*0.538*	*0.017*	*-0.422*	*0.045*
		ø fin EQ Multiples	*0.239*	*0.038*	*-0.110*	*0.061*	*0.294*	*0.075*	*-0.099*	*0.091*
		ø carbon EV Multiples	*0.760*	*0.250*	*-0.115*	*0.302*	*0.749*	*0.204*	*-0.206*	*0.227*
		ø fin. EV Multiples	*0.304*	*0.113*	*-0.049*	*0.127*	*0.327*	*0.130*	*-0.057*	*0.135*
	alog error	ø carbon EQ Multiples	*0.785*	*0.657*	*0.709*	*0.660*	*0.789*	*0.672*	*0.746*	*0.657*
		ø fin EQ Multiples	*0.419*	*0.354*	*0.376*	*0.362*	*0.426*	*0.347*	*0.371*	*0.356*
		ø carbon EV Multiples	*0.994*	*0.761*	*0.735*	*0.782*	*0.960*	*0.723*	*0.730*	*0.728*
		ø fin. EV Multiples	*0.517*	*0.474*	*0.456*	*0.462*	*0.512*	*0.444*	*0.442*	*0.451*
	overval.	ø carbon EQ Multiples	*49.7%*	*49.6%*	*34.2%*	*51.5%*	*49.2%*	*50.9%*	*32.7%*	*51.8%*
		ø fin EQ Multiples	*67.7%*	*53.4%*	*41.6%*	*54.7%*	*71.4%*	*56.3%*	*41.3%*	*57.2%*
		ø carbon EV Multiples	*63.0%*	*58.6%*	*43.9%*	*59.3%*	*58.3%*	*56.6%*	*40.7%*	*58.1%*
		ø fin. EV Multiples	*68.2%*	*57.3%*	*46.6%*	*57.7%*	*70.5%*	*57.6%*	*45.3%*	*58.3%*
	alog over.	ø carbon EQ Multiples	*8.4%*	*12.8%*	*11.5%*	*12.5%*	*8.7%*	*12.5%*	*11.2%*	*12.4%*
		ø fin EQ Multiples	*19.9%*	*23.6%*	*22.5%*	*22.9%*	*17.6%*	*23.1%*	*22.0%*	*21.9%*
		ø carbon EV Multiples	*7.3%*	*11.1%*	*11.3%*	*10.7%*	*8.3%*	*11.2%*	*11.2%*	*11.0%*
		ø fin. EV Multiples	*15.8%*	*18.0%*	*18.5%*	*18.0%*	*15.4%*	*18.5%*	*18.1%*	*18.0%*
Panel B. Multiples	**log error**	ø carbon EQ Multiples	*0.874*	*0.013*	*-0.723*	*0.035*	*0.812*	*0.026*	*-0.646*	*0.051*
		ø fin EQ Multiples	*0.490*	*0.066*	*-0.199*	*0.104*	*0.639*	*0.092*	*-0.232*	*0.150*
		ø carbon EV Multiples	*1.144*	*0.208*	*-0.374*	*0.287*	*1.062*	*0.202*	*-0.375*	*0.269*
		ø fin. EV Multiples	*0.517*	*0.099*	*-0.233*	*0.118*	*0.640*	*0.143*	*-0.243*	*0.180*
	alog error	ø carbon EQ Multiples	*1.147*	*0.820*	*0.980*	*0.837*	*1.031*	*0.750*	*0.925*	*0.782*
		ø fin EQ Multiples	*0.637*	*0.440*	*0.454*	*0.457*	*0.746*	*0.492*	*0.506*	*0.513*
		ø carbon EV Multiples	*1.320*	*0.869*	*0.887*	*0.912*	*1.197*	*0.814*	*0.847*	*0.857*
		ø fin. EV Multiples	*0.680*	*0.505*	*0.525*	*0.512*	*0.764*	*0.551*	*0.564*	*0.566*
	overval.	ø carbon EQ Multiples	*47.3%*	*49.1%*	*27.8%*	*50.9%*	*47.8%*	*50.2%*	*27.6%*	*51.3%*
		ø fin EQ Multiples	*75.3%*	*54.9%*	*39.4%*	*57.2%*	*78.3%*	*55.8%*	*38.6%*	*58.8%*
		ø carbon EV Multiples	*60.0%*	*55.7%*	*37.2%*	*57.9%*	*60.4%*	*56.1%*	*36.2%*	*58.3%*
		ø fin. EV Multiples	*74.5%*	*56.8%*	*39.6%*	*57.7%*	*77.0%*	*57.5%*	*39.5%*	*59.4%*
	alog over.	ø carbon EQ Multiples	*6.6%*	*10.4%*	*8.5%*	*9.8%*	*6.6%*	*11.0%*	*8.8%*	*10.9%*
		ø fin EQ Multiples	*13.6%*	*19.3%*	*18.9%*	*18.8%*	*11.0%*	*17.9%*	*17.7%*	*16.9%*
		ø carbon EV Multiples	*6.7%*	*9.9%*	*9.5%*	*9.4%*	*6.6%*	*10.6%*	*9.9%*	*10.1%*
		ø fin. EV Multiples	*12.5%*	*16.7%*	*16.6%*	*16.4%*	*10.8%*	*15.6%*	*15.5%*	*15.0%*

This table presents the overview of the results for case (7) and (8). Each measure (logarithmic error, absolute logarithmic error, overvaluation percentage, and absolute log. error percentage) represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups in Panel A. are compiled using carbon emissions. The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table A.7
Overview of all results

			(9) Since 2010				(10) Before 2010			
			AM	ME	HM	GM	AM	ME	HM	GM
Panel A. Peer Group	log error	ø carbon EQ Multiples	*0.582*	*0.009*	*-0.543*	*0.013*	*0.310*	*0.013*	*-0.334*	*-0.004*
		ø fin EQ Multiples	*0.352*	*0.056*	*-0.167*	*0.070*	*0.186*	*0.083*	*0.017*	*0.090*
		ø carbon EV Multiples	*0.770*	*0.180*	*-0.282*	*0.226*	*0.554*	*0.222*	*-0.115*	*0.227*
		ø fin. EV Multiples	*0.373*	*0.121*	*-0.110*	*0.126*	*0.267*	*0.139*	*0.013*	*0.139*
	alog error	ø carbon EQ Multiples	*0.856*	*0.714*	*0.844*	*0.712*	*0.645*	*0.599*	*0.612*	*0.561*
		ø fin EQ Multiples	*0.519*	*0.403*	*0.427*	*0.410*	*0.329*	*0.281*	*0.275*	*0.287*
		ø carbon EV Multiples	*1.002*	*0.753*	*0.781*	*0.768*	*0.693*	*0.596*	*0.655*	*0.598*
		ø fin. EV Multiples	*0.569*	*0.485*	*0.491*	*0.488*	*0.415*	*0.357*	*0.352*	*0.366*
	overval.	ø carbon EQ Multiples	*49.1%*	*50.8%*	*31.0%*	*50.9%*	*48.1%*	*51.6%*	*37.9%*	*51.1%*
		ø fin EQ Multiples	*70.8%*	*54.3%*	*39.0%*	*55.2%*	*66.5%*	*55.1%*	*45.8%*	*56.4%*
		ø carbon EV Multiples	*58.6%*	*56.7%*	*39.6%*	*57.9%*	*64.0%*	*57.9%*	*46.5%*	*58.3%*
		ø fin. EV Multiples	*70.3%*	*56.6%*	*43.9%*	*57.3%*	*68.7%*	*58.9%*	*48.8%*	*59.4%*
	alog over.	ø carbon EQ Multiples	*8.3%*	*12.0%*	*9.8%*	*11.8%*	*11.1%*	*13.1%*	*12.2%*	*9.9%*
		ø fin EQ Multiples	*16.8%*	*21.5%*	*20.1%*	*20.8%*	*22.8%*	*27.0%*	*27.8%*	*26.4%*
		ø carbon EV Multiples	*8.1%*	*10.9%*	*10.6%*	*10.7%*	*10.3%*	*9.6%*	*12.1%*	*11.4%*
		ø fin. EV Multiples	*14.6%*	*17.5%*	*17.0%*	*17.2%*	*18.6%*	*20.5%*	*21.8%*	*20.7%*
Panel B. Multiples	log error	ø carbon EQ Multiples	*0.866*	*0.019*	*-0.818*	*0.039*	*0.777*	*0.035*	*-0.477*	*0.106*
		ø fin EQ Multiples	*0.652*	*0.047*	*-0.287*	*0.108*	*0.647*	*0.112*	*-0.235*	*0.153*
		ø carbon EV Multiples	*1.072*	*0.170*	*-0.487*	*0.237*	*1.173*	*0.331*	*-0.249*	*0.360*
		ø fin. EV Multiples	*0.608*	*0.100*	*-0.297*	*0.136*	*0.665*	*0.193*	*-0.250*	*0.210*
	alog error	ø carbon EQ Multiples	*1.100*	*0.776*	*1.020*	*0.796*	*0.996*	*0.685*	*0.787*	*0.737*
		ø fin EQ Multiples	*0.775*	*0.494*	*0.526*	*0.511*	*0.767*	*0.509*	*0.518*	*0.524*
		ø carbon EV Multiples	*1.230*	*0.792*	*0.879*	*0.835*	*1.329*	*0.865*	*0.857*	*0.936*
		ø fin. EV Multiples	*0.756*	*0.549*	*0.576*	*0.560*	*0.779*	*0.557*	*0.579*	*0.569*
	overval.	ø carbon EQ Multiples	*47.6%*	*50.1%*	*26.0%*	*51.1%*	*49.2%*	*51.3%*	*33.6%*	*53.3%*
		ø fin EQ Multiples	*77.9%*	*53.6%*	*35.5%*	*56.5%*	*78.2%*	*56.1%*	*38.0%*	*58.4%*
		ø carbon EV Multiples	*60.6%*	*56.0%*	*34.4%*	*58.1%*	*61.8%*	*59.4%*	*43.1%*	*62.2%*
		ø fin. EV Multiples	*76.1%*	*55.7%*	*36.5%*	*57.3%*	*78.0%*	*59.0%*	*39.3%*	*60.3%*
	alog over.	ø carbon EQ Multiples	*6.4%*	*10.6%*	*8.1%*	*10.4%*	*7.4%*	*10.6%*	*9.9%*	*10.1%*
		ø fin EQ Multiples	*11.0%*	*17.6%*	*16.8%*	*16.8%*	*10.9%*	*17.2%*	*16.9%*	*16.5%*
		ø carbon EV Multiples	*6.5%*	*10.3%*	*9.4%*	*9.8%*	*7.1%*	*8.6%*	*9.6%*	*8.9%*
		ø fin. EV Multiples	*10.8%*	*15.3%*	*14.7%*	*14.8%*	*10.6%*	*15.5%*	*15.4%*	*15.0%*

This table presents the overview of the results for case (9) and (10). Each measure (logarithmic error, absolute logarithmic error, overvaluation percentage, and absolute log. error percentage) represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups in Panel A. are compiled using carbon emissions. The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table A.8
Overview of all results

			(11) USA				(12) Europe			
			AM	ME	HM	GM	AM	ME	HM	GM
Panel A. Peer Group	log error	ø carbon EQ Multiples	*0.505*	*0.077*	*-0.247*	*0.110*	*0.543*	*-0.057*	*-0.475*	*-0.001*
		ø fin EQ Multiples	*0.278*	*0.095*	*-0.008*	*0.124*	*0.276*	*0.037*	*-0.173*	*0.036*
		ø carbon EV Multiples	*0.801*	*0.245*	*-0.077*	*0.304*	*1.227*	*0.430*	*-0.007*	*0.533*
		ø fin. EV Multiples	*0.281*	*0.119*	*-0.023*	*0.136*	*0.415*	*0.220*	*-0.006*	*0.198*
	alog error	ø carbon EQ Multiples	*0.713*	*0.559*	*0.608*	*0.573*	*0.933*	*0.720*	*0.816*	*0.735*
		ø fin EQ Multiples	*0.382*	*0.277*	*0.279*	*0.292*	*0.484*	*0.386*	*0.409*	*0.403*
		ø carbon EV Multiples	*0.932*	*0.613*	*0.647*	*0.708*	*1.364*	*0.893*	*0.835*	*0.986*
		ø fin. EV Multiples	*0.441*	*0.376*	*0.398*	*0.386*	*0.632*	*0.528*	*0.550*	*0.526*
	overval.	ø carbon EQ Multiples	*48.0%*	*52.5%*	*34.5%*	*52.3%*	*48.4%*	*48.6%*	*31.1%*	*50.0%*
		ø fin EQ Multiples	*75.6%*	*61.1%*	*49.0%*	*63.4%*	*66.4%*	*51.9%*	*38.1%*	*52.4%*
		ø carbon EV Multiples	*55.5%*	*57.5%*	*41.4%*	*58.3%*	*71.8%*	*64.2%*	*50.4%*	*66.8%*
		ø fin. EV Multiples	*72.3%*	*60.1%*	*49.3%*	*61.5%*	*69.9%*	*59.2%*	*47.0%*	*58.4%*
	alog over.	ø carbon EQ Multiples	*11.2%*	*15.7%*	*13.5%*	*15.7%*	*5.9%*	*11.7%*	*10.3%*	*11.6%*
		ø fin EQ Multiples	*18.1%*	*26.5%*	*26.7%*	*24.0%*	*18.3%*	*22.2%*	*19.9%*	*21.5%*
		ø carbon EV Multiples	*10.8%*	*13.6%*	*12.4%*	*13.1%*	*5.1%*	*10.3%*	*8.3%*	*8.9%*
		ø fin. EV Multiples	*16.4%*	*20.1%*	*20.5%*	*19.3%*	*14.1%*	*16.5%*	*15.4%*	*16.2%*
Panel B. Multiples	log error	ø carbon EQ Multiples	*0.657*	*0.039*	*-0.503*	*0.095*	*0.895*	*-0.003*	*-0.788*	*0.035*
		ø fin EQ Multiples	*0.458*	*0.098*	*-0.147*	*0.133*	*0.497*	*0.067*	*-0.236*	*0.097*
		ø carbon EV Multiples	*0.796*	*0.193*	*-0.258*	*0.244*	*1.247*	*0.263*	*-0.370*	*0.331*
		ø fin. EV Multiples	*0.465*	*0.135*	*-0.168*	*0.155*	*0.529*	*0.123*	*-0.204*	*0.141*
	alog error	ø carbon EQ Multiples	*0.898*	*0.667*	*0.824*	*0.722*	*1.171*	*0.849*	*1.067*	*0.873*
		ø fin EQ Multiples	*0.577*	*0.386*	*0.416*	*0.407*	*0.641*	*0.449*	*0.481*	*0.462*
		ø carbon EV Multiples	*1.001*	*0.713*	*0.787*	*0.740*	*1.424*	*0.885*	*0.973*	*0.936*
		ø fin. EV Multiples	*0.594*	*0.444*	*0.481*	*0.456*	*0.688*	*0.521*	*0.535*	*0.525*
	overval.	ø carbon EQ Multiples	*48.0%*	*51.2%*	*30.7%*	*51.9%*	*47.3%*	*48.9%*	*26.4%*	*50.0%*
		ø fin EQ Multiples	*77.0%*	*57.3%*	*41.2%*	*59.8%*	*75.0%*	*55.2%*	*38.1%*	*56.9%*
		ø carbon EV Multiples	*59.8%*	*55.8%*	*37.9%*	*57.3%*	*62.1%*	*56.7%*	*37.9%*	*58.2%*
		ø fin. EV Multiples	*75.3%*	*58.4%*	*41.3%*	*59.5%*	*74.6%*	*57.7%*	*41.0%*	*58.5%*
	alog over.	ø carbon EQ Multiples	*6.7%*	*12.8%*	*11.0%*	*12.6%*	*5.6%*	*9.8%*	*7.8%*	*9.4%*
		ø fin EQ Multiples	*14.2%*	*21.8%*	*21.3%*	*20.4%*	*13.5%*	*19.2%*	*18.2%*	*18.6%*
		ø carbon EV Multiples	*6.8%*	*12.0%*	*11.3%*	*11.7%*	*5.3%*	*9.5%*	*8.7%*	*9.0%*
		ø fin. EV Multiples	*13.8%*	*19.0%*	*18.4%*	*18.1%*	*12.3%*	*16.5%*	*16.0%*	*16.1%*

This table presents the overview of the results for case (11) and (12). Each measure (logarithmic error, absolute logarithmic error, overvaluation percentage, and absolute log. error percentage) represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups in Panel A. are compiled using carbon emissions. The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table A.9
Overview of all results

			(13) Americas				(14) Asia			
			AM	**ME**	**HM**	**GM**	**AM**	**ME**	**HM**	**GM**
Panel A. Peer Group	**log error**	ø carbon EQ Multiples	*0.522*	*0.077*	*-0.312*	*0.090*	*0.410*	*-0.005*	*-0.433*	*0.002*
		ø fin EQ Multiples	*0.288*	*0.091*	*-0.076*	*0.106*	*0.279*	*0.043*	*-0.126*	*0.065*
		ø carbon EV Multiples	*0.744*	*0.249*	*-0.067*	*0.318*	*0.558*	*0.190*	*-0.166*	*0.210*
		ø fin. EV Multiples	*0.309*	*0.125*	*-0.042*	*0.134*	*0.386*	*0.134*	*0.024*	*0.185*
	alog error	ø carbon EQ Multiples	*0.729*	*0.577*	*0.646*	*0.597*	*0.751*	*0.625*	*0.759*	*0.631*
		ø fin EQ Multiples	*0.412*	*0.310*	*0.333*	*0.328*	*0.486*	*0.406*	*0.423*	*0.413*
		ø carbon EV Multiples	*0.904*	*0.649*	*0.656*	*0.720*	*0.859*	*0.701*	*0.720*	*0.709*
		ø fin. EV Multiples	*0.472*	*0.406*	*0.416*	*0.411*	*0.573*	*0.504*	*0.490*	*0.501*
	overval.	ø carbon EQ Multiples	*48.4%*	*52.3%*	*34.2%*	*52.3%*	*48.7%*	*49.9%*	*32.9%*	*50.3%*
		ø fin EQ Multiples	*73.4%*	*59.3%*	*43.4%*	*59.7%*	*68.3%*	*53.9%*	*40.5%*	*54.6%*
		ø carbon EV Multiples	*56.8%*	*58.0%*	*42.2%*	*58.6%*	*60.7%*	*57.0%*	*44.6%*	*58.3%*
		ø fin. EV Multiples	*71.5%*	*59.6%*	*47.4%*	*60.2%*	*70.7%*	*58.2%*	*49.5%*	*60.3%*
	alog over.	ø carbon EQ Multiples	*10.4%*	*14.6%*	*12.8%*	*14.4%*	*8.9%*	*12.4%*	*11.0%*	*12.4%*
		ø fin EQ Multiples	*18.0%*	*25.5%*	*23.6%*	*23.3%*	*17.2%*	*20.2%*	*19.0%*	*19.8%*
		ø carbon EV Multiples	*9.8%*	*13.4%*	*12.3%*	*12.3%*	*8.2%*	*11.5%*	*11.8%*	*11.9%*
		ø fin. EV Multiples	*16.3%*	*19.9%*	*19.6%*	*18.9%*	*13.2%*	*16.1%*	*16.6%*	*15.8%*
Panel B. Multiples	**log error**	ø carbon EQ Multiples	*0.718*	*0.056*	*-0.503*	*0.102*	*0.738*	*0.010*	*-0.747*	*0.009*
		ø fin EQ Multiples	*0.504*	*0.093*	*-0.245*	*0.108*	*0.674*	*0.071*	*-0.244*	*0.148*
		ø carbon EV Multiples	*0.911*	*0.206*	*-0.284*	*0.288*	*0.897*	*0.141*	*-0.423*	*0.197*
		ø fin. EV Multiples	*0.507*	*0.143*	*-0.220*	*0.149*	*0.644*	*0.141*	*-0.235*	*0.187*
	alog error	ø carbon EQ Multiples	*0.919*	*0.692*	*0.812*	*0.713*	*1.016*	*0.751*	*1.018*	*0.773*
		ø fin EQ Multiples	*0.625*	*0.419*	*0.477*	*0.434*	*0.814*	*0.548*	*0.549*	*0.564*
		ø carbon EV Multiples	*1.071*	*0.738*	*0.766*	*0.759*	*1.099*	*0.757*	*0.850*	*0.790*
		ø fin. EV Multiples	*0.637*	*0.469*	*0.524*	*0.482*	*0.804*	*0.598*	*0.593*	*0.609*
	overval.	ø carbon EQ Multiples	*48.1%*	*51.3%*	*30.1%*	*52.3%*	*47.6%*	*50.0%*	*26.9%*	*50.0%*
		ø fin EQ Multiples	*77.0%*	*56.7%*	*36.8%*	*57.7%*	*76.5%*	*54.3%*	*38.6%*	*57.3%*
		ø carbon EV Multiples	*60.8%*	*56.6%*	*38.3%*	*58.6%*	*59.3%*	*55.3%*	*35.7%*	*57.1%*
		ø fin. EV Multiples	*75.9%*	*58.4%*	*39.3%*	*58.9%*	*75.3%*	*56.9%*	*40.2%*	*58.6%*
	alog over.	ø carbon EQ Multiples	*6.6%*	*12.2%*	*10.4%*	*11.9%*	*6.6%*	*10.8%*	*8.3%*	*10.6%*
		ø fin EQ Multiples	*13.5%*	*20.6%*	*18.8%*	*19.7%*	*10.6%*	*15.5%*	*15.6%*	*14.9%*
		ø carbon EV Multiples	*6.4%*	*11.8%*	*11.1%*	*11.1%*	*6.9%*	*10.9%*	*10.0%*	*10.3%*
		ø fin. EV Multiples	*12.9%*	*18.0%*	*16.8%*	*17.3%*	*10.3%*	*13.8%*	*14.3%*	*13.4%*

This table presents the overview of the results for case (13) and (14). Each measure (logarithmic error, absolute logarithmic error, overvaluation percentage, and absolute log. error percentage) represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups in Panel A. are compiled using carbon emissions. The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table A.10
Overview of all results

			(15) Oceania				(16) Africa			
			AM	**ME**	**HM**	**GM**	**AM**	**ME**	**HM**	**GM**
Panel A. Peer Group	**log error**	ø carbon EQ Multiples	*0.396*	*0.028*	*-0.644*	*-0.016*	*0.533*	*0.318*	*-0.547*	*0.001*
		ø fin EQ Multiples	*0.337*	*0.133*	*0.045*	*0.183*	*0.147*	*0.076*	*-0.097*	*0.042*
		ø carbon EV Multiples	*0.511*	*0.022*	*-0.338*	*0.126*	*0.498*	*0.285*	*-0.635*	*-0.091*
		ø fin. EV Multiples	*0.270*	*0.101*	*0.027*	*0.140*	*0.193*	*0.136*	*0.040*	*0.122*
	alog error	ø carbon EQ Multiples	*0.961*	*0.893*	*1.060*	*0.915*	*1.040*	*1.182*	*1.091*	*1.017*
		ø fin EQ Multiples	*0.493*	*0.323*	*0.324*	*0.357*	*0.377*	*0.369*	*0.373*	*0.363*
		ø carbon EV Multiples	*0.970*	*0.940*	*0.926*	*1.100*	*1.088*	*1.197*	*1.196*	*1.054*
		ø fin. EV Multiples	*0.486*	*0.331*	*0.363*	*0.381*	*0.425*	*0.453*	*0.475*	*0.427*
	overval.	ø carbon EQ Multiples	*46.8%*	*52.4%*	*36.1%*	*49.0%*	*60.0%*	*56.7%*	*33.3%*	*50.0%*
		ø fin EQ Multiples	*73.1%*	*62.2%*	*54.8%*	*65.0%*	*61.6%*	*56.9%*	*47.9%*	*56.6%*
		ø carbon EV Multiples	*50.7%*	*55.5%*	*44.6%*	*51.8%*	*56.7%*	*53.3%*	*34.4%*	*50.0%*
		ø fin. EV Multiples	*69.0%*	*61.9%*	*52.5%*	*62.1%*	*63.7%*	*60.8%*	*52.3%*	*57.6%*
	alog over.	ø carbon EQ Multiples	*4.0%*	*10.3%*	*11.5%*	*9.1%*	*3.3%*	*3.3%*	*13.3%*	*3.3%*
		ø fin EQ Multiples	*20.6%*	*28.1%*	*25.0%*	*23.4%*	*20.2%*	*23.1%*	*20.3%*	*18.9%*
		ø carbon EV Multiples	*5.2%*	*10.8%*	*11.9%*	*10.2%*	*3.3%*	*3.3%*	*0.0%*	*0.0%*
		ø fin. EV Multiples	*21.4%*	*26.7%*	*25.1%*	*26.1%*	*16.0%*	*15.7%*	*15.6%*	*14.5%*
Panel B. Multiples	**log error**	ø carbon EQ Multiples	*0.945*	*0.096*	*-0.468*	*0.150*	*0.444*	*0.209*	*-0.594*	*-0.018*
		ø fin EQ Multiples	*0.550*	*0.111*	*-0.176*	*0.134*	*0.303*	*0.056*	*-0.131*	*0.083*
		ø carbon EV Multiples	*1.104*	*0.291*	*-0.207*	*0.362*	*0.492*	*0.234*	*-0.321*	*-0.016*
		ø fin. EV Multiples	*0.638*	*0.176*	*-0.154*	*0.196*	*0.344*	*0.104*	*-0.054*	*0.128*
	alog error	ø carbon EQ Multiples	*1.277*	*0.875*	*0.945*	*0.898*	*1.062*	*1.161*	*1.198*	*1.047*
		ø fin EQ Multiples	*0.713*	*0.496*	*0.529*	*0.526*	*0.490*	*0.429*	*0.460*	*0.418*
		ø carbon EV Multiples	*1.304*	*0.915*	*0.797*	*0.961*	*1.067*	*1.137*	*1.175*	*1.050*
		ø fin. EV Multiples	*0.796*	*0.551*	*0.541*	*0.572*	*0.560*	*0.486*	*0.465*	*0.481*
	overval.	ø carbon EQ Multiples	*44.9%*	*54.3%*	*36.2%*	*56.4%*	*48.8%*	*53.6%*	*40.4%*	*50.6%*
		ø fin EQ Multiples	*74.4%*	*56.7%*	*40.4%*	*57.9%*	*68.6%*	*54.0%*	*40.7%*	*55.0%*
		ø carbon EV Multiples	*57.1%*	*57.9%*	*41.7%*	*61.4%*	*51.5%*	*54.9%*	*42.4%*	*52.1%*
		ø fin. EV Multiples	*75.8%*	*58.8%*	*41.8%*	*59.6%*	*68.2%*	*55.4%*	*44.9%*	*56.5%*
	alog over.	ø carbon EQ Multiples	*6.5%*	*9.4%*	*8.2%*	*10.1%*	*9.4%*	*2.4%*	*5.4%*	*4.2%*
		ø fin EQ Multiples	*14.2%*	*19.2%*	*17.8%*	*17.8%*	*17.2%*	*20.2%*	*19.4%*	*19.9%*
		ø carbon EV Multiples	*7.7%*	*9.9%*	*10.2%*	*9.1%*	*7.9%*	*0.6%*	*6.3%*	*3.6%*
		ø fin. EV Multiples	*12.0%*	*16.3%*	*15.9%*	*15.6%*	*15.0%*	*17.0%*	*17.4%*	*16.8%*

This table presents the overview of the results for case (15) and (16). Each measure (logarithmic error, absolute logarithmic error, overvaluation percentage, and absolute log. error percentage) represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups in Panel A. are compiled using carbon emissions. The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table A.11
Overview of all results

			(17) High ESG firms				(18) Low ESG Firms			
			AM	ME	HM	GM	AM	ME	HM	GM
Panel A. Peer Group	**log error**	ø carbon EQ Multiples	*0.362*	*0.024*	*-0.270*	*0.056*	*0.357*	*-0.024*	*-0.276*	*0.009*
		ø fin EQ Multiples	*0.158*	*0.015*	*-0.126*	*0.012*	*0.193*	*0.063*	*-0.136*	*0.042*
		ø carbon EV Multiples	*0.918*	*0.432*	*0.152*	*0.480*	*0.667*	*0.234*	*-0.088*	*0.252*
		ø fin. EV Multiples	*0.317*	*0.140*	*-0.008*	*0.169*	*0.387*	*0.229*	*0.015*	*0.186*
	alog error	ø carbon EQ Multiples	*0.673*	*0.591*	*0.641*	*0.590*	*0.637*	*0.564*	*0.608*	*0.580*
		ø fin EQ Multiples	*0.333*	*0.305*	*0.332*	*0.322*	*0.465*	*0.401*	*0.435*	*0.401*
		ø carbon EV Multiples	*1.111*	*0.791*	*0.719*	*0.816*	*0.877*	*0.744*	*0.726*	*0.679*
		ø fin. EV Multiples	*0.542*	*0.498*	*0.483*	*0.486*	*0.657*	*0.548*	*0.529*	*0.546*
	overval.	ø carbon EQ Multiples	*50.5%*	*51.2%*	*37.8%*	*52.5%*	*50.5%*	*49.9%*	*37.2%*	*50.3%*
		ø fin EQ Multiples	*64.2%*	*54.4%*	*42.6%*	*53.5%*	*65.3%*	*54.9%*	*42.7%*	*54.1%*
		ø carbon EV Multiples	*70.2%*	*66.0%*	*57.2%*	*66.8%*	*62.0%*	*59.6%*	*47.2%*	*61.8%*
		ø fin. EV Multiples	*68.8%*	*59.4%*	*51.4%*	*60.0%*	*69.0%*	*60.4%*	*50.4%*	*60.9%*
	alog over.	ø carbon EQ Multiples	*8.4%*	*14.4%*	*13.8%*	*12.3%*	*12.6%*	*13.9%*	*11.9%*	*11.9%*
		ø fin EQ Multiples	*23.9%*	*27.7%*	*25.9%*	*26.4%*	*20.2%*	*21.4%*	*19.8%*	*21.1%*
		ø carbon EV Multiples	*6.8%*	*9.7%*	*9.9%*	*9.1%*	*11.2%*	*12.8%*	*13.8%*	*13.0%*
		ø fin. EV Multiples	*16.2%*	*17.6%*	*18.3%*	*17.8%*	*14.2%*	*15.2%*	*15.6%*	*16.1%*
Panel B. Multiples	**log error**	ø carbon EQ Multiples	*0.655*	*0.007*	*-0.488*	*0.047*	*0.673*	*-0.023*	*-0.396*	*0.076*
		ø fin EQ Multiples	*0.197*	*0.041*	*-0.099*	*0.047*	*0.347*	*0.069*	*-0.204*	*0.052*
		ø carbon EV Multiples	*1.197*	*0.283*	*-0.247*	*0.379*	*0.877*	*0.296*	*-0.115*	*0.350*
		ø fin. EV Multiples	*0.274*	*0.103*	*-0.041*	*0.109*	*0.465*	*0.186*	*-0.102*	*0.188*
	alog error	ø carbon EQ Multiples	*0.948*	*0.703*	*0.791*	*0.729*	*1.000*	*0.707*	*0.789*	*0.726*
		ø fin EQ Multiples	*0.379*	*0.335*	*0.344*	*0.335*	*0.536*	*0.428*	*0.473*	*0.440*
		ø carbon EV Multiples	*1.311*	*0.842*	*0.872*	*0.887*	*1.081*	*0.727*	*0.757*	*0.768*
		ø fin. EV Multiples	*0.494*	*0.454*	*0.459*	*0.452*	*0.650*	*0.545*	*0.548*	*0.548*
	overval.	ø carbon EQ Multiples	*48.8%*	*49.9%*	*31.2%*	*50.6%*	*47.9%*	*50.5%*	*34.4%*	*54.4%*
		ø fin EQ Multiples	*66.2%*	*53.7%*	*42.4%*	*54.3%*	*70.1%*	*54.9%*	*38.1%*	*54.4%*
		ø carbon EV Multiples	*61.6%*	*57.6%*	*41.6%*	*60.0%*	*62.4%*	*59.4%*	*45.0%*	*63.5%*
		ø fin. EV Multiples	*66.4%*	*56.0%*	*46.3%*	*56.1%*	*71.5%*	*58.5%*	*44.4%*	*59.1%*
	alog over.	ø carbon EQ Multiples	*8.2%*	*11.6%*	*9.0%*	*11.1%*	*10.9%*	*13.9%*	*10.8%*	*12.5%*
		ø fin EQ Multiples	*22.3%*	*25.5%*	*24.6%*	*25.1%*	*15.5%*	*20.0%*	*19.0%*	*19.9%*
		ø carbon EV Multiples	*6.7%*	*9.3%*	*8.0%*	*9.6%*	*8.7%*	*11.9%*	*13.4%*	*10.9%*
		ø fin. EV Multiples	*18.3%*	*19.7%*	*18.8%*	*19.3%*	*12.4%*	*15.0%*	*15.8%*	*15.1%*

This table presents the overview of the results for case (17) and (18). Each measure (logarithmic error, absolute logarithmic error, overvaluation percentage, and absolute log. error percentage) represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups in Panel A. are compiled using carbon emissions. The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

Table A.12
Overview of all results

			(19) High SDG Countries				(20) Low SDG Countries			
			AM	**ME**	**HM**	**GM**	**AM**	**ME**	**HM**	**GM**
Panel A. Peer Group	**log error**	ø carbon EQ Multiples	*0.511*	*0.000*	*-0.343*	*0.034*	*0.552*	*0.094*	*-0.260*	*0.103*
		ø fin EQ Multiples	*0.227*	*0.041*	*-0.084*	*0.070*	*0.240*	*0.031*	*-0.143*	*0.061*
		ø carbon EV Multiples	*0.708*	*0.170*	*-0.144*	*0.234*	*0.718*	*0.301*	*0.051*	*0.377*
		ø fin. EV Multiples	*0.298*	*0.112*	*-0.072*	*0.112*	*0.382*	*0.196*	*0.043*	*0.214*
	alog error	ø carbon EQ Multiples	*0.801*	*0.619*	*0.693*	*0.638*	*0.921*	*0.799*	*0.711*	*0.794*
		ø fin EQ Multiples	*0.411*	*0.354*	*0.366*	*0.365*	*0.585*	*0.477*	*0.467*	*0.500*
		ø carbon EV Multiples	*0.928*	*0.689*	*0.676*	*0.714*	*1.018*	*0.838*	*0.777*	*0.858*
		ø fin. EV Multiples	*0.507*	*0.458*	*0.444*	*0.458*	*0.560*	*0.503*	*0.496*	*0.516*
	overval.	ø carbon EQ Multiples	*49.5%*	*49.3%*	*35.0%*	*51.9%*	*51.4%*	*53.4%*	*40.4%*	*55.4%*
		ø fin EQ Multiples	*67.0%*	*53.6%*	*42.9%*	*54.9%*	*64.6%*	*52.7%*	*43.8%*	*54.3%*
		ø carbon EV Multiples	*60.9%*	*57.0%*	*43.5%*	*59.5%*	*65.5%*	*63.7%*	*53.7%*	*63.7%*
		ø fin. EV Multiples	*67.8%*	*56.8%*	*46.1%*	*57.2%*	*71.3%*	*62.4%*	*53.4%*	*61.8%*
	alog over.	ø carbon EQ Multiples	*8.6%*	*13.2%*	*12.1%*	*12.8%*	*8.4%*	*10.3%*	*11.3%*	*11.4%*
		ø fin EQ Multiples	*20.3%*	*23.3%*	*22.7%*	*23.1%*	*16.7%*	*19.9%*	*19.7%*	*18.9%*
		ø carbon EV Multiples	*8.6%*	*11.8%*	*13.0%*	*11.3%*	*6.6%*	*9.2%*	*10.6%*	*8.5%*
		ø fin. EV Multiples	*16.0%*	*18.1%*	*18.3%*	*18.1%*	*14.9%*	*16.8%*	*17.8%*	*17.5%*
Panel B. Multiples	**log error**	ø carbon EQ Multiples	*0.884*	*0.006*	*-0.663*	*0.050*	*0.826*	*0.005*	*-0.577*	*0.119*
		ø fin EQ Multiples	*0.476*	*0.066*	*-0.191*	*0.105*	*0.592*	*0.082*	*-0.277*	*0.102*
		ø carbon EV Multiples	*1.152*	*0.200*	*-0.350*	*0.286*	*1.068*	*0.348*	*-0.279*	*0.367*
		ø fin. EV Multiples	*0.511*	*0.100*	*-0.243*	*0.120*	*0.563*	*0.179*	*-0.129*	*0.204*
	alog error	ø carbon EQ Multiples	*1.145*	*0.813*	*0.948*	*0.834*	*1.158*	*0.874*	*1.030*	*0.943*
		ø fin EQ Multiples	*0.622*	*0.441*	*0.449*	*0.454*	*0.794*	*0.546*	*0.572*	*0.557*
		ø carbon EV Multiples	*1.311*	*0.835*	*0.879*	*0.916*	*1.268*	*0.995*	*0.979*	*0.998*
		ø fin. EV Multiples	*0.674*	*0.501*	*0.521*	*0.510*	*0.739*	*0.586*	*0.581*	*0.596*
	overval.	ø carbon EQ Multiples	*47.3%*	*49.2%*	*28.6%*	*51.3%*	*47.8%*	*50.3%*	*32.0%*	*53.3%*
		ø fin EQ Multiples	*74.9%*	*54.8%*	*39.4%*	*57.1%*	*73.1%*	*54.0%*	*37.7%*	*55.3%*
		ø carbon EV Multiples	*59.3%*	*55.6%*	*37.5%*	*58.0%*	*62.1%*	*59.6%*	*44.0%*	*59.1%*
		ø fin. EV Multiples	*74.8%*	*56.8%*	*39.1%*	*57.6%*	*74.0%*	*58.6%*	*44.5%*	*59.7%*
	alog over.	ø carbon EQ Multiples	*6.8%*	*10.5%*	*8.6%*	*10.2%*	*5.5%*	*9.3%*	*9.0%*	*8.2%*
		ø fin EQ Multiples	*13.7%*	*19.1%*	*18.9%*	*18.7%*	*12.5%*	*15.7%*	*14.6%*	*15.5%*
		ø carbon EV Multiples	*7.1%*	*10.3%*	*9.6%*	*9.5%*	*5.5%*	*7.4%*	*8.4%*	*8.5%*
		ø fin. EV Multiples	*12.4%*	*16.7%*	*16.5%*	*16.4%*	*12.1%*	*14.4%*	*14.1%*	*14.3%*

This table presents the overview of the results for case (19) and (20). Each measure (logarithmic error, absolute logarithmic error, overvaluation percentage, and absolute log. error percentage) represents the aggregated error value over all firm valuations. We use four different methods to aggregate multiples across peer groups: average mean (AM), median (ME), harmonic mean (HM), and geometric mean (GM). The used peer groups in Panel A. are compiled using carbon emissions. The analysis is based on yearly values for all firms within the data sample from 2002 to 2019.

6 You never know the value of water before the well runs dry - The impact of Sustainable Development Goals on firm value

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Abstract. The contribution to the 17 Sustainable Development Goals (SDGs) represents the next generation of measures for the sustainability of firms. We are the first to study the impact of a firm's SDG performance on its value using unique data on SDG-aligned products and services from more than 5,800 global firms. Comparing firms that disclose their SDG performance to 25,800 non-disclosing firms reveals significant differences. We estimate an SDG disclosure-choice model and integrate the results into a firm-value model. Our results reveal the impact on firm value of specific SDGs; for example "combating hunger", "attaining gender equality", and "optimizing material use" have a significantly negative, whereas "ensuring health" and "mitigating climate change" have a significantly positive impact. The results remain robust after controlling for firms' environmental, social und governance (ESG) scores and countries' SDG performance. We recommend including a firm's SDG performance to more precisely assess its value.

Keywords: Corporate finance, Firm value, Tobin's Q, Non-financial disclosures, Sustainable finance, Sustainable Development Goals

JEL Classification: G14, G30, G32, Q56

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6.1 Introduction

"I believe we are on the edge of a fundamental reshaping of finance." (Larry Fink, 2020)

Beyond achieving a global climate policy to successfully combat climate change as expressed in the Paris Agreement, the world agreed on adopting the Sustainable Development Goals (SDGs) outlined by the UN in 2015. Their introduction marks the challenging start of a worldwide societal and economic transition towards a sustainable future. Despite the fact, that the 13th objective of the SDGs is to take urgent action on climate change and its impacts, there is no formal interrelationship between the SDGs and the Paris Agreement. However, both agendas intersect in many ways (Stechow et al., 2016). But the SDGs are encompassing also diverse objectives as the fight against poverty, hunger and inequality who may be in dispute over the fight against climate change. As the SDGs primarily target states and the public sector, not all of the goals are relevant for firms; however SDG 17 does aim to strengthen and revitalize partnerships between governments, the private sector and civil society in building sustainable development. Indeed, it is essential to incorporate corporations and capital markets into efforts to achieve the 17 SDGs for sustainable development by 2030.

This insight is currently gaining ground in capital markets. Ever more asset managers consider SDGs to be an important investment aspect and plan to integrate SDGs into their investment processes.[33] Many investors are currently exploring how to embed the goals into their ESG frameworks. SDGs have thus become a highly relevant investment consideration. The Global Impact Investing Network states in its 2019 whitepaper that over 1,340 active impact-investing organizations across the world intend to achieve positive changes towards sustainability goals. These organizations collectively manage USD 502 billion in investments.

[33] We have found recent reports about SDGs in investment processes by e.g., Franklin Templeton, Amundi, Robeco, American Century Investments, DWS, Liontrust, BlackRock, Berenberg, Union Investment, Hermes Investment Management, Majedie Asset Management, and Summa Equity among many others.

In addition, 29% of the Principles of Responsible Investment (PRI) signatories mentioned SDGs in their 2019 PRI reporting.[34] Beyond this, data providers are addressing SDGs by adding such data to their databases and conducting respective analyses. For example, MSCI recently analyzed the alignment of all 1,600 constituents of the MSCI World Index with SDGs by providing a detailed overview of listed firms' status with regard to each SDG.

In the last years, many investors are exploring how to embed the SDGs into their ESG frameworks. Until recently, an investor has focused primarily on establishing ESG policies and processes and providing basic reporting, either qualitative or through a selection of ESG-related KPIs. However, when measuring a firm's sustainability, the investor limits his/her assessment to the conduct dimension of sustainability. When an investor wants to look also at the sustainability of a firm's product and services, the SDGs allow him to measure their impact towards achieving sustainability targets that have been globally agreed and quantitatively defined. By considering this product dimension, the investor can therefore obtain a more holistic picture of the sustainability of a firm.

This paper is the first to analyze whether the performance of a firm in contributing to SDGs has an impact on its value. More specifically, we investigate whether scores based on SDG-aligned products and services have an impact on Tobin's Q. We measure the SDG-performance of a firm at different aggregation levels, after correcting for self-selection bias. We are thus one of the first studies to focus on the little-studied product (SDGs) rather than the conduct (ESG) dimension of sustainability.

Our paper contributes to the emerging literature on the relationship between SDG performance and firm value. Results of studies usually differ due to low sample sizes and different definitions of sustainable performance (Hussain et al., 2018). Early studies show that

[34] PRI has over 1,200 signatories with more than $70,000 billion AUM as of 2019.

investors recognize that economic, social, and environmental practices, as part of a firm's sustainable behavior, generates a positive effect on financial performance (Martínez-Ferrero & Frías-Aceituno, 2015). By incorporating sustainability practices into their business operations, firms can create shareholder value and improve financial performance (Gómez-Bezares et al., 2017), especially if these issues are relevant and material (Betti et al., 2018). Moreover, the reputations of large firms with incentives to develop a strong commitment to sustainability are harmed if they do not engage in such a strategy and are consequentially penalized by the market (Lourenço et al., 2012).

Although investing in SDGs offers not only challenges but also opportunities for both investors and firms, there is still a lack of proper disclosure by firms with regard to SDGs (Schramade, 2017). Therefore, it is important to know the reasons for a firm to adopt SDGs reporting and study its relationship with a series of organizational factors (Rosati & Faria, 2019). Institutional investors can be a driving force behind the disclosure of SDG information by pushing firms to adopt the SDG-disclosure strategy established by the UN and the Global Reporting Initiative (GRI) (García-Sánchez et al., 2020). The literature on this subject is supplemented by papers that study the effect of SDG disclosure in specific sectors or regions.

Our paper also contributes to a growing body of related finance literature on corporate social responsibility (CSR), environmental, social und governance (ESG) behavior, and impact investing. Of general interest are studies that analyze the valuation and performance effects of CSR (Fatemi et al., 2015) and ESG (Friede et al., 2015). The value of CSR increases during financial crises (Lins et al., 2017) and is often accompanied by a decrease in firm risk (Albuquerque et al., 2019). An increasing perception of the environmental product market (Bardos et al., 2020), the influence of CSR in institutional ownership (Buchanan et al., 2018), and the effect of CSR in smoothing earnings (Gao & Zhang, 2015) lead to higher firm values. Other studies provide insights on the value-enhancing relationship between CSR or ESG and the cost of capital (El Ghoul et al., 2011). This positive relationship is also discussed in studies which focus on the disclosure effect (Crifo et al., 2015) and the effect of market interest in ESG performance and policies (Eccles et al., 2011).

We use a unique SDG dataset from ISS-oekom to assess the SDG performance of over 5,800 firms. We analyze the aggregated SDG performance scores (based on a number of performance measures) as well as the contribution of a firm towards each SDG objective. In doing so, we address the pronounced conflict involved in the pursuit of SDGs objectives. In many times, pursuing social goals is often associated with higher environmental impacts. Studies have shown e.g., that eliminating extreme poverty and reducing income inequality often leads to higher environmental impacts (Scherer et al., 2018). We also add ESG data from ISS ESG to provide insights on the relationship between the conduct versus the product dimensions of sustainability. Throughout all our analyses, we match financial and accounting data from Refinitiv Datastream and Worldscope to compile a global firm data sample of more than 28,000 firms.[35] Furthermore, we use ownership data from Refinitiv Eikon and ESG disclosure variables from MSCI ESG, Refinitiv ESG, Sustainalytics and CDP to gain further insights on the decision of a firm to disclose sustainability data.

Our analyses are threefold. First, we conduct two mean comparison tests to compare firms that have disclosed SDG data with firms that have not, and firms with high versus low SDG performance. We show that firms disclosing SDG data are larger on average, have higher net sales and a lower book-to-market ratio, are more profitable, pay higher dividends, spend more on R&D, have higher cash holdings, higher cash flows and a higher leverage ratio. Furthermore, a higher number of institutional investors than individual investors own disclosing firms. These differences provide further insights on the decision of a firm do disclose SDG information as part of their reporting (García-Sánchez et al., 2020; Rosati & Faria, 2019). In a

[35] Formerly known as Thomson Reuters Datastream and Worldscope.

second step, we show that firms with a high SDG performance have a significantly larger Tobin's Q than low SDG-performing firms. They are also significantly smaller, have lower net sales and a lower book-to-market ratio, are less profitable and have lower cash flows and cash holdings. They pay less dividends and have a lower leverage ratio. We conclude that disclosing and non-disclosing firms have different firm characteristics that need to be captured in our firm-value model. Furthermore, we find that on average firms with a higher contribution to SDGs through the alignment of their products and services with these goals leads to a higher firm value. Our results are consistent with those of other studies on the performance effects of sustainability: "Does it pay to be sustainable" (Hussain et al., 2018) or environmental performance: "Does it pay to be green? (Friede et al., 2015).

Second, besides the usual pooled and panel regressions, we apply a Heckman correction to check for a potential self-selection bias by estimating both a disclosure-choice and a firm-value model using the full information maximum likelihood (FIML) approach. The disclosure-choice model reveals the determinants of a firm's decision to disclose SDG data and enables us to correct for a possible self-selection bias (Schramade, 2017). Reinforcing our results from the mean comparison tests, firms are in addition more likely to disclose if they are reporting to other ESG databases and when their sector peers are also disclosing SDG data. Our firm-value model shows that the aggregated SDG measures have no clear and constant impact on firm value. In the next step, we identify specific SDG objectives, such as "combating hunger", "attaining gender equality", and "optimizing material use" that have a significantly negative impact on firm value – as well as goals such as "ensuring health" and "mitigating climate change" that have a significantly positive impact on firm value. We can explain these results by suggesting that these Sustainable Objective Scores (SOSs) are based on either a potentially profitable business choice or more on a philanthropic venture. Our results remain robust if we add country and industry fixed effects, both with and without the Heckman correction.

Third, we conduct several tests to analyze the robustness of our results regarding the impact of a firm's SDG performance on its value. Initially, we analyze the relationship between ESG and SDG and provide insights on the difference between the product and the conduct dimension of sustainability. We find that the ESG score of a firm still has a significant impact on its value. However, the ESG score has only a small influence on the relationship between a firm's SDG performance and its value. Therefore, we can conclude that sustainability is having an influence on a firm's value in both dimensions. In the next analyses, we take the SDG performance of countries into account, assuming that this has an influence on the SDG performance of a firm and its impact on firm value (Cai et al., 2016). If we control for this country-specific effect in our analyses, our results remain essentially the same. In our last robustness test, we analyze different methods of aggregating the SDG objectives because the aggregated measures (Sustainable Solutions Score, Social Pillar Score and Environmental Pillar Score) did not lead to clear and constant results. As a first step, we aggregate the 15 objectives using their mean. In a second step, we conduct a principal component analysis (PCA) to obtain a lower number of components describing the SDG performance of a firm variance. Our findings show that we cannot aggregate the SDG objectives due to a pronounced conflict between the environmental and social goals.

Our results are meaningful for asset managers, investors, and firms. Recent studies show that investors want to contribute towards sustainable development goals with their investments. Pension funds, for example, prefer sustainable investments and for their sake even accept lower expected returns (Bauer et al., 2019) or show more willingness-to-pay in venture capital funds (Barber et al., 2019). Asset managers have found that the introduction of the Morningstar Sustainability Rating has had a significant impact on their mutual fund flows and performance (Hartzmark & Sussman, 2019). Following this line of reasoning, we add to existing studies and provide insight for investors, asset managers and firms regarding the inclusion of a firm's SDG performance in their investment decisions; such information can help to achieve not only a more holistic sustainability but also better financial performance.

The remainder of this paper is structured as follows: Section 1 presents the SDGs and financial data; Section 2 provides our results on the impact of SDGs on firm values. Section 3 provides several robustness tests and Section 4 concludes.

6.2 Data on SDGs

We construct a global sample of firms following Hou, Karolyi, and Kho (2011) taking yearly worldwide financial data from Refinitiv Datastream and Worldscope.[36] Applying common screening techniques introduced in Ince and Porter (2006), we exclude all firms that are not identified as "equity" or are not primarily listed. Furthermore, we include only firms that account in total for approximately 99.5% of a country's market capitalization to reduce liquidity biases. This provides us with a global sample of firm data from more than 28,000 unique firms for a sample period from 2017 to 2019.[37] The fact that SDG data is very new is reflected in the short sample period – however the large cross-section is sufficient for our following analyses.

6.2.1 Assessment of sustainability solutions

We use a unique SDG dataset from ISS-oekom to assess the SDG performance of over 5,800 firms from August 2017 to December 2019. Founded in 1985, the Institutional Shareholder Services group of companies ("ISS") is today the world's leading provider of corporate governance and responsible investment solutions, market intelligence and fund services. Since March 2018, ISS-oekom has been a member of the ISS family,[38] providing high-quality solutions for sustainable and responsible investment and corporate governance. Originally founded in 1993, and formerly known as oekom research, the company is now one of the

[36] Formerly known as Thomson Reuters Datastream and Worldscope.

[37] A geographic and sectoral breakdown can be found in the appendix in Table A.1.

[38] ISS also includes ESG-providing firms like Ethix SRI Advisor, RepRisk and the South Pole Group Zurich, CNI.

world’s leading ESG research and rating agencies for sustainable investments with a well-proven rating methodology and quality recognition (Eccles & Stroehle, 2018).

Information about the SDG performance of a firm is collected from public sources (e.g., international media), from interviews with independent experts in corporate sustainability (e.g., international NGOs and scientific institutions) and from the firms evaluated (e.g., annual report, CSR report and website). During the evaluation process, ISS could receive feedback from the firms involved, so that they could comment and add information. An international methodology board ensures high-quality analysis, indicators, rating structures and results. An external rating committee (formed by ESG & SDGs experts) supports the design of industry-specific criteria and carries out a final check of the results (Diez-Cañamero et al., 2020).

Our dataset of over 5,800 firms comprises information on the impact of a firm’s product and service portfolio on the UN Sustainable Development Goals (SDGs). As the UN SDGs primarily target states and the public sector, not all of the goals are relevant for firms. For this reason, ISS rates firms according to its own 15 specified firm-relevant Sustainability Objectives that are closely aligned with the UN’s 17 SDGs; the ISS-oekom objectives belong to either the environment pillar or the social pillar. as shown in Table 1.

[Insert Table 1 here.]

For each individual Sustainability Objective, ISS performs a qualitative analysis to determine: (1) whether a product or service category makes a significant or a limited net contribution to achieving the objective; (2) whether it has neither an explicitly positive nor an explicitly negative impact; (3) or whether the product or service actually acts as a limited or significant barrier to achieving the objective. The relevant share of net sales is stated for each of the product and service categories classified for which a net sales share of 1% or higher can reasonably be estimated.[39]

The above qualitative analysis provides a Sustainable Objective Score (SOS) that assesses the overall contribution of a firms' product portfolio towards achieving the respective SDG. The firm-specific SOSs are calculated by multiplying the net sales shares achieved with the relevant products and services by the numerical grades assigned to them. They range from -10.0 (i.e. 100% of net sales are achieved with products and services that are defined as having a significant obstructive impact) to 10.0 (i.e. 100% of net sales are achieved with products/services that are defined as significantly contributing to sustainable objectives).

The ISS-oekom Sustainability Solutions Score (SSS) is a single value that evaluates the aggregated contribution of a firm's product portfolio towards the achievement of SDGs − in a nutshell it represents the overall SDG performance of a firm. The SSS only considers the most distinct SOSs (i.e. the highest positive and/or the lowest negative assessment score). For firms without negative target values, it is determined by the highest positive SOS, and vice versa. For firms that have both positive and obstructive impacts on sustainability objectives, the SSS is calculated as the sum of the highest positive and lowest negative SOSs. The SSS ranges on a scale from -10.0 to 10.0. The Social (SPS) and Environmental Pillar Scores (EPS) follow the same general idea, however, they only take the social or environmental objective scores into account.

In order to gain a better understanding of this dataset, we have created an extensive Internet Appendix. It contains figures and tables on the development of the SSS, the SPS and the EPS over time (Figure IA.1), the distribution of these scores over 61 sectors (Figure IA.2, Figure IA.3 and Table IA.1), and across 32 countries (Figure IA.4 and Figure IA.5). Table IA.2

[39] The displayed net sales shares represent the majority, and unless otherwise noted, estimations are based on a firm's financial, segmental and other reporting.

also provides examples of firms with a high-contribution or a high-obstruction SDG product for each individual sustainable objective.

Using this product and service data yields comprehensible, accountable and precise measures of sustainable performance. Since the approach is directly based on the sales percentage of individual products and services and, furthermore, the products are evaluated with the help of the extensive documentation of the UN SDG framework, the SDG data do not depend heavily on an assessment within a certain rating methodology. In general, rating methodologies can differ widely between providers and produce different assessments of a firm's sustainability and ESG performance, leading to inconclusive results (Christensen et al., 2019; Gibson et al., 2019). The focus of the following analyses is on the individual SOSs and on the aggregated SDG performance measures, namely the SSS, SPS and EPS.

We include the ISS ESG Performance Score to provide insights on the relationship between SDG and ESG data. The ESG score aggregates the relevant, material and forward-looking environmental, social and governance data. It also incorporates norm-based controversy research assessments and considers industry-specific materiality.

6.2.2 Financial and firm characteristic data

In addition, we use common financial data from Refinitiv Datastream and Worldscope. We calculate Tobin's Q as the market value of a firm as captured by the enterprise value divided by the book value of total assets. For our different analyses, we take various variables as controls into account. We use the log of the firm's total assets at the end of the fiscal year as our proxy variable for size and the firm's book-to-market ratio for value. Profitability is captured by different variables, e.g. EBIT, EBITDA, and the return on assets. We further compare firms according to their net sales, operating cash flows, and cash holdings to obtain additional information. Research and development expenses are all direct and indirect costs related to the creation and development of new processes and products, and are used to account for the (sustainable) innovation potential of a firm. The total common and preferred dividends paid to shareholders of a firm are included as a control variable to address the value-influencing dividend behavior of a firm. Moreover, we include the leverage ratio of a firm, measured as the ratio of total debt to common equity.

Further firm characteristics are included in addition to the financial data. We consider the ownership structure of a firm and its influence on a firm's decision to engage in and disclose its status on sustainability. Therefore, we include in our analyses the percentage of total shares outstanding held by institutional investors and by individuals, both provided by the Refinitiv Eikon 13-F database. We also determine whether a firm has reported to any another major ESG database, as we are able to access four comprehensive ESG databases, namely CDP, MSCI ESG (and former KLD), Refinitiv ESG (and former Asset4), and Sustainalytics. We count the number of databases to which a firm reports or where a firm's ESG performance is available, and take this number into account in the subsequent analyses. We also consider the proportion of firms that have disclosed sustainability data within a sector. We identify a firm's sector using the ISS Business Classification and its country using the 2-character ISO country code.

6.3 Impact of SDGs on firm value

Our analyses are structured as follows. First, we provide descriptive statistics on the different SDG performance measures (SSS, SPS, EPS and SOSs) and the financial and firm characteristic data used. We find that the SDG performance measures are mostly positively correlated to each other and that they are also positively correlated with financial performance measures (e.g. Tobin's Q). In the next part, we conduct a mean comparison test of SDG products and services of firms that do or do not disclose data on their SDG performance. The observed differences in firm characteristics helps us to analyze what factors determine firms' willingness to disclose SDG data. It also provides first insights into the impact of SDG performance on firm value by calculating the mean differences in value between high and low SDG-performing firms. Next, we implement a two-step Heckman procedure by estimating both a disclosure-choice and a firm-value model for each SDG performance measure. The first model reveals the determinants causing a firm to disclose SDG data and enables us to correct in the firm-value model for a potential self-selection bias. In addition, the second model provides insights on the impact of different SDG performance measures on firm value.

6.3.1 Descriptive statistics and correlations

Table 2 provides descriptive statistics for all variables in our three-year comprehensive firm data sample. Overall, our sample consists of more than 80,000 firm-year observations for more than 28,000 firms worldwide. We have data on the SDG performance of about 13% of our sample, representing more than 5,800 firms. In the SDGs data sample, it is apparent that many firms offer products and services contributing to or obstructing only a few SDGs. In the case of financials, all variables are used in logarithmic form, unless it is a percentage rate. The firm characteristics comprise either percentages or absolute figures.

[Insert Table 2 here.]

Next, if we look at the correlations of different SDG performance measures in Table 3, we observe that the SSS is highly positively correlated with the SPS and EPS. This is due to the applied aggregation methodology, which is described in the data section. The same applies to the relationship between SPS and EPS and the 15 SOSs. The individual SOSs have a different relationship to each other. While in most cases they are uncorrelated, some SOSs are highly correlated with each other; for example, “mitigating climate change” correlates strongly with “contributing to sustainable energy use”. However, some SOSs are also negatively correlated to each other, an important reason to conduct analyses based on non-aggregated SDG performance measures, so as to account for the conflicting sustainable objective relationships.

[Insert Table 3 here.]

Table 4 shows the correlations between SDG performance measures, financials and firm characteristics. On the one hand, SDG performance measures are correlated positively to financials, e.g. Tobin's Q. On the other hand, other firm characteristics play a role, but mainly a minor one with regard to the relation to the SDGs. This will be used later, in particular to take a closer look at the decision of firms to disclosure SDG data. Furthermore, we observe a positive correlation between the ESG score and all SDG performance measures. We explicitly investigate the SDGs and ESG relationship in a robustness test.

[Insert Table 4 here.]

6.3.2 Mean comparison tests

Let us consider the differences between (1) firms that provide SDG data and those that do not, and (2) firms with high and a low SDG performance as measured by the SSS. For this purpose, we perform two mean comparison tests. First, we find that firms that disclose SDG data have a significantly higher Tobin's Q than non-disclosing firms. Furthermore, they are significantly larger and have higher net sales on average. Firms disclosing SDG data are more profitable, having a higher return on assets, a higher EBIT and a higher EBITDA. In contrast, we find that non-disclosers tend to have a higher book-to-market ratio. When looking at other financials, the disclosers also have higher cash flows, cash holdings and pay more dividends. They also spend more on research and development and have a higher leverage ratio. Looking at their ownership structure, firms disclosing SDG data are owned by a higher proportion of institutional investors than individual investors.

[Insert Table 5 here.]

We conclude that firms disclosing SDG data are fundamentally different from non-disclosing ones, and that this difference may influence its decision to disclose SDG data (García-Sánchez et al., 2020; Rosati & Faria, 2019). Moreover, this difference is an indicator for a self-selection bias that can have a distorting influence on the estimation of a firm-value model.

Second, firms with a high SSS have a significantly larger Tobin's Q than firms with a low SSS.[40] They are also significantly smaller and have lower net sales. Furthermore, the high SSS firms have a lower book-to-market ratio, are less profitable and have lower cash flows and cash holdings. These firms pay less dividends and have a lower leverage ratio. However, there is no significant difference in the ownership structure of the high- and low-SSS firms. We conclude that a firm with high SSS, will likewise having products and services that contribute to the SDGs overall, and have on average a higher firm value as measured by Tobin's Q (Hussain et al., 2018). We investigate whether this difference remains in a firm-value model, where we can address a self-selection bias associated with firms that disclose SDG data, and further firm value enhancing impacts.

6.3.3 Probability of SDG data disclosure

Based on the findings of our previous analyses, we believe that it is necessary to analyze the likelihood of a firm to publish SDG data, so as to avoid a self-selection bias distorting the the following firm-value model. To correct for self-selection, we apply the Heckman model using the Full Information Maximum Likelihood (FIML) approach (Heckman, 1979; Tucker, 2010). In doing so, we jointly estimate a disclosure-choice model (Equation 1) with a firm-value model (Equation 2). We do not estimate them separately to avoid obtaining incorrect standard errors. Correcting for self-selection bias allows us to make inferences about the average effect of SDG performance on firm value for all the firms in our data sample, not just for the firms that disclose SDGs data.[41]

[40] For this analysis, all firms are used which have both a value for the Sustainable Solutions Score and the corresponding financials.

[41] In addition to FIML, we also conduct a two-step estimation, using Limited Information Maximum Likelihood (LIML). Specifically, we calculate the Inverse Mills Ratio (IMR) from the disclosure-choice model and include it in the regression model. Our results remain robust and can be found for the Sustainable Objective Scores (SOSs) in the appendix Table A.4 and A.5.

We derive our disclosure-choice model (Equation 1) from previous literature on the disclosure by firms of non-financial and environmental data (Matsumura et al., 2014). Taking their respective firm characteristics into account, we use our model to study the decision of firms that address the SDGs in their sustainability reports and that disclose their SDG performance (Grewal et al., 2019). Several common proxies are used, e.g. total assets for size, book-to-market ratio for value, and return on assets and dividends for profitability. We further include the proportion of institutional investors and of individual investors to account for ownership-driven disclosure effects (Buchanan et al., 2018). Moreover, we calculate the proportion of disclosing firms within a sector and include it in our disclosure-choice model. Finally, we consider for each firm its number of appearances in other major ESG databases.

$$\begin{aligned} Disclosing\_SDGs_i = {} & \alpha_i + \beta_{1,i}\, Size_i + \beta_{2,i}\, Value_i + \beta_{3,i}\, Profitability_i \\ & + \beta_{4,i}\, Leverage_i + \beta_{5,i}\, Dividends_i + \beta_{6,i}\, Sector\ disc.proportion_i \\ & + \beta_{7,i}\, Institutional\ investors_i + \beta_{8,i}\, Individual\ investors_i \\ & + \beta_{9,i}\, Reporting\ databases_i + \varepsilon_i \end{aligned} \tag{1}$$

Table 6 shows the results of the disclosure-choice model that was estimated jointly with the firm-value model using the SSS. Our results show that the probability of a firm disclosing SDGs data increases if it is larger and more profitable. Furthermore, firms are more likely to disclose if they have a low leverage ratio and a low market-to-book ratio. Firms are also under significant pressure to disclose ESG and other non-financial data if most of the firms in its sector have done so. A high proportion of institutional investors do not seem to encourage disclosure and a high proportion of individual investors reduces the probability that a disclosure will be made. Lastly, firms that report to several ESG databases are also more prone to report SDG data.[42]

[42] Due to the joint-model interrelation, the results of the disclosure-choice model changes, depending on the related firm-value model. We enclose the results for the disclosure-choice models for SPS and EPS as well as for SOSs in the appendix Table A.2 and A.3 and show that the findings remain the same.

[Insert Table 6 here.]

After identifying the determinants underlying a decision to disclose SDG-related data (or not) − thus providing investors and firms with valuable information (Schramade, 2017) − we can integrate these determinants into our firm-value model by including a Heckman correction.

6.3.4 Impact of SDG-aligned products and services on firm value

Our firm-value model (Equation 2) consists of a specific SDG performance measure and several control variables.[43] We alter the model using six different specifications. In the first specification (1), we estimate the firm-value model in a pooled regression. In the second specification (2), we add country fixed effects to control for country differences. In the third specification (3), we replace the country fixed effects with industry fixed effects so as to examine sector effects separately. The combination of both fixed effects can be found in the fourth specification (4). A consideration of the self-selection bias using the FIML approach takes place in specification five (5) and is extended in specification six (6) by the inclusion of fixed effects. The control set of variables we use in all parts comprises proxies for size, value, profitability and dividends.

$$Tobin's\ Q_i = \alpha_i + \beta_i\ SDG_i + \gamma_i\ Controls_i + \delta_i\ FE_i + \theta_i\ Heckmann_i + \varepsilon_i \qquad (2)$$

Our analysis tries out different aggregations of SDG performance measures in estimating the overall Sustainability Solutions Score (SSS), the aggregated Social (SPS) and the Environmental Pillar Score (EPS), and all 15 Sustainable Objective Scores (SOSs). We expect varying results here, since a firm with its products and services usually only contributes to a few SDGs and sometimes a product or service may contribute to one SDG but obstruct another,

[43] We use for this analysis all firms with a corresponding value for the SDG performance measure and also include the information of all additional firms that are included in the disclosure-choice model.

e.g. eliminating extreme poverty and reducing income inequality often leads to higher environmental impacts (Scherer et al., 2018).

Sustainability Solutions Score (SSS)

We begin by analyzing the SSS, this being the highest aggregated measure of a firm's SDG performance. Initially, our firm-value model shows good model quality across all specifications. We find a significant impact of the SSS on Tobin's Q using a pooled regression or including country fixed effects. The positive impact remains significant if we apply the Heckman correction. However, our effect seems to be driven by industry-specific effects. As soon as we include that fixed effects in our estimate, the positive effect disappears.[44]

[Insert Table 7 here.]

In certain sectors, it is common to offer SDG-aligned products and services. These products represent a business activity that can increase the value of a firm and contribute to sustainability. Some SDGs specifically address certain sectors (for example the energy sector in SDG 7). Indeed, a firm's strategy often explicitly address concrete sub-targets of the SDG (e.g., Target 7.1. "By 2030, ensure universal access to affordable, reliable and modern energy services"). The underlying indicators are also quantitatively measurable and were already being used by numerous firms before the SDGs were introduced (e.g., Indicator 7.2.1: "Renewable energy share in the total final energy consumption"), and may represent key performance indicators of a firm. However, this is not the case in all sectors, since some SDGs, for example "alleviating poverty", are usually not part of firms' strategy for increasing firm value.

Social Pillar Score (SPS) and Environmental Pillar Score (EPS)

Another problem with aggregating the SSS is that doing so does not take the possible conflicting of aims of SDGs into account. This can be seen, for example, in the diverse nature of social

[44] In untabulated results, we cluster standard errors on the firm-level. Our results remain robust.

versus environmental objectives. The second part of our study therefore examines the two pillar scores, SPS and EPS. Our firm-value model shows that the SPS has a similar effect to the SSS in terms of both magnitude and significance. However, the EPS's impact is only significant when we apply the Heckman correction.

[Insert Table 8 here.]

The SPS combines different objectives which may have widely differing relevance for firm value. The SPS is made up of SOSs that particularly involve social goals, such as "alleviating poverty" (SDG 1) that unlikely to be the direct objective of a profit-oriented business model for firms. In contrast, there are goals, such as "ensuring health" (SDG 3), that are the business model of numerous healthcare firms. For some of the social SDGs, firms also focus mainly on the reputational effect, for example the goal of "attaining gender equality" (SDG 5). Overall, it can be said with regard to the social pillar, that each SOS must be examined to determine the extent of its relevance to the firm value and its SPS.

In contrast, it is surprising that the environmental score has almost no significant effect on Tobin's Q. Nevertheless, it can be assumed that the objectives underlying the EPS play a relevant role for firms, especially when considering that firms have been addressing climate aspects, sustainable building and sustainable energy production in their reporting and strategy for a long time. However, SOSs within a pillar can also conflict with one another. For example, electricity generation based on nuclear power helps "mitigate climate change" (SDG 13), but it conflicts with the goal of "contributing to sustainable energy use" (SDG 7). These contradictions may lead to the conclusion that the EPS does not have an aggregated impact on firm value. Further analyses at the level of environmental SOSs are necessary to provide a clear picture.

Sustainable Objective Scores (SOSs)

The previous two analyses show that the aggregated SDG performance measures have only a limited impact on the value of a firm. We will therefore look at all 15 SOSs in the following analysis.[45] Using our six model specifications, we obtain significant results for several SOSs.

[Insert Table 9 here.]

First, we examine the SOSs that have a significant positive relevance for firm value. From the social SDGs, only "ensuring health" has a positive significant impact on Tobin's Q. With regard to the environmental SDGs, only "mitigating climate change" leads to a significant increase in Tobin's Q. In the former case, we see a high "ensuring health" SOS as the essential business model for healthcare firms. A firm that is particularly committed to contributing to this SOS is also able to offer excellent products and services that ensure its future financial success across a number of sectors. For the target of mitigating climate change, the literature has shown that it is cost-effective to minimize emissions, thereby reducing, inter alia, the level and likelihood of physical and transitory risks (Görgen et al., 2020; Matsumura et al., 2014). Both effects result in an increase in the value of a firm and lead firms to engage in policies that improve this SOS.

Next, we look at the SOSs with a negative impact on firm value. Both a contribution to the objectives of "combating hunger and malnutrition" and to "attaining gender equality" are significantly associated with a reduction in Tobin's Q. For the first SOS, combating hunger and malnutrition, it can be assumed that a firm's commitment may involve providing certain products and services at lower profit margins, such as fruits and vegetables. In addition, the production of financially profitable products such as alcohol or red meat is rated very negatively in a firm's SDG performance and hence have a negative impact on firm value. A high SDG-

[45] While here we include all the different SOSs at the same time, we have also performed this analysis with the inclusion of each individual SOS. The results remain essentially the same.

performance score in attaining gender equality, as applied to a firm's products, is currently only achieved by providing specific products, such as female sanitary products or financial services targeted at women. On the one hand, only a few firms offer such products, and on the other, a statement on the value enhancement of such products cannot be made here easily, since many sector-specific factors play a large role. To contribute to the SOS of attaining gender equality, it seems to be more important to address gender-related issues within the organization of a firm – represented by the conduct dimension of sustainability and captured in ESG scores – rather than providing certain products and services. [46]

The SOS of "optimizing material use" has a significant, negative impact on Tobin's Q. To investigate this counterintuitive effect, we consider products and activities that contribute to this SOS. These are mainly waste recycling services and reusable packaging, which are only offered by a few specialized firms. To draw a conclusion for all firms on the overall relationship between optimizing material use and firm value is only limitedly possible since again many sector-specific factors play dominant roles.

On looking at the remaining SOSs, no consistent effects in connection with firm value can be seen. The social SOSs of "alleviating poverty" and "providing basic services" are mainly driven by sector-specific effects. Both "safeguarding peace" and "delivering education" have no significant impact on Tobin's Q across all six model specifications. "Achieving sustainable agriculture and forestry" also only represents a niche business opportunity in the environmental sector, but is not a general value-driving issue for most firms. The other SOSs of "conserving water", "promoting sustainable buildings" and "preserving marine ecosystems" lose their significant impact on firm value with the inclusion of industry fixed effects. The effect of "contributing to sustainable energy use" is largely influenced by "mitigating climate change".

[46] The consideration of gender equality within a firm's organization is part of an ESG assessment based on various factors, e.g. the number of female board members.

Significant results can be found if the latter SOS is omitted from the firm-value model. Finally, “preserving terrestrial ecosystems” has a slightly negative effect on firm value, which disappears with the inclusion of both the country and industry fixed effects. Overall, it can be stated that while some SOSs already have a significant impact on firm value, most so far have little or none.

6.4 Robustness

To check the robustness of our results, we perform three different analyses. First, we include an ESG score in our firm-value model and check whether it has an impact on the significance of our SOSs. In the next step, we look at whether the SDG performance of a country has an amplifying effect on the impact of SOSs on firm value. Finally, we consider two different aggregation methods to combine all or only a few of the 15 SOSs to form just a single SDG performance measure.

6.4.1 The relationship between SDGs and ESG

In our first robustness test, we investigate the relationship between the product dimension (SDGs) and the conduct dimension (ESG) of sustainability. Looking first at Table 4 and the correlations between SDG performance measures and the ISS ESG Performance Score, we see consistently low positive values. We now include this ESG score in our firm value model.

$$Tobin's\ Q_i = \alpha_i + \beta_i\ SDG_i + \varphi_i\ ESG_i + \gamma_i\ Controls_i + \delta_i\ FE_i + \theta_i\ Heckmann_i + \varepsilon_i \qquad (4)$$

The results in Table 10 show that the firm's ESG score has a positively significant effect in four out of the six model specifications. Only if industry fixed effects are included in the panel regression and if both industry and country fixed effects are included in the Heckman correction model do the effects become non-significant. Let us now examine the impact of the ESG measure on the SOSs. We see that no sign changes were induced nor were there any shifts in significance. The magnitude or significance of the impact of individual SOSs on firm value were only marginal. Overall, we therefore conclude that SDGs and ESGs essentially measure different dimensions of sustainability – conduct versus product dimension – and have a heterogeneous impact on firm values.

[Insert Table 10 here.]

6.4.2 Considering the country-specific SDG performance

The SDGs lay out the expected contribution of countries and governments needed to achieve a sustainable future. The performance of each individual country is measured and aggregated using numerous indicators within the UN SDGs framework. We now look at one aggregated SDG country performance measure from the Sustainable Development Report: the SDG Global Index Score. The top five SDG-performing countries in 2019, for example, were Denmark, followed by Sweden, Finland, France and Austria. The UK ranked 13th, the USA 35th and China 39th out of 162. We aim to measure whether the SDG performance of countries has an amplifying effect on SDG performance measures of firms (Cai et al., 2016).

$$Tobin's\ Q_i = \alpha_i + \beta_i\ SDG_i + \omega_i\ SDG_c + \gamma_i\ Controls_i + \delta_i\ FE_i + \theta_i\ Heckmann_i + \varepsilon_i \tag{5}$$

The SDG Global Index Score has a significant negative impact on Tobin's Q. This means that in a country with high SDG performance, firms might be expected to have a higher sustainability performance. However, the SDG Global Index Score showed no direct influence on the impact of individual SOSs on firm values, as there was no significant change in the signs, significances or magnitudes of the SOSs. We therefore conclude that a country's SDG performance does not amplify the impact of SOSs on firm value.

[Insert Table 11 here.]

6.4.3 Aggregating Sustainable Objective Scores

In our last robustness test, we aim to construct an aggregated measure of the SDG performance of a firm. The previous analyses showed that neither SSS, SPS or EPS is suitable for this purpose in any model specifications. Beginning with the simple approach we take the average of all of the SOSs. We then conduct an analysis using a principal component analyses (PCA) to obtain the main principal components of the 15 SDGs.

$$Tobin's\ Q_i = \alpha_i + \beta_i\ \overline{SOS}_i + \gamma_i\ Controls_i + \delta_i\ FE_i + \theta_i\ Heckmann_i + \varepsilon_i \quad (6)$$

First, we take the mean of all SOSs for each firm and examine its impact on firm value. We see the have a similar impact on Tobin's Q as with the SSS. The significance disappears with the inclusion of industry fixed effects. However, the magnitude of the impact is now much greater. The mean is strongly influenced by outliers, but according to its methodology the SSS considers only positive and negative outliers. In most cases, where a firm contributes to only a few SDGs, the mean of all SOSs will be lower than the SSS. In our sample, the SSS is on average 0.34 compared to -0.01 which is the mean of all of the SOSs. Overall, however, the mean of all of the SOSs does not appear to be a meaningful aggregated SDG performance measure, since it has no consistent significance. It is influenced by industry fixed effects and does not explicitly address the observed conflicting aims of the SDGs.

[Insert Table 12 here.]

In the last robustness test, we perform a principal component analysis (PCA) to obtain the principal components (PC) of all 15 SOSs. We insert all PCs with an eigenvalue greater than one into our firm-value model. This leads to a reduction of all 15 SOSs to 7 PCs, which can explain sixty percent of the variance in all of the SOSs.

$$Tobin's\ Q_i = \alpha_i + \beta_i\ PC_{n,i} + \gamma_i\ Controls_i + \delta_i\ FE_i + \theta_i\ Heckmann_i + \varepsilon_i \quad (6)$$

The first PC has a significantly positive impact on firm value. If we look at the normalized component loadings, the first PC consists of the following SOSs: "mitigating climate change", "contributing to sustainable energy use" und "conserving water". Therefore, it represents most of the significant positive impacts on firm value. The significantly positive effect of the SOS "ensuring health" is mainly addressed in the second PC, which is also strongly influenced by the SOSs "combating hunger and malnutrition", "alleviating poverty" and "providing basic services”, which have no or even a significantly negative effect on firm value. Overall, the negative effect on firm value is predominant in the second PC. The third PC has positive component loadings on “achieving sustainable agriculture and forestry” and “preserving terrestrial ecosystems” and negative component loadings on “alleviating poverty” and “attaining gender equality”. When we aggregate the different impacts on firm value of these different SOSs, we get an overall negative effect that is significant across nearly all six model specifications. Finally, only the sixth PC still has a significantly negative impact, which disappears after controlling for industry fixed effects. Therefore, we can only construct an SDG performance measure with the help of the PCA − to a limited extent − and thus still recommend measuring the SDG performance of a firm using the individual SOSs.

[Insert Table 13 here.]

Overall, our robustness tests show that ESG and SDGs measure different dimensions of sustainability and that they impact firm values differently. In addition, the SDG performance of countries does not amplify the impact of a firm’s SDG performance on its firm value. Finally, aggregating the SOSs is of limited use due to the conflicting relationship between sustainable objectives.

6.5 Conclusion

Our findings reveal that certain SDG-aligned products and services have a significant impact on the value of a firm. We provide some first insights into why firms disclose SDG data and how they differ from non-disclosing firms. Overall, we contribute to a better understanding of the relationship between SDGs and firm values, even after considering a firm’s ESG performance. Our results encourage asset managers, investors and firms to contribute to SOSs and achieve a high and tangible sustainability performance, which can also be financially rewarding.

Our results give rise to the question, to what extent firms should offer SDG-aligned products and services in order to both improve their overall sustainability performance and to generate a higher firm value. We show that currently the engagement of a firm towards SDGs has a significant impact on the firm value only with regard to a few, mostly also materially important, SDGs. We state that a firm achieves a more holistic sustainability performance if, in addition to aligning its organization with ESG criteria, it also includes sustainable products and services. Nevertheless, the sustainability of a firm also depends on the economic sustainability of its business. Here it is important to pay attention to which SDGs represent a profitable firm policy and which ones can only be become so through new framework and market conditions. Indeed, some SDGs may be met more efficiently through philanthropic action than through interventions in markets. Overall, some questions remain open for research and society, namely how the fulfillment of SDGs can be promoted efficiently from the point of view of both firms and capital markets.

This paper is the first to examine the impact of SDG-aligned products and services on financial performance. Based on this, there are many further research directions, such as investigating the risk to firms in connection with good or poor SDG performance or the reaction of capital markets to firms disclosing SDG data. In addition, the relationship between ESG and SDGs data should be further investigated. Another important question is to what extent SDG-aligned products and services are or should be incorporated into ESG methodologies. Also, how does the conduct dimension of ESG effect the product dimension of SDG-aligned products? Answers to such questions may help to determine the amplifying effects that could help accelerate the transition towards a sustainable future.

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Figures and Tables

Table 1

Sustainable Development Objectives

Objective	SDG
Social Objectives	
Alleviating poverty	SDG 1
Combating hunger and malnutrition	SDG 2
Ensuring health	SDG 3
Delivering education	SDG 4
Attaining gender equality	SDG 5
Providing basic services	SDG 6
Safeguarding peace	SDG 16
Environmental Objectives	
Achieving sustainable agriculture & forestry	SDG 2, SDG 13, SDG 15
Conserving water	SDG 6, SDG 14
Contributing to sustainable energy use	SDG 7
Promoting sustainable buildings	SDG 11, SDG 12
Optimizing material use	SDG 12
Mitigating climate change	SDG 13
Preserving marine ecosystems	SDG 14
Preserving terrestrial ecosystems	SDG 15

This table provides an overview of all 15 Sustainable Objectives Scores (SOSs) covered in the ISS-oekom Sustainable Performance Assessment. Each objective is part of either an environment or a social pillar. The second column shows how each objective score contributes to a specific SDG.

Table 2

Descriptive statistics

Variable	N	Mean	P5	Median	P95	SD
Panel A. SDGs						
Sustainability Solution Score	10,984	0.34	-6.30	0.00	9.10	3.74
Social Pillar Score	10,984	0.71	-1.90	0.00	8.80	2.89
Environmental Pillar Score	10,984	-0.31	-5.00	0.00	3.00	2.46
Alleviating poverty	10,984	-0.02	0.00	0.00	0.00	0.42
Combating hunger and malnutrition	10,984	-0.19	-0.60	0.00	0.00	1.22
Ensuring health	10,984	0.56	-1.50	0.00	8.80	2.64
Delivering education	10,984	0.05	0.00	0.00	0.00	0.52
Attaining gender equality	10,984	0.01	0.00	0.00	0.00	0.20
Providing basic services	10,984	0.24	0.00	0.00	1.80	0.81
Safeguarding peace	10,984	-0.01	-0.10	0.00	0.00	0.41
Achieving sustainable agr. & forestry	10,984	0.03	0.00	0.00	0.10	0.44
Conserving water	10,984	-0.03	-0.10	0.00	0.00	0.76
Contributing to sustainable energy use	10,984	-0.37	-4.70	0.00	1.00	2.01
Promoting sustainable buildings	10,984	0.10	0.00	0.00	0.10	0.67
Optimizing material use	10,984	0.04	0.00	0.00	0.00	0.42
Mitigating climate change	10,984	-0.35	-4.60	0.00	1.30	2.03
Preserving marine ecosystems	10,984	-0.05	-0.20	0.00	0.00	0.33
Preserving terrestrial ecosystems	10,984	-0.10	-0.10	0.00	0.00	1.01
Panel B. Financials						
Tobin's Q	75,131	1.24	0.15	0.89	4.29	1.08
Total assets	51,063	20.49	17.43	20.33	24.08	1.79
Net sales	45,401	19.29	15.10	19.44	22.17	1.79
Book-to-market	49,309	0.79	0.06	0.59	2.57	0.66
Dividends	36,192	16.55	13.56	16.53	19.66	1.92
EBIT	40,539	17.90	15.02	17.85	21.01	1.79
EBITDA	41,741	18.19	15.35	18.13	21.35	1.78
Cash flow	39,723	17.82	14.75	17.79	20.99	1.87
Cash	49,129	17.20	11.10	17.53	21.00	2.47
R&D	21,378	15.96	12.07	15.96	19.57	1.96
Return on assets	51,317	0.05	0.00	0.04	0.16	0.05
Leverage	49,467	0.62	0.00	0.43	2.00	0.64
Panel C. Firm characteristics						
ESG performance score	10,984	30.23	10.65	27.90	56.42	14.54
Institutional ownership	83,911	0.41	0.00	0.43	0.96	0.33
Individual investors	68,084	0.11	0.00	0.02	0.55	0.18
Number of reporting databases	31,379	1.80	1.00	2.00	4.00	0.92
Sector disclosure proportion	83,911	0.13	0.07	0.12	0.23	0.05

This table provides descriptive statistics for all variables used to describe the sustainability (Panel A), the financials (Panel B) and the characteristics (Panel C) of a firm. All variables are shown on a yearly basis for all firms within the data sample from 2017 to 2019. The sustainability variables in Panel A are all absolute values; the financials in Panel B are either logarithmized (Tobin's Q, total assets, net sales, dividends, EBIT, EBITDA, cash flow, cash, and R&D) or shown as ratios (book-to-market, return on assets, leverage); the characteristics in Panel C are either absolute values (ESG performance score, number of reporting databases) or ratios (institutional ownership, individual investors, sector disclosure proportion).

Table 3
Correlations of SDG performance measures

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1)	Sustainability Solution Score	1																
(2)	Social Score	0.78	1															
(3)	Environmental Score	0.67	0.09	1														
(4)	Alleviating poverty	0.11	0.16	-0.00	1													
(5)	Combating hunger and malnutrition	0.33	0.46	0.02	-0.00	1												
(6)	Ensuring health	0.73	0.93	0.08	0.15	0.30	1											
(7)	Delivering education	0.12	0.14	0.01	0.00	0.01	-0.01	1										
(8)	Attaining gender equality	0.06	0.08	0.00	0.13	0.00	0.02	0.15	1									
(9)	Providing basic services	0.20	0.26	0.07	0.09	0.04	0.11	0.01	0.08	1								
(10)	Safeguarding peace	0.11	0.14	0.06	-0.00	-0.00	0.06	-0.01	0.00	0.00	1							
(11)	Achieving sustainable agr. & forestry	0.07	-0.01	0.16	0.01	0.00	-0.02	-0.00	0.00	-0.02	0.00	1						
(12)	Conserving water	0.27	0.13	0.36	-0.00	0.13	0.13	0.00	0.00	0.12	-0.00	0.06	1					
(13)	Contributing to sustainable energy use	0.55	0.05	0.80	-0.01	-0.02	0.05	0.01	0.00	0.03	0.08	0.01	0.17	1				
(14)	Promoting sustainable buildings	0.16	-0.03	0.29	-0.02	0.02	-0.03	-0.00	-0.00	-0.01	0.00	0.00	0.00	0.06	1			
(15)	Optimizing material use	0.10	-0.00	0.17	0.00	0.01	-0.00	-0.00	-0.00	-0.00	0.00	0.05	0.03	0.02	-0.01	1		
(16)	Mitigating climate change	0.56	0.07	0.81	-0.00	0.00	0.05	0.01	0.00	0.06	0.05	0.04	0.20	0.94	0.06	0.01	1	
(17)	Preserving marine ecosystems	0.11	0.07	0.11	-0.00	-0.00	0.08	0.01	0.00	0.03	-0.00	-0.01	0.01	0.00	0.02	0.00	0.00	1
(18)	Preserving terrestrial ecosystems	0.27	0.04	0.39	-0.00	-0.01	0.04	0.00	0.00	0.01	0.01	0.19	0.02	0.01	0.01	0.03	-0.00	0.11

This table shows the correlations between different SDG performance measures: the overall Sustainability Solutions Score (SSS), the aggregated Social Pillar Score (SPS) and the Environmental Pillar Score (EPS), and each of the 15 Sustainable Objective Scores (SOSs).

Table 4
Correlations of SDG performance measures, financials and firm characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Tobin's Q	0.16	0.15	0.07	-0.02	-0.07	0.19	0.00	0.02	-0.08	0.04	0.01	0.00	0.11	-0.04	0.01	0.10	-0.03	-0.00
Total assets	-0.12	-0.08	-0.09	0.02	-0.00	-0.10	-0.04	-0.05	0.11	-0.05	-0.05	-0.02	-0.14	0.01	-0.05	-0.12	0.03	0.03
Net sales	-0.19	-0.20	-0.08	-0.01	-0.09	-0.24	0.00	0.01	0.02	-0.01	-0.05	-0.02	-0.13	-0.04	0.00	-0.15	-0.00	0.09
Book-to-market	-0.08	-0.05	-0.05	0.02	0.04	-0.08	0.00	-0.00	0.03	-0.00	-0.01	-0.03	-0.09	0.06	-0.00	-0.08	0.00	-0.00
Return on assets	-0.07	-0.03	-0.07	-0.02	-0.01	-0.04	-0.04	-0.01	0.05	-0.00	-0.00	-0.00	-0.11	0.03	-0.03	-0.09	0.03	0.00
EBIT	-0.08	-0.03	-0.10	0.01	-0.02	-0.03	-0.05	-0.01	0.07	-0.02	-0.01	-0.01	-0.13	-0.01	-0.04	-0.12	0.00	0.04
EBITDA	-0.11	-0.04	-0.12	0.00	-0.02	-0.05	-0.05	-0.02	0.08	-0.02	-0.04	-0.03	-0.15	-0.02	-0.04	-0.13	0.00	0.03
Cash flow	-0.10	-0.03	-0.12	0.00	-0.02	-0.04	-0.04	-0.01	0.08	-0.02	-0.02	-0.03	-0.14	-0.04	-0.03	-0.12	-0.00	0.00
Cash	-0.05	-0.03	-0.06	-0.00	-0.03	-0.02	-0.02	-0.03	-0.00	-0.02	-0.06	0.02	-0.05	-0.06	-0.04	-0.04	0.01	0.00
R&D	0.08	0.10	-0.03	-0.01	0.09	0.11	-0.03	-0.02	-0.10	-0.03	-0.03	-0.07	-0.00	-0.06	-0.10	0.00	0.14	0.01
Dividends	0.00	-0.01	0.00	-0.02	-0.04	0.01	-0.00	-0.00	-0.08	-0.00	0.03	-0.00	0.02	-0.02	-0.00	0.01	-0.02	0.01
Leverage	-0.06	-0.07	-0.00	-0.01	-0.03	-0.10	-0.00	0.01	0.08	0.01	-0.02	0.01	-0.03	-0.00	-0.01	-0.03	0.00	0.04
ESG performance core	0.27	0.16	0.27	0.05	0.05	0.14	0.06	0.04	0.13	0.01	0.12	0.14	0.20	0.10	0.11	0.21	0.03	0.05
Institutional ownership	-0.01	0.00	-0.03	0.01	-0.02	0.01	0.02	-0.02	-0.00	-0.02	-0.00	-0.03	-0.04	0.00	0.01	-0.04	-0.00	0.00
Individual investors	0.03	0.00	0.05	-0.01	-0.00	0.00	-0.00	0.01	-0.02	0.03	-0.00	-0.01	0.06	0.00	0.00	0.05	-0.02	0.02
Number of reporting databases	-0.03	-0.02	-0.03	0.00	-0.01	-0.01	0.00	-0.01	0.00	-0.01	0.01	-0.01	-0.02	-0.03	0.01	-0.02	0.00	0.01
Sector disclosure proportion	-0.03	-0.02	-0.02	0.00	0.01	-0.06	-0.03	-0.01	0.18	-0.11	-0.00	0.05	-0.09	0.06	-0.00	-0.07	0.03	0.04

This table shows the correlations between financials data, firm characteristics and different SDG performance measures: the overall Sustainability Solutions Score (SSS, (1)), the aggregated Social Pillar Score (SPS, (2)) and the Environmental Pillar Score (EPS, (3)), and each of the 15 Sustainable Objective Scores (SOSs, (4)-(18)) The corresponding number for each SOSs can be found in the previous Table 3.

Table 5
Mean comparison test

Panel A. SDGs disclosing and non-disclosing firms

Variable	SDGs firm	Non-SDGs firm	Diff.	Std. error	Obs.
Tobin's Q	1.3730	1.2182	0.1548***	0.0112	75,131
Total assets	22.5669	20.1344	2.4325***	0.0198	51,063
Net sales	20.4017	19.2459	1.1557***	0.0439	45,401
Book-to-market	0.6022	0.8116	-0.2093***	0.0092	49,309
Return on assets	18.6039	16.1393	2.4646***	0.0238	36,192
EBIT	19.8590	17.5106	2.3485***	0.0208	40,539
EBITDA	20.2177	17.8045	2.4132***	0.0207	41,741
Cash flow	19.8764	17.4108	2.4656***	0.0220	39,723
Cash	19.3888	16.8298	2.5589***	0.0295	49,129
R&D	18.0635	15.6199	2.4437***	0.0349	21,378
Dividends	0.0693	0.0506	0.0187***	0.0006	51,317
Leverage	0.6702	0.6147	0.0555***	0.0089	49,467
Institutional ownership	0.6779	0.3754	0.3025***	0.0033	83,911
Individual investors	0.0466	0.1233	-0.0767***	0.0019	68,084

Panel B. High and low SSS firms

Variable	High SSS firm	Low SSS firm	Diff.	Std. error	Obs.
Tobin's Q	1.5132	1.2700	0.2433***	0.0220	10,893
Total assets	22.4675	22.6368	-0.1693***	0.0337	7,438
Net sales	20.2654	20.4876	-0.2222***	0.0725	1,697
Book-to-market	0.5598	0.6319	-0.0720***	0.0131	5,831
Return on assets	18.5956	18.6097	-0.0141	0.0319	6,025
EBIT	19.8194	19.8869	-0.0674**	0.0313	6,744
EBITDA	20.1639	20.2559	-0.0920***	0.0308	6,657
Cash flow	19.8334	19.9079	-0.0745**	0.0313	6,606
Cash	19.3487	19.4217	-0.0730*	0.0402	7,098
R&D	18.1433	17.9858	0.1576**	0.0631	2,964
Dividends	0.0675	0.0706	-0.0031*	0.0017	7,533
Leverage	0.6563	0.6799	-0.0236*	0.0136	5,831
Institutional ownership	0.6743	0.6805	-0.0061	0.0044	10,984
Individual investors	0.0483	0.0453	0.0030	0.0021	10,944

This table provides the results of mean comparison tests of SDG data-disclosing and non-disclosing firms in Panel A and of high and low SSS firms in Panel B. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6

Disclosure-choice model – Sustainable Solutions Score

	(1) Disclosing SDGs	(2) Disclosing SDGs
Total assets	0.51***	0.48***
	(33.46)	(31.02)
Book-to-market	-0.61***	-0.55***
	(-22.43)	(-19.42)
Return on assets	8.35***	7.96***
	(27.29)	(24.85)
Leverage	-0.23***	-0.21***
	(-9.34)	(-8.61)
Dividends	0.073***	0.091***
	(5.36)	(6.54)
Sector disclosure proportion	0.19	0.50**
	(0.87)	(2.14)
Institutional investors	-0.24***	-0.54***
	(-3.92)	(-8.57)
Individual investor	-0.73***	-1.05***
	(-6.53)	(-8.94)
Number of reporting databases	0.25***	0.27***
	(19.24)	(20.42)
Constant	-13.5***	-13.1***
	(-53.95)	(-51.60)
Country fixed effects	no	yes
Industry fixed effects	no	yes
adj. R^2	0.33	0.33
N	14,861	14,861

This table shows the results of the SDGs disclosure-choice model of the Heckman correction. It is estimated jointly with a firm-value model estimating the impact of the Sustainable Solutions Score (SSS) on firm value. We estimate the probability of a firm disclosing SDG data, using various controls for e.g. size, value, profitability, dividends, leverage, disclosure proportion within a firm's sector, ownership structure and number of reports to different ESG databases. We include country and industry fixed effects in the second column. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7
Firm-value model – Impact of the Sustainability Solutions Score on firm value

	(1) Tobin's Q	(2) Tobin's Q	(3) Tobin's Q	(4) Tobin's Q	(5) Tobin's Q	(6) Tobin's Q
Sustainability Solutions Score	0.016***	0.017***	-0.0041	0.0012	0.014***	0.0015
	(4.12)	(4.52)	(-0.75)	(0.23)	(3.80)	(0.31)
Controls	yes	yes	yes	yes	yes	yes
Country fixed effects	no	yes	no	yes	no	yes
Industry fixed effects	no	no	yes	yes	no	yes
Heckman	no	no	no	no	yes	yes
adj. R^2	0.41	0.48	0.56	0.60		
within R^2		0.42	0.33	0.32		
log likelihood					-10,869	-10,131
Wald test of independence					3,312	6,289
p-value					0.00	0.00
N	4,418	4,412	4,417	4,411	14,861	14,861
N uncensored					4,269	4,269

This table shows the results of six different specifications of a firm-value model. Specifically, we estimate the impact of the Sustainability Solutions Score (SSS) on Tobin's Q. (1) provides the results of a pooled regression. Country and industry fixed effects are included in (2), (3) and (4). (5) and (6) incorporate a Heckman correction and are estimated jointly with a SDG disclosing-choice model. We estimate the impact on firm value of a firm's SDG performance using various controls for e.g. size, value, profitability, dividends and leverage. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8
Firm-value model – Impact of the Social and the Environmental Pillar Scores on firm value

	(1) Tobin's Q	(2) Tobin's Q	(3) Tobin's Q	(4) Tobin's Q	(5) Tobin's Q	(6) Tobin's Q
Social Pillar Score	0.017***	0.019***	-0.0057	-0.00043	0.013***	0.00040
	(3.56)	(4.21)	(-0.80)	(-0.06)	(2.92)	(0.06)
Environmental Pillar Score	0.0070	0.0070	0.00021	0.0060	0.0095*	0.0067
	(1.23)	(1.25)	(0.03)	(0.88)	(1.72)	(1.04)
Controls	yes	yes	yes	yes	yes	yes
Country fixed effects	no	yes	no	yes	no	yes
Industry fixed effects	no	no	yes	yes	no	yes
Heckman	no	no	no	no	yes	yes
adj. R^2	0.41	0.48	0.56	0.60		
within R^2		0.42	0.33	0.32		
log likelihood					-10,870	-10,131
Wald test of independence					3,308	6,292
p-value					0.00	0.00
N	4,418	4,412	4,417	4,411	14,861	14,861
N uncensored					4,269	4,269

This table shows the results of six different specifications of a firm-value model. Specifically, we estimate the impact of the Social and Environmental Pillar Scores (SPS and EPS) on Tobin's Q. (1) provides the results of a pooled regression. Country and industry fixed effects are included in (2), (3) and (4). (5) and (6) incorporate a Heckman correction and are estimated jointly with a SDG disclosing-choice model. We estimate the impact on firm value of a firm's SDG performance using various controls for e.g. size, value, profitability, dividends and leverage. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 9

Firm-value model – Impact of the Sustainable Objective Scores on firm value

	(1) Tobin's Q	(2) Tobin's Q	(3) Tobin's Q	(4) Tobin's Q	(5) Tobin's Q	(6) Tobin's Q
Alleviating poverty	-0.11***	-0.10***	-0.0086	-0.015	-0.087***	-0.010
	(-3.48)	(-3.04)	(-0.26)	(-0.44)	(-3.02)	(-0.30)
Combating hunger and malnutrition	-0.087***	-0.084***	-0.044***	-0.047***	-0.072***	-0.030***
	(-8.97)	(-9.03)	(-3.71)	(-4.05)	(-7.52)	(-2.70)
Ensuring health	0.063***	0.060***	0.025**	0.030**	0.052***	0.020*
	(10.50)	(10.43)	(2.05)	(2.57)	(8.96)	(1.80)
Delivering education	0.012	0.016	0.028	0.028	0.0029	0.017
	(0.46)	(0.63)	(0.91)	(0.92)	(0.12)	(0.62)
Attaining gender equality	-0.0081	0.00078	-0.29**	-0.28**	-0.028	-0.25**
	(-0.05)	(0.01)	(-2.00)	(-1.99)	(-0.20)	(-2.07)
Providing basic services	-0.059***	-0.041***	0.0031	0.0030	-0.057***	-0.0019
	(-3.76)	(-2.68)	(0.17)	(0.17)	(-3.84)	(-0.11)
Safeguarding peace	-0.063**	-0.037	-0.042	-0.025	-0.028	-0.0045
	(-2.08)	(-1.28)	(-1.17)	(-0.73)	(-0.95)	(-0.13)
Achieving sustainable agr. and forestry	0.0071	0.018	0.0038	0.019	0.010	0.017
	(0.21)	(0.55)	(0.10)	(0.51)	(0.33)	(0.49)
Conserving water	-0.058***	-0.038**	-0.048**	-0.023	-0.049***	-0.015
	(-3.11)	(-2.11)	(-2.29)	(-1.12)	(-2.81)	(-0.76)
Contributing to sustainable energy use	-0.0075	0.0020	-0.028	-0.013	-0.0078	-0.017
	(-0.37)	(0.10)	(-1.35)	(-0.67)	(-0.42)	(-0.92)
Promoting sustainable buildings	-0.065***	-0.059***	-0.0095	-0.011	-0.038**	-0.0016
	(-3.76)	(-3.56)	(-0.56)	(-0.64)	(-2.31)	(-0.10)
Optimizing material use	-0.067**	-0.088***	-0.068**	-0.070**	-0.070***	-0.079***
	(-2.46)	(-3.38)	(-2.28)	(-2.45)	(-2.82)	(-3.10)
Mitigating climate change	0.047**	0.036*	0.045**	0.037**	0.045**	0.038**
	(2.33)	(1.87)	(2.35)	(1.98)	(2.42)	(2.19)
Preserving marine ecosystems	-0.11**	-0.12***	0.046	0.029	-0.097**	0.018
	(-2.57)	(-3.01)	(1.17)	(0.75)	(-2.35)	(0.50)
Preserving terrestrial ecosystems	-0.030*	-0.030*	-0.036**	-0.024	-0.024*	-0.020
	(-1.88)	(-1.94)	(-2.30)	(-1.55)	(-1.69)	(-1.41)
Controls	yes	yes	yes	yes	yes	yes
Country fixed effects	no	yes	no	yes	no	yes
Industry fixed effects	no	no	yes	yes	no	yes
Heckman	no	no	no	no	yes	yes
adj. R^2	0.44	0.50	0.56	0.60		
within R^2		0.44	0.34	0.33		
log likelihood					-10,794	-10,114
Wald test of independence					3,593	6,376
p-value					0.00	0.00
N	4,418	4,412	4,417	4,411	14,861	14,861
N uncensored					4,269	4,269

This table shows the results of six different specifications of a firm-value model. Specifically, we estimate the impact of the 15 Sustainable Objective Scores (SOSs) on Tobin's Q. (1) provides the results of a pooled regression. Country and industry fixed effects are included in (2), (3) and (4). (5) and (6) incorporate a Heckman correction and are estimated jointly with a SDG disclosing-choice model. We estimate the impact on firm value of a firm's SDG performance using various controls. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 10

Firm-value model – Impact of the Sustainable Objective Scores and the ESG Performance Score on firm value

	(1) Tobin's Q	(2) Tobin's Q	(3) Tobin's Q	(4) Tobin's Q	(5) Tobin's Q	(6) Tobin's Q
Alleviating poverty	-0.11***	-0.11***	-0.0081	-0.021	-0.090***	-0.014
	(-3.68)	(-3.29)	(-0.25)	(-0.59)	(-3.11)	(-0.40)
Combating hunger and malnutrition	-0.086***	-0.082***	-0.044***	-0.046***	-0.071***	-0.030***
	(-8.81)	(-8.82)	(-3.71)	(-4.02)	(-7.45)	(-2.69)
Ensuring health	0.059***	0.054***	0.025**	0.029**	0.051***	0.019*
	(9.83)	(9.41)	(2.06)	(2.53)	(8.58)	(1.77)
Delivering education	0.0019	-0.0024	0.029	0.023	-0.0020	0.015
	(0.07)	(-0.10)	(0.92)	(0.78)	(-0.08)	(0.52)
Attaining gender equality	-0.023	-0.028	-0.29**	-0.28**	-0.035	-0.25**
	(-0.14)	(-0.19)	(-2.00)	(-2.00)	(-0.25)	(-2.08)
Providing basic services	-0.062***	-0.045***	0.0032	0.0023	-0.059***	-0.0024
	(-3.97)	(-2.96)	(0.17)	(0.13)	(-3.95)	(-0.14)
Safeguarding peace	-0.065**	-0.043	-0.042	-0.024	-0.029	-0.0035
	(-2.15)	(-1.50)	(-1.18)	(-0.69)	(-0.99)	(-0.10)
Achieving sustainable agr. and forestry	-0.0079	0.00031	0.0046	0.012	0.0038	0.013
	(-0.23)	(0.01)	(0.12)	(0.33)	(0.12)	(0.38)
Conserving water	-0.067***	-0.052***	-0.048**	-0.025	-0.053***	-0.016
	(-3.55)	(-2.90)	(-2.27)	(-1.19)	(-3.04)	(-0.81)
Contributing to sustainable energy use	-0.0095	0.00040	-0.028	-0.015	-0.0088	-0.018
	(-0.47)	(0.02)	(-1.34)	(-0.72)	(-0.47)	(-0.95)
Promoting sustainable buildings	-0.073***	-0.072***	-0.0089	-0.017	-0.042**	-0.0055
	(-4.24)	(-4.36)	(-0.51)	(-1.00)	(-2.58)	(-0.34)
Optimizing material use	-0.085***	-0.12***	-0.068**	-0.074**	-0.078***	-0.082***
	(-3.10)	(-4.64)	(-2.27)	(-2.56)	(-3.14)	(-3.18)
Mitigating climate change	0.043**	0.028	0.045**	0.035*	0.043**	0.037**
	(2.14)	(1.43)	(2.35)	(1.88)	(2.33)	(2.13)
Preserving marine ecosystems	-0.10**	-0.11***	0.046	0.032	-0.094**	0.021
	(-2.46)	(-2.78)	(1.16)	(0.83)	(-2.27)	(0.55)
Preserving terrestrial ecosystems	-0.032**	-0.033**	-0.036**	-0.024	-0.025*	-0.019
	(-2.02)	(-2.15)	(-2.30)	(-1.54)	(-1.78)	(-1.40)
ESG performance score	0.0046***	0.0081***	-0.00020	0.0022**	0.0023**	0.0014
	(4.98)	(8.08)	(-0.23)	(2.19)	(2.53)	(1.42)
Controls	yes	yes	yes	yes	yes	yes
Country fixed effects	no	yes	no	yes	no	yes
Industry fixed effects	no	no	yes	yes	no	yes
Heckman	no	no	no	no	yes	yes
adj. R^2	0.44	0.51	0.56	0.60		
within R^2		0.45	0.34	0.33		
log likelihood					-10,791	-10,113
Wald test of independence					3,615	6,389
p-value					0.00	0.00
N	4,418	4,412	4,417	4,411	14,861	14,861
N uncensored					4,269	4,269

This table shows the results of six different specifications of a firm-value model. Specifically, we estimate the impact of the 15 Sustainable Objective Scores (SOSs) and the ISS ESG performance score on Tobin's Q. (1) provides the results of a pooled regression. Country and industry fixed effects are included in (2), (3) and (4). (5) and (6) incorporate a Heckman correction and are estimated jointly with a SDG disclosing-choice model. We estimate the impact on firm value of a firm's SDG performance using various controls. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 11
Firm-value model – Impact of the Sustainable Objective Scores and the SDG Global Index Score on firm value

	(1) Tobin's Q	(2) Tobin's Q	(3) Tobin's Q	(4) Tobin's Q	(5) Tobin's Q	(6) Tobin's Q
Alleviating poverty	-0.065*	-0.099***	0.038	-0.010	-0.051	-0.010
	(-1.81)	(-2.63)	(1.05)	(-0.28)	(-1.52)	(-0.29)
Combating hunger and malnutrition	-0.089***	-0.084***	-0.048***	-0.047***	-0.074***	-0.031***
	(-9.03)	(-8.87)	(-4.08)	(-4.06)	(-7.69)	(-2.75)
Ensuring health	0.067***	0.062***	0.028**	0.030**	0.057***	0.019*
	(11.12)	(10.54)	(2.33)	(2.54)	(9.69)	(1.78)
Delivering education	0.013	0.016	0.032	0.027	0.0026	0.017
	(0.49)	(0.64)	(1.05)	(0.90)	(0.11)	(0.60)
Attaining gender equality	-0.032	-0.00082	-0.31**	-0.29**	-0.050	-0.25**
	(-0.20)	(-0.01)	(-2.14)	(-2.02)	(-0.36)	(-2.09)
Providing basic services	-0.063***	-0.045***	0.0036	0.00086	-0.060***	-0.0025
	(-3.94)	(-2.92)	(0.19)	(0.05)	(-4.02)	(-0.14)
Safeguarding peace	-0.059**	-0.038	-0.033	-0.026	-0.024	-0.0055
	(-1.97)	(-1.32)	(-0.94)	(-0.74)	(-0.82)	(-0.16)
Achieving sustainable agr. and forestry	0.021	0.018	0.024	0.018	0.025	0.017
	(0.63)	(0.56)	(0.63)	(0.48)	(0.79)	(0.49)
Conserving water	-0.054***	-0.039**	-0.042*	-0.023	-0.049***	-0.015
	(-2.79)	(-2.05)	(-1.95)	(-1.07)	(-2.69)	(-0.75)
Contributing to sustainable energy use	-0.0072	0.0018	-0.025	-0.013	-0.0085	-0.013
	(-0.36)	(0.09)	(-1.23)	(-0.64)	(-0.45)	(-0.69)
Promoting sustainable buildings	-0.063***	-0.062***	-0.0072	-0.015	-0.035**	-0.0032
	(-3.64)	(-3.68)	(-0.42)	(-0.91)	(-2.13)	(-0.20)
Optimizing material use	-0.067**	-0.087***	-0.066**	-0.071**	-0.071***	-0.079***
	(-2.42)	(-3.31)	(-2.21)	(-2.42)	(-2.86)	(-3.04)
Mitigating climate change	0.050**	0.038*	0.047**	0.038**	0.050***	0.036**
	(2.53)	(1.90)	(2.51)	(1.98)	(2.69)	(2.00)
Preserving marine ecosystems	-0.11***	-0.12***	0.034	0.027	-0.10**	0.015
	(-2.62)	(-2.94)	(0.86)	(0.68)	(-2.43)	(0.41)
Preserving terrestrial ecosystems	-0.021	-0.031**	-0.026*	-0.025	-0.014	-0.019
	(-1.32)	(-1.98)	(-1.71)	(-1.60)	(-0.99)	(-1.39)
SDG Global Index Score	-0.021***	-0.0061	-0.023***	-0.0040	-0.023***	-0.0087
	(-7.88)	(-0.37)	(-9.28)	(-0.26)	(-8.85)	(-0.62)
Controls	yes	yes	yes	yes	yes	yes
Country fixed effects	no	yes	no	yes	no	yes
Industry fixed effects	no	no	yes	yes	no	yes
Heckman	No	no	no	no	yes	yes
adj. R^2	0.44	0.49	0.57	0.60		
within R^2		0.44	0.35	0.33		
log likelihood					-10,542	-9,914
Wald test of independence					3,594	6,192
p-value					0	0
N	4,296	4,290	4,295	4,289	14,742	14,742
N uncensored					4,150	4,150

This table shows the results of six different specifications of a firm-value model. Specifically, we estimate the impact of the 15 Sustainable Objective Scores (SOSs) and the SDG Global Index Score on Tobin's Q. (1) provides the results of a pooled regression. Country and industry fixed effects are included in (2), (3) and (4). (5) and (6) incorporate a Heckman correction and are estimated jointly with a SDG disclosing-choice model. We estimate the impact on firm value of a firm's SDG performance using various controls. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 12
Firm-value model – Impact of the mean of Sustainable Objective Scores on firm value

	(1) Tobin's Q	(2) Tobin's Q	(3) Tobin's Q	(4) Tobin's Q	(5) Tobin's Q	(6) Tobin's Q
Mean Sustainability Objective Scores	0.084**	0.099***	-0.020	0.031	0.081**	0.041
	(2.46)	(3.01)	(-0.44)	(0.68)	(2.51)	(0.96)
Controls	yes	yes	yes	yes	yes	yes
Country fixed effects	no	yes	no	yes	no	yes
Industry fixed effects	no	no	yes	yes	no	yes
Heckman	no	no	no	no	yes	yes
adj. R^2	0.41	0.47	0.56	0.60		
within R^2		0.41	0.33	0.32		
log likelihood					-10,873	-10,131
Wald test of independence					3,297	6,291
p-value					0.00	0.00
N	4,418	4,412	4,417	4,411	14,861	14,861
N uncensored					4,269	4,269

This table shows the results of six different specifications of a firm-value model. Specifically, we estimate the impact of the mean of all Sustainable Objective Scores (SOSs) on Tobin's Q. (1) provides the results of a pooled regression. Country and industry fixed effects are included in (2), (3) and (4). (5) and (6) incorporate a Heckman correction and are estimated jointly with a SDG disclosing-choice model. We estimate the impact on firm value of a firm's SDG performance using various controls for e.g. size, value, profitability, dividends and leverage. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table 13
Firm-value model – Impact of the principal components of the Sustainable Objective Scores on firm value

	(1) Tobin's Q	(2) Tobin's Q	(3) Tobin's Q	(4) Tobin's Q	(5) Tobin's Q	(6) Tobin's Q
Principal component 1	0.037***	0.041***	0.013	0.027**	0.037***	0.027**
	(3.71)	(4.26)	(1.02)	(2.14)	(3.89)	(2.22)
Principal component 2	-0.033***	-0.022**	-0.030**	-0.024*	-0.032***	-0.019
	(-2.98)	(-2.01)	(-2.18)	(-1.72)	(-3.14)	(-1.49)
Principal component 3	-0.041***	-0.048***	-0.035**	-0.025*	-0.031**	-0.019
	(-3.06)	(-3.68)	(-2.35)	(-1.68)	(-2.50)	(-1.42)
Principal component 4	0.0019	0.0078	0.010	0.011	-0.0046	-0.0019
	(0.13)	(0.55)	(0.62)	(0.66)	(-0.36)	(-0.13)
Principal component 5	0.0013	0.0024	0.025*	0.021	0.0092	0.021*
	(0.10)	(0.19)	(1.86)	(1.60)	(0.75)	(1.76)
Principal component 6	-0.037***	-0.040***	-0.011	-0.014	-0.030***	-0.0088
	(-3.01)	(-3.37)	(-0.81)	(-1.02)	(-2.66)	(-0.69)
Principal component 7	0.0057	0.0060	-0.025*	-0.022	0.017	-0.011
	(0.44)	(0.49)	(-1.66)	(-1.51)	(1.42)	(-0.78)
Controls	yes	yes	yes	yes	yes	yes
Country fixed effects	no	yes	no	yes	no	yes
Industry fixed effects	no	no	yes	yes	no	yes
Heckman	no	no	no	no	yes	yes
adj. R^2	0.42	0.48	0.56	0.60		
within R^2		0.42	0.33	0.33		
log likelihood					-10,856	-10,124
Wald test of independence					3,354	6,322
p-value					0.00	0.00
N	4,418	4,412	4,417	4,411	14,861	14,861
N uncensored					4,269	4,269

This table shows the results of six different specifications of a firm-value model. Specifically, we estimate the impact of the first seven principal components (PCs) of all 15 Sustainability Objective Scores (SOSs) on Tobin's Q. (1) provides the results of a pooled regression. Country and industry fixed effects are included in (2), (3) and (4). (5) and (6) incorporate a Heckman correction and are estimated jointly with a SDG disclosing-choice model. We estimate the impact on firm value of a firm's SDG performance using various controls for e.g. size, value, profitability, dividends and leverage. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix A.

Table A.1
Geographic and sectoral breakdown

Panel A. SDG dataset

Country	#	%	Sector	#	%
USA	2,346	39.99	Financials	1,342	22.88
Japan	357	6.09	Industrials	926	15.79
Australia	306	5.22	Cyclical Consumer Goods & Services	824	14.05
Canada	270	4.60	Technology	594	10.13
UK	266	4.53	Healthcare	555	9.46
Sweden	249	4.24	Basic Materials	496	8.46
Germany	168	2.86	Non-Cyclical Consumer Goods & Services	418	7.13
China	158	2.69	Energy	355	6.05
Hong Kong	142	2.42	Utilities	232	3.95
France	139	2.37	Telecommunications Services	124	2.11
Other Europe	654	11.15			
Other Asia	576	9.82			
Other Americas	121	2.06			
Other Africa	63	1.07			
Other Oceania	51	0.87			
Total	5,866	100.00	Total	5,866	100.00

Panel B. Full dataset

Country	#	%	Sector	#	%
USA	5,933	21.13	Financials	5,403	19.24
China	3,490	12.43	Industrials	4,616	16.44
Japan	2,781	9.90	Cyclical Consumer Goods & Services	4,285	15.26
Hong Kong	1,240	4.42	Technology	3,430	12.22
Canada	1,238	4.41	Basic Materials	3,014	10.73
UK	1,185	4.22	Healthcare	2,302	8.20
India	1,171	4.17	Non-Cyclical Consumer Goods & Services	2,037	7.25
South Korea	1,123	4.00	Energy	1,756	6.25
Taiwan	1,019	3.63	Utilities	794	2.83
Australia	864	3.08	Telecommunications Services	441	1.57
Other Europe	3,869	13.78			
Other Asia	2,771	9.87			
Other Americas	764	2.72			
Other Africa	529	1.88			
Other Oceania	101	0.36			
Total	28,078	100.00	Total	28,078	100.00

This table shows the geographic and sectoral breakdown for the SDG subsample (Panel A) and all firms (Panel B) in absolute numbers and percentages for the data sample for the period from 2017 to 2019. The sectoral breakdown is based on the Thomson Reuters Business Classification (TRBC).

Table A.2

Disclosure-choice model – Social and Environmental Pillar Scores

	(1) Disclosing SDGs	(2) Disclosing SDGs
Total assets	0.50***	0.48***
	(33.12)	(30.93)
Book-to-market	-0.60***	-0.55***
	(-21.84)	(-19.27)
Return on assets	8.29***	7.94***
	(26.99)	(24.74)
Leverage	-0.23***	-0.21***
	(-9.39)	(-8.62)
Dividends	0.075***	0.091***
	(5.52)	(6.60)
Sector disclosure proportion	0.39*	0.50**
	(1.75)	(2.13)
Institutional investors	-0.23***	-0.54***
	(-3.71)	(-8.51)
Individual investor	-0.73***	-1.04***
	(-6.43)	(-8.85)
Number of reporting databases	0.25***	0.27***
	(19.04)	(20.49)
Constant	-13.5***	-13.1***
	(-53.83)	(-51.57)
Country fixed effects	no	yes
Industry fixed effects	no	yes
adj. R^2	0.33	0.33
N	14,861	14,861

This table shows the results of the SDGs disclosure-choice model of the Heckman correction. It is estimated jointly with a firm-value model estimating the impact of the Social Pillar Score (SPS) and the Environmental Pilar Score (EPS) on firm value. We estimate the probability of firms disclosing SDG data using various controls for e.g. size, value, profitability, dividends, leverage, disclosure proportion within a firm's sector, ownership structure and number of reports to different ESG databases. We include country and industry fixed effects in the second column. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.3

Disclosure-choice model – Sustainable Objective Scores

	(1) Disclosing SDGs	(2) Disclosing SDGs
Total assets	0.51***	0.48***
	(33.48)	(31.01)
Book-to-market	-0.61***	-0.55***
	(-22.45)	(-19.40)
Return on assets	8.35***	7.96***
	(27.31)	(24.85)
Leverage	-0.23***	-0.21***
	(-9.33)	(-8.61)
Dividends	0.073***	0.091***
	(5.35)	(6.54)
Sector disclosure proportion	0.19	0.50**
	(0.86)	(2.13)
Institutional investors	-0.24***	-0.54***
	(-3.91)	(-8.57)
Individual investor	-0.73***	-1.05***
	(-6.52)	(-8.94)
Number of reporting databases	0.25***	0.27***
	(19.22)	(20.44)
Constant	-13.5***	-13.1***
	(-53.96)	(-51.59)
Country fixed effects	no	yes
Industry fixed effects	no	yes
adj. R^2	0.33	0.33
N	14,861	14,861

This table shows the results of the SDGs disclosure-choice model of the Heckman correction. It is estimated jointly with a firm-value model estimating the impact of Sustainable Objectives Scores (SOSs) on firm value. We estimate the probability of firms disclosing SDG data using various controls for e.g. size, value, profitability, dividends, leverage, disclosure proportion within a firm's sector, ownership structure and number of reports to different ESG databases. We include country and industry fixed effects in the second column. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.4

Disclosure-choice model – Sustainable Objective Scores – Two-step Heckman correction

	(1) Disclosing SDGs	(2) Disclosing SDGs
Total assets	0.40***	0.40***
	(24.51)	(24.51)
Book-to-market	-0.50***	-0.50***
	(-16.14)	(-16.14)
Return on assets	4.90***	4.90***
	(15.08)	(15.08)
Leverage	-0.23***	-0.23***
	(-9.13)	(-9.13)
Dividends	0.17***	0.17***
	(11.41)	(11.41)
Sector disclosure proportion	0.16	0.16
	(0.65)	(0.65)
Institutional investors	-0.51***	-0.51***
	(-7.64)	(-7.64)
Individual investor	-1.09***	-1.09***
	(-8.43)	(-8.43)
Number of reporting databases	0.32***	0.32***
	(22.88)	(22.88)
Constant	-12.4***	-12.4***
	(-47.83)	(-47.83)
Country fixed effects	no	yes
Industry fixed effects	no	yes
adj. R^2	0.33	0.33
N	14,861	14,861

This table shows the results of the disclosure-choice model of the two-step estimated Heckman correction on the impact of the Sustainable Objective Scores (SOSs) on firm value. We estimate in a first step the probability of firms disclosing SDG data using various controls for e.g. size, value, profitability, dividends, leverage, disclosure proportion within a firm's sector, ownership structure and number of reports to different ESG databases. We include country and industry fixed effects in the second column. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.5
Firm-value model – Impact of the Sustainability Objective Scores on firm value – Two-step Heckman correction

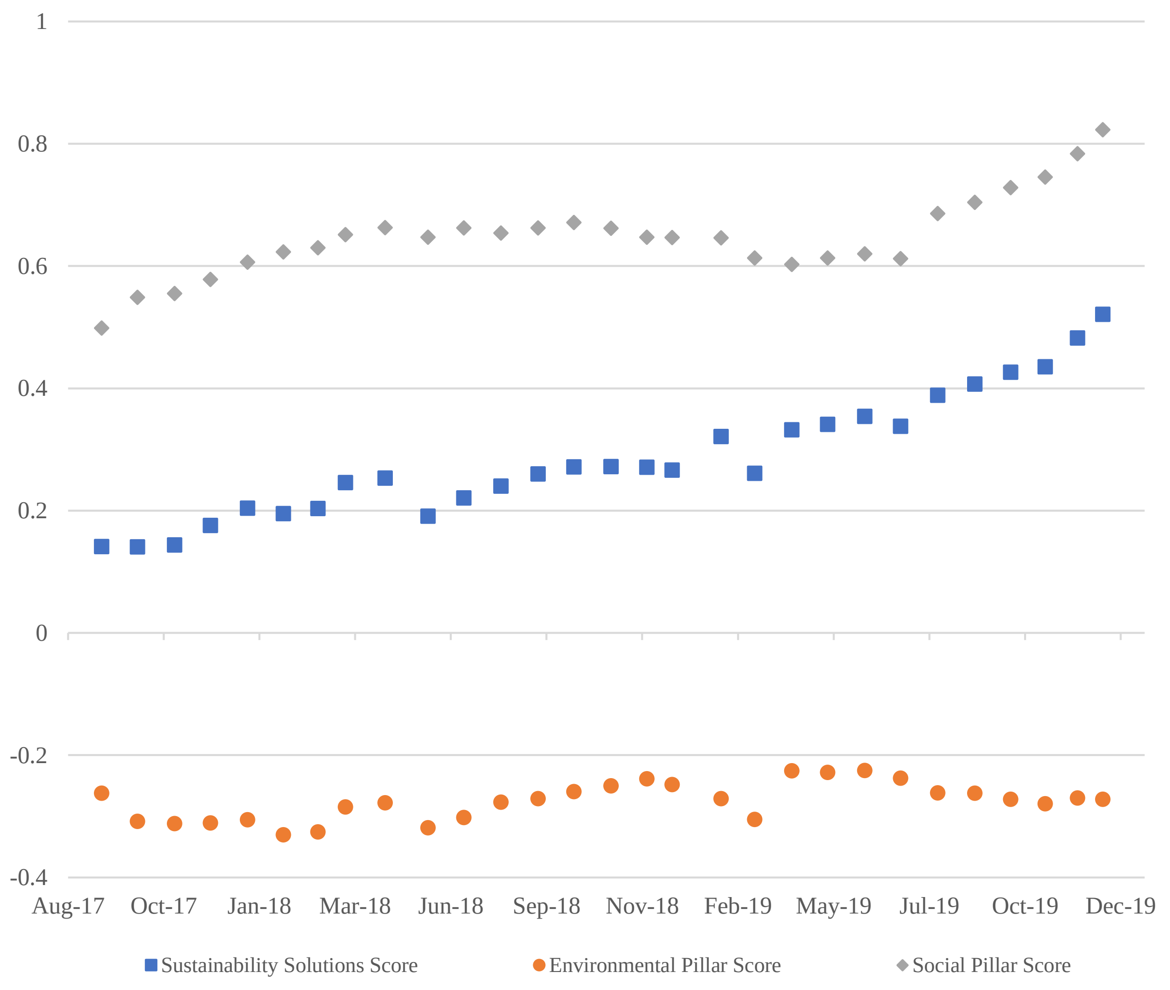
	(1) Tobin's Q	(2) Tobin's Q	(3) Tobin's Q	(4) Tobin's Q	(5) Tobin's Q	(6) Tobin's Q
Alleviating poverty	-0.11***	-0.10***	-0.0086	-0.015	-0.082***	-0.0019
	(-3.48)	(-3.04)	(-0.26)	(-0.44)	(-2.67)	(-0.05)
Combating hunger and malnutrition	-0.087***	-0.084***	-0.044***	-0.047***	-0.075***	-0.031***
	(-8.97)	(-9.03)	(-3.71)	(-4.05)	(-7.22)	(-2.65)
Ensuring health	0.063***	0.060***	0.025**	0.030**	0.049***	0.016
	(10.50)	(10.43)	(2.05)	(2.57)	(7.20)	(1.39)
Delivering education	0.012	0.016	0.028	0.028	-0.013	0.013
	(0.46)	(0.63)	(0.91)	(0.92)	(-0.54)	(0.46)
Attaining gender equality	-0.0081	0.00078	-0.29**	-0.28**	0.019	-0.23**
	(-0.05)	(0.01)	(-2.00)	(-1.99)	(0.16)	(-2.16)
Providing basic services	-0.059***	-0.041***	0.0031	0.0030	-0.048***	-0.0077
	(-3.76)	(-2.68)	(0.17)	(0.17)	(-2.99)	(-0.42)
Safeguarding peace	-0.063**	-0.037	-0.042	-0.025	-0.047	-0.017
	(-2.08)	(-1.28)	(-1.17)	(-0.73)	(-1.49)	(-0.49)
Achieving sustainable agr. and forestry	0.0071	0.018	0.0038	0.019	0.0037	0.015
	(0.21)	(0.55)	(0.10)	(0.51)	(0.11)	(0.41)
Conserving water	-0.058***	-0.038**	-0.048**	-0.023	-0.054***	-0.012
	(-3.11)	(-2.11)	(-2.29)	(-1.12)	(-2.95)	(-0.59)
Contributing to sustainable energy use	-0.0075	0.0020	-0.028	-0.013	-0.021	-0.024
	(-0.37)	(0.10)	(-1.35)	(-0.67)	(-1.04)	(-1.21)
Promoting sustainable buildings	-0.065***	-0.059***	-0.0095	-0.011	-0.029*	0.0023
	(-3.76)	(-3.56)	(-0.56)	(-0.64)	(-1.74)	(0.14)
Optimizing material use	-0.067**	-0.088***	-0.068**	-0.070**	-0.072***	-0.081***
	(-2.46)	(-3.38)	(-2.28)	(-2.45)	(-2.96)	(-3.23)
Mitigating climate change	0.047**	0.036*	0.045**	0.037**	0.053***	0.044**
	(2.33)	(1.87)	(2.35)	(1.98)	(2.66)	(2.34)
Preserving marine ecosystems	-0.11**	-0.12***	0.046	0.029	-0.12***	-0.0032
	(-2.57)	(-3.01)	(1.17)	(0.75)	(-2.72)	(-0.08)
Preserving terrestrial ecosystems	-0.030*	-0.030*	-0.036**	-0.024	-0.014	-0.011
	-0.11***	-0.10***	-0.0086	-0.015	-0.082***	-0.0019
Controls	yes	yes	yes	yes	yes	yes
Country fixed effects	no	yes	no	yes	no	yes
Industry fixed effects	no	no	yes	yes	no	yes
Heckman	no	no	no	no	yes	yes
adj. R^2	0.44	0.50	0.56	0.60		
within R^2		0.44	0.34	0.33		
Wald test of independence					2,622	4,557
p-value					0.00	0.00
N	4,418	4,412	4,417	4,411	14,861	14,861
N uncensored					4,269	4,269

This table shows the results of six different specifications of a firm-value model. Specifically, we estimate the impact of the 15 Sustainable Objective Scores (SOSs) on Tobin's Q. (1) provides the results of a pooled regression. Country and industry fixed effects are included in (2), (3) and (4). (5) and (6) incorporate a two-step Heckman correction by incorporating the inverse Mills ratio of a SDG disclosing-choice model into this firm-value model. We estimate the impact on firm value of a firm's SDG performance using various controls. *, **, and *** denote statistical significance at the 10%, 5%, and 1% level, respectively.

Internet Appendix IA.

Figure IA.1

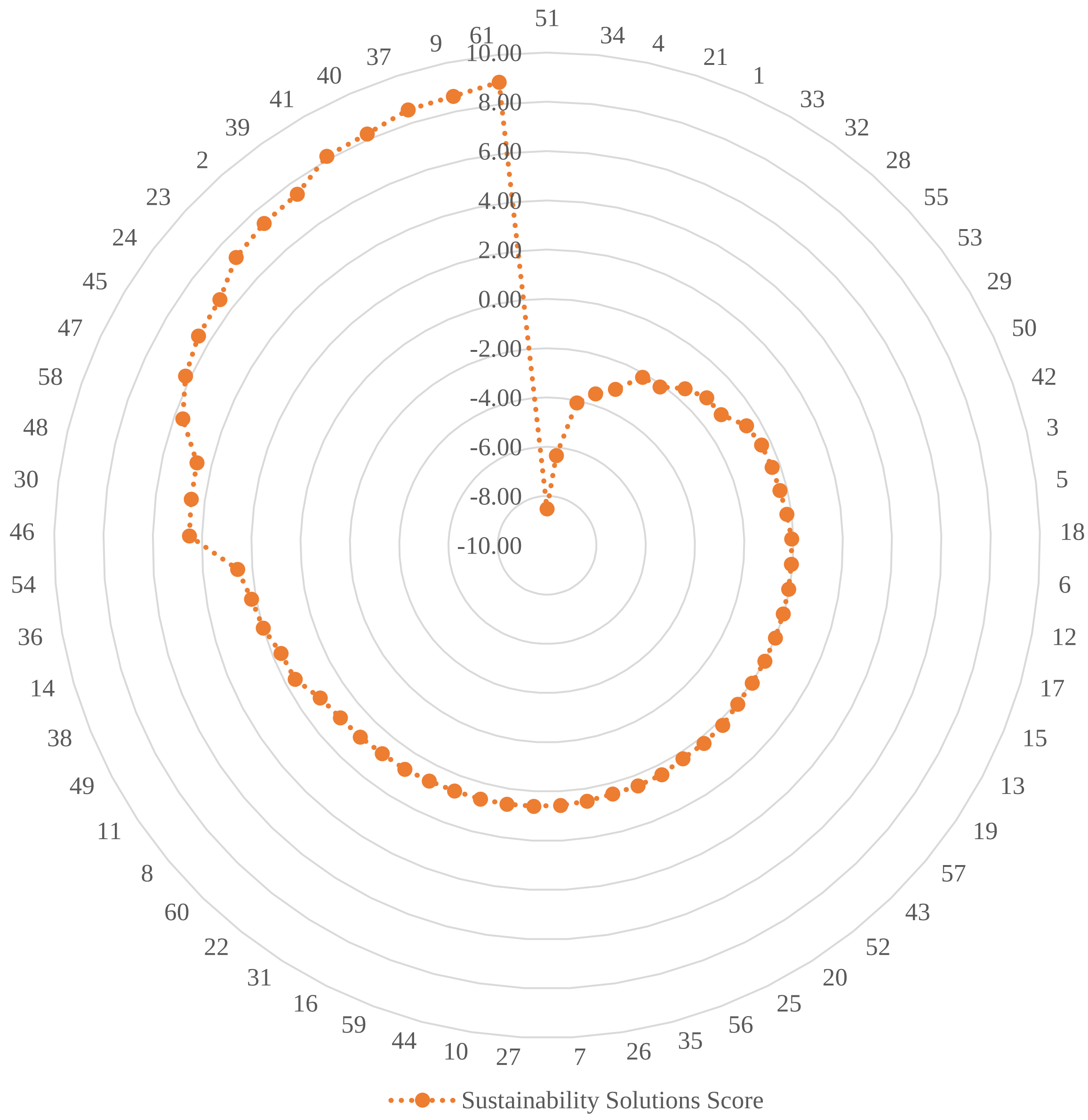
SDG Score Development over Time



This figure shows the development of the mean of four different SDG scores (Sustainability Solutions Score, Environmental Pillar Score, Social Pillar Score and the ESG Performance Score) for the period from August 2017 to December 2019.

Figure IA.2

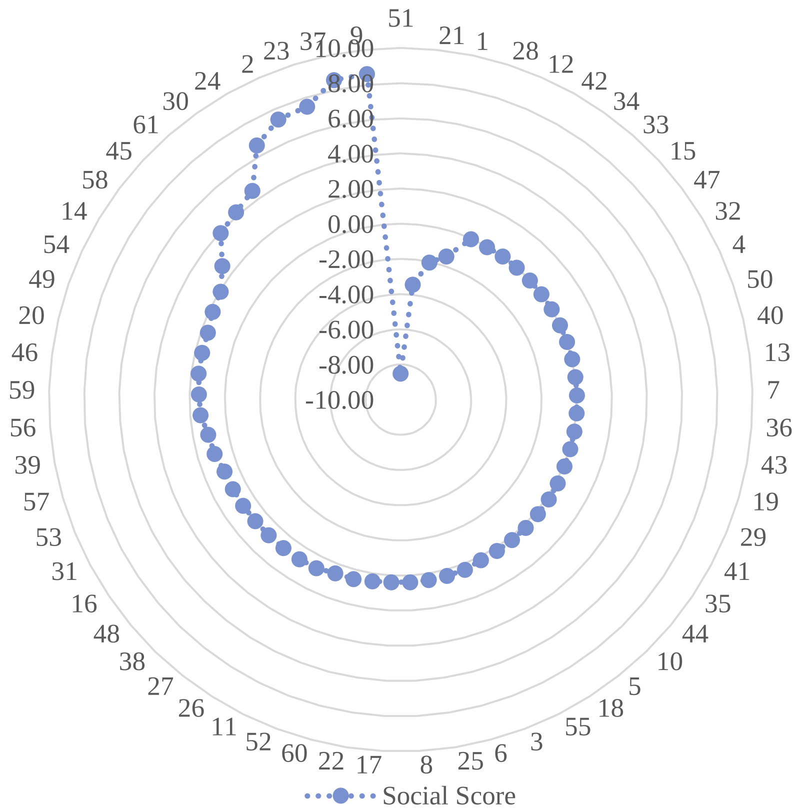
Sectoral Distribution of the Sustainability Solutions Score

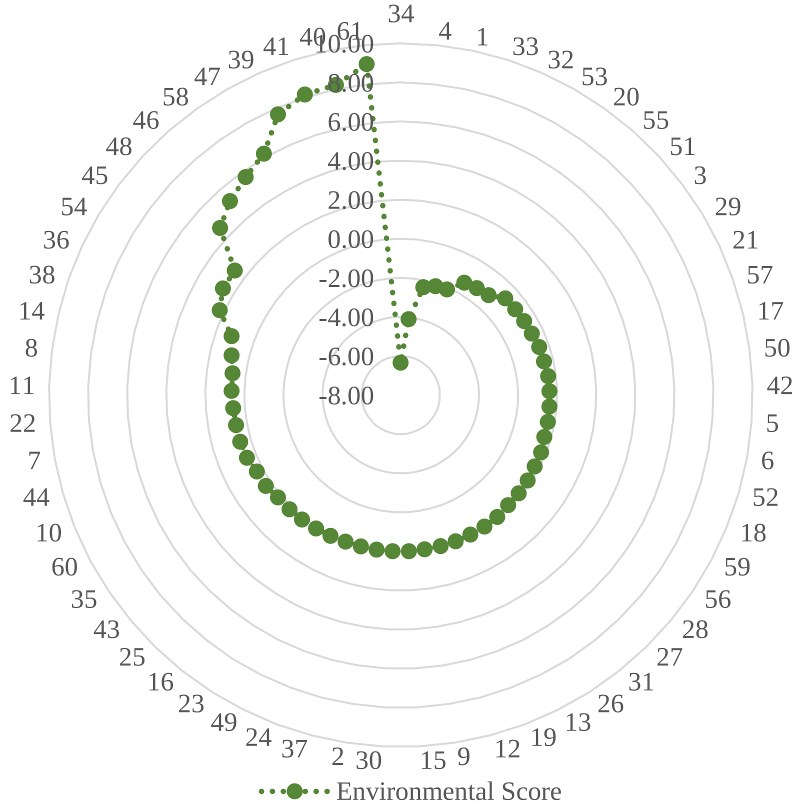


This figure shows the distribution of the Sustainability Solutions Score across 61 sectors. The sector 51 "Tobacco" has the lowest and the sector 61 "Water Efficiency & Treatment" has the highest mean Sustainability Solutions Score within the sample period from 2017 to 2019. The corresponding sector for each number can be found in table IA.1.

Figure IA.3

Sectoral Distribution of the Environmental and Social Pillar Score

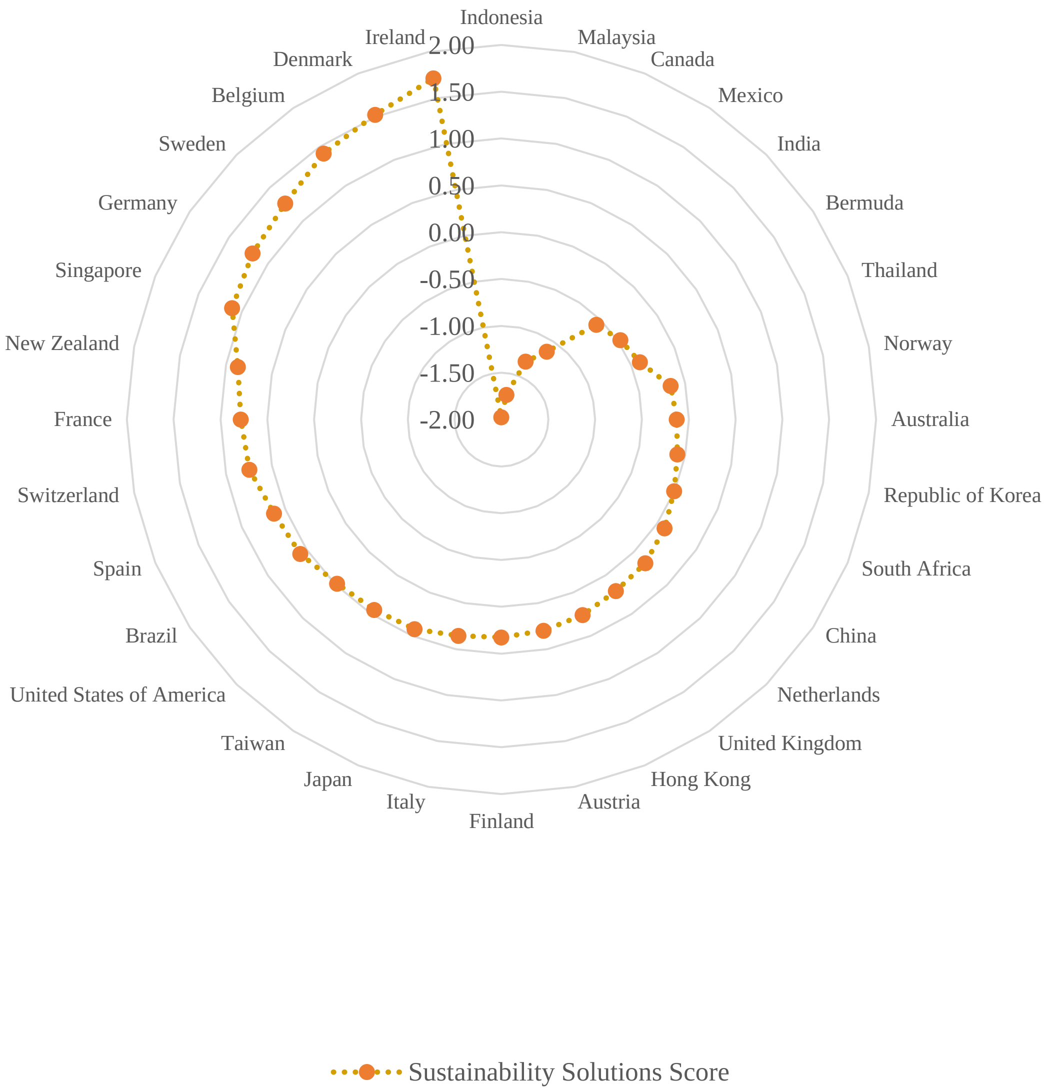




This figure shows the distribution of the Social Pillar Score and the Environmental Pillar Score across 61 sectors. The sector 51 "Tobacco" has the lowest and the sector 9 "Water Efficiency & Treatment" has the highest mean Social Pillar Score, the sector 34 "Oil, Gas & Consumable Fuels" has the lowest and the sector 61 "Water Efficiency & Treatment" has the highest mean Environmental Pillar Score within the sample period from 2017 to 2019. The corresponding sector for each number can be found in table IA.1.

Figure IA.4

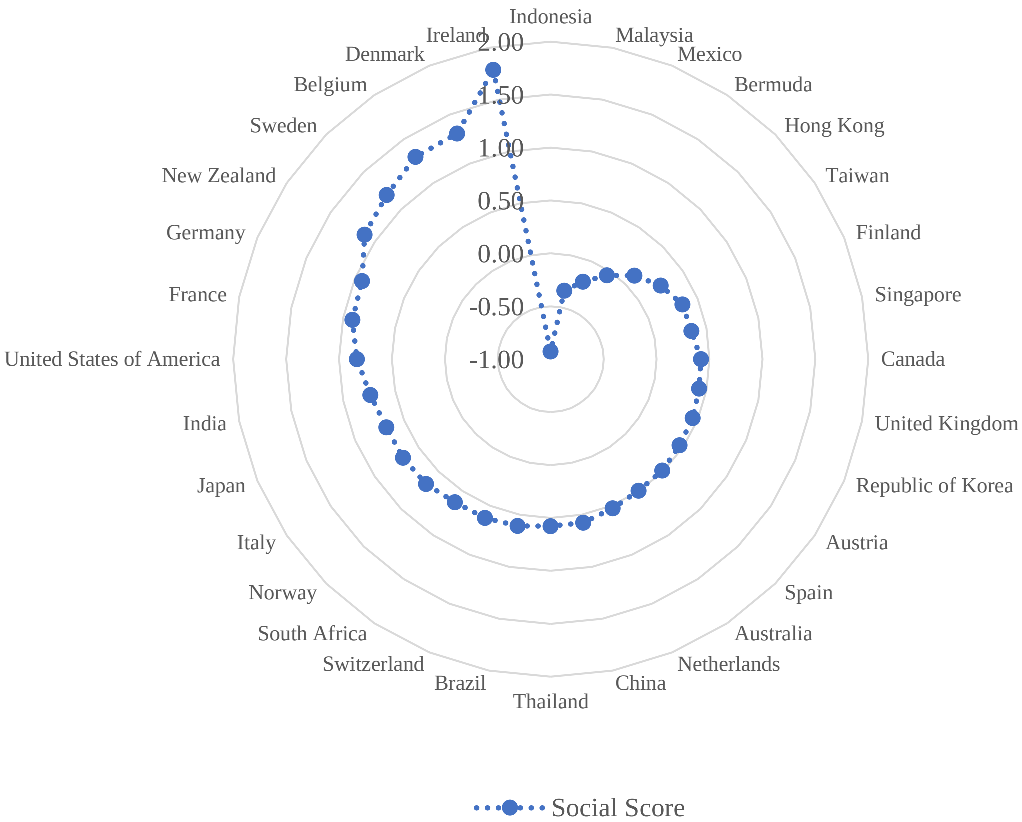
Geographical Distribution of the Sustainability Solutions Score

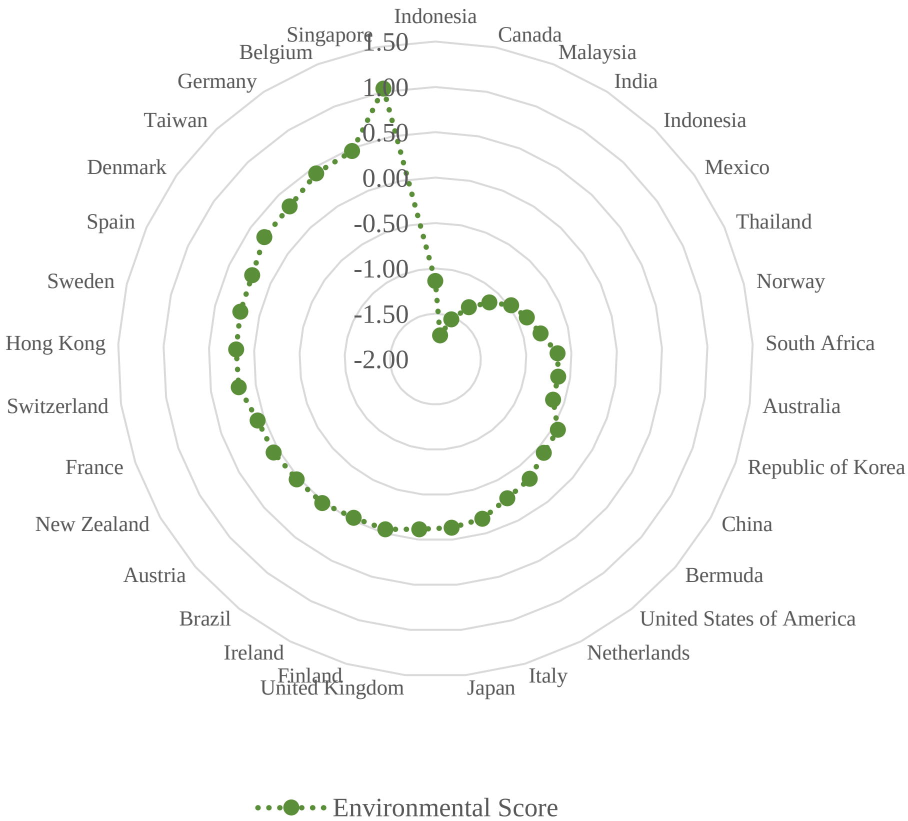


This figure shows the distribution of the Sustainability Solutions Score across 32 countries. Indonesia has the lowest and Ireland has the highest mean Sustainability Solutions Score within the sample period from 2017 to 2019.

Figure IA.5

Geographic and sectoral breakdown





This figure shows the distribution of the Social Pillar Score and the Environmental Pillar Score across 32 countries. Indonesia has the lowest and Ireland has the highest mean Social Pillar Score, Indonesia has the lowest and Singapore has the highest mean Environmental Pillar Score within the sample period from 2017 to 2019.

Table IA.1

List of all Sectors

Number	Sector	Number	Sector
1	Aerospace & Defense	32	Metals & Mining
2	Alternative Health	33	Oil & Gas Equipment/Services
3	Auto Components	34	Oil, Gas & Consumable Fuels
4	Automobile	35	Packaging
5	Chemicals	36	Paper & Forest Products
6	Commercial Services & Supplies	37	Pharmaceuticals & Biotechnology
7	Construction	38	Real Estate
8	Construction Materials	39	Recycling & Emissions Reduction
9	Education	40	Renewable Energy & Energy Effic.
10	Electronic Components	41	Renewable Energy Operation
11	Electronic Devices & Appliances	42	Retail
12	Financials/Asset Managers & Sec.	43	Semiconductors
13	Financials/Commercial Banks & Ca	44	Software & IT Services
14	Financials/Development Banks	45	Sustainable Finance
15	Financials/Exchanges	46	Sustainable Food
16	Financials/Mortgage & Public Sec.	47	Sustainable Materials
17	Financials/Multi-Sector Holdings	48	Sustainable Transportation
18	Financials/Others	49	Telecommunications
19	Financials/Public & Regional Ban	50	Textiles & Apparel
20	Financials/Specialized Finance	51	Tobacco
21	Food & Beverages	52	Trading Companies & Distributors
22	Furniture & Fittings	53	Transport & Logistics
23	Health Care Equipment & Supplies	54	Transport & Logistics/Rail
24	Health Care Facilities & Service	55	Transportation Infrastructure
25	Household & Personal Products	56	Utilities
26	Industrial Conglomerates	57	Utilities/Electric Utilities
27	Insurance	58	Utilities/Environmental Services
28	Leisure	59	Utilities/Multi Utilities
29	Machinery	60	Utilities/Network Operators
30	Managed Health Care	61	Water Efficiency & Treatment
31	Media		

This table shows a list of all 61 sectors and their corresponding number in alphabetical order.

Table IA.2

Examples of SDG Contributors and Obstructers

Objective	High SDG Contributors	High SDG Obstructers
Social Objectives		
Alleviating poverty	Molina Healthcare Inc. (health plans for low-income population)	PlayAGS Inc. (gambling devices and solutions)
Combating hunger and malnutrition	Limoneira Co. (fruits)	United Spirits Ltd. (alcoholic beverages)
Ensuring health	Carl Zeiss Meditec AG (professional diagnostic and treatment devices)	Philip Morris International Inc. (cigarettes, cigars and other tobacco-related products)
Delivering education	G8 Education Ltd. (developmental and educational childcare services)	*no high obstructing firm*
Attaining gender equality	Veru Inc. (female condoms)	*no high obstructing firm*
Providing basic services	Genossenschaft Emissionszentrale für gemeinnützige Wohnbauträger EGW (funding of social housing)	*no high obstructing firm*
Safeguarding peace	Sophos Group plc (IT security solutions)	Huntington Ingalls Industries Inc. (key components for nuclear weapons, armed submarines)
Environmental Objectives		
Achieving sustainable agriculture & forestry	Bellamy's Australia Ltd. (certified organic products)	Bumitama Agri Ltd. (conventional palm oil, non-certified energy-crop based biofuels)
Conserving water	California Water Service Group (water/wastewater services)	Paramount Resources Ltd. (hydrocarbons produced using hydraulic fracturing)
Contributing to sustainable energy use	Vestas Wind Systems A/S (wind power equipment)	Africa Oil Corp. (oil exploration)
Promoting sustainable buildings	Meritage Homes Corp. (buildings certified to a sustainable building standard (Energy Star))	*no high obstructing firm*
Optimizing material use	ALBA SE (Recycling services (e.g. metals, e-waste))	*no high obstructing firm*
Mitigating climate change	Yingli Green Energy Holding Co. Ltd. (solar power equipment and projects)	Coal India Ltd. (coal, coal-related services)
Preserving marine ecosystems	Angel Seafood Holdings Ltd. (certified organic products)	Pingtan Marine Enterprise Ltd. (products based on uncertified fish)
Preserving terrestrial ecosystems	Daiseki Eco. Solution Co. Ltd. (Industrial effluent and wastewater treatment, soil remediation, improvement)	AngloGold Ashanti Ltd. (gold mining)

This table provides examples of firms with high-contributing or high-obstructing SDG products as of December 2019 within the sample.

7 Will the DAX 50 ESG establish the standard for German sustainable investments? A sustainability and financial performance analysis

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University of Augsburg

Credit and Capital Markets (2020), **4.**

https://www.credit-and-capital-markets.de/pdf/68577C9C831F.PDF

Abstract. The demand for sustainable investments is growing worldwide. As a result, the DAX 50 ESG was introduced in March 2020 as the first ESG index by the German stock exchange. It is promoted as the new standard for German sustainable investments. We are the first to comprehensively examine the sustainability performance of the index and its constituents and compare it to major German and global indices. We examine the sustainability performance using both ESG criteria and the alignment of products and services with the Sustainable Development Goals. In addition, we carry out a financial performance analysis. Our results show that the DAX 50 ESG may only to a limited extent be promoted as the most sustainable German index. Moreover, since inception as well as during the COVID-19 crisis, the DAX 50 ESG's financial performance is comparatively worse. Our findings suggest that stock markets penalize the inclusion of a firm in the DAX 50 ESG in the short run, thus affecting the overall index performance. Our analysis increases investor attention to sustainable financial products and enables better investment decisions.

Keywords: Sustainable finance, Equity indices, Sustainability performance, Financial performance, ESG, SDG, ESG disagreement, Investor, Event study

JEL Classification: G11, G15, G34, Q56

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I would like to thank ISS ESG for the good cooperation in obtaining the data. I am responsible for all errors.

7.1 Introduction

There is a growing demand from investors for sustainable finance opportunities. PRI, the world's leading proponent of responsible investments, has more than 3,000 signatories with more than 90 trillion US dollar in assets under management (PRI, 2019). Key figures in the financial industry, such as Larry Fink of Blackrock, are observing a fundamental reshaping of finance and predict a significant reallocation of capital into sustainable investments (Fink, 2020). The total of sustainable investments reaches a new high of 219 billion euros in Germany. Sustainable funds and mandates have recorded their greatest growth since the FNG survey began, increasing by a total of 41 billion euros (FNG, 2019).

To meet these new demands, Qontigo and the Deutsche Börse Group introduced a new German sustainability index in March 2020: the DAX 50 ESG. It is promoted as the new leading index for sustainable investments in Germany (Qontigo, 2020). The DAX 50 ESG is designed as a sustainable flagship index that should be liquid and diversified, while also including ESG criteria. The DAX 50 ESG eligible universe is based on securities from the HDAX after standardized ESG exclusion screens are applied for controversial weapons, tobacco production, thermal coal, nuclear power, and military contracting. Subsequently, 50 constituents are selected according to market capitalization, order book volume and Sustainalytics' ESG score. They are then weighted by free float market capitalization with a 7% cap. The current composition of the DAX 50 ESG comprises of 23 DAX, 27 MDAX and 8 TecDAX firms.[47] After all, the index is intended to achieve high sustainability performance and investability.

In this paper, we investigate the non-financial and financial performance of the DAX 50 ESG index. We look at both the index and on its constituents on its own as well as in

[47] Five firms are constituents of both MDAX and TecDAX, and three firms are constituents of both DAX and TecDAX after the change of the MDAX and TecDAX composition in 2018.

comparison to major German indices and global ESG indices. Thereby, we have to address first two main challenges to assess the sustainability performance of the DAX 50 ESG: (1) the lack of a comprehensive assessment of a firm’s sustainability and (2) the disagreement of data providers on the sustainability performance of a firm within their different frameworks.

In recent years, many investors have asked how the various CSR, ESG and Sustainable Development Goals (SDGs) frameworks can assess the sustainability of a firm. Until recently, an investor's primary focus has been on defining ESG policies and processes and providing basic reporting, either qualitative or through a selection of ESG-related KPIs. However, when measuring the sustainability of a firm, an investor usually limits the assessment only to the conduct dimension of sustainability. This dimension describes the sustainability of a firm’s organization, usually measured by ESG ratings. In addition, an investor should also look at the sustainability of a firm's products and services. A SDGs framework enables investors to measure the impact of products and services on the achievement of sustainability goals (Schramade, 2017). By considering both the conduct and the product dimension of sustainability, an investor can gain a holistic picture of a firm's sustainability. In our study, we therefore consider both ESG criteria and its individual pillars (Environmental, Social and Governance) as well as the contribution of a firm's products and services to the SDGs.

The differences in the approach taken by rating providers to calculate ESG scores can result in the same firm being rated quite high by one provider and quite low by another (Christensen, Serafeim, & Sikochi, 2019; Li & Polychronopoulos, 2020). ESG metrics are very diverse in application and in terms of indicators measured, methodology used, and weights applied (Chatterji, Durand, Levine, & Touboul, 2016; Kotsantonis & Serafeim, 2019). Studies try to explain why there is so little agreement on how to capture ESG performance using the social origin of data providers and their necessity to create an unique profile in a maturing market (Eccles & Stroehle, 2018). The difference in ESG ratings have implications for the relationship between sustainability and financial performance (Busch, Johnson, Pioch, & Kopp, 2018; Gibson, Krueger, Riand, & Schmidt, 2019) or risk (Monk, Prins, & Rook, 2019). To address this disagreement, we use two major ESG databases Refinitiv ESG and ISS ESG for our analyses to take database differences within the sustainability assessment of a firm into account.

Our results on the sustainability performance of the DAX 50 ESG constituents show a mixed picture. If we look at all German firms that are not included in the DAX 50 ESG, it becomes clear they have performed consistently worse according to several sustainability measures. However, the DAX 50 ESG constituents are not significantly more sustainable compared to, e.g., the DAX constituents. Nonetheless, the new index can compete with other German indices as well as with global ESG indices from MSCI. Looking at the product dimension of sustainability, the results for the DAX 50 ESG are ambivalent again. In some areas, its constituents contribute positively to SDGs, but in others, they harm them. A comparison with other indices also shows the same conflicting pattern.

In the second part of the paper, we look at the financial performance of the DAX 50 ESG since its inception compared to German and global ESG indices. We find a relatively poor performance measured by its raw return, as well as by risk-adjusted performance measures such as Sharpe Ratio and Carhart Alpha. Looking at different risk measures like standard deviation, market beta or maximum drawdown, the index performs more or less as well as the average index within our sample. To explain the performance differences, we first examine the indices for different factor exposures. We find that the DAX 50 ESG Index has only a notable size exposure, which is however comparable in magnitude to the DAX and the HDAX. To further analyze the underperformance of the DAX 50 ESG, we analyze the risk and return of the index before and during the COVID-19 crisis. Thereby, we attempt to identify whether the focus of the index on sustainability has a positive financial impact. However, we do not find any significant improvements in the financial performance in any period. In a further investigation, we apply an event study approach following Oberndorfer, Schmidt, Wagner, and Ziegler (2013). Our results shows that firms are currently penalized for their inclusion in the DAX 50 ESG. This may explain the relatively poor performance of the index currently, but future long-term performance studies should discuss this insight critically.

Our paper contributes to both the emerging literature on sustainability measurement in finance and on the relationship between sustainability and financial performance. Results of related studies usually differ due to different definitions of sustainable performance in various frameworks based on, e.g., CSR (Fatemi, Fooladi, & Tehranian, 2015), ESG (Friede, Busch, & Bassen, 2015), or SDGs (Hussain, Rigoni, & Cavezzali, 2018) concepts. Therefore, it is important that sustainability performance is assessed comprehensively. In particular, our work is related to studies that focus on a holistic perspective of sustainability (Carolina Rezende de Carvalho Ferrei, Amorim Sobreiro, Kimura, & Luiz de Moraes Barboza, 2016). Regarding our research object, an equity index, there are also closely related studies analyzing the characteristics of U.S. sustainable indices (Bianchi & Drew, 2012; López, Garcia, & Rodriguez, 2007). In addition, there are also numerous studies on the impact of sustainability in other financial products, e.g., mutual funds (Ceccarelli, Ramelli, & Wagner, 2020), bonds (Zerbib, 2019), credit (Attig, El Ghoul, Guedhami, & Suh, 2013), or portfolios (Alessandrini & Jondeau, 2020). Nevertheless, to the best of our knowledge, no one has ever dealt in detail with the DAX 50 ESG nor measured the sustainability performance of an index in such depth.

Our results are especially meaningful for investors. Recent studies show that investors want to contribute towards a more sustainable world with their investments. Some research studies deal with stakeholder preferring sustainable investments and for their sake even accept lower expected returns (Bauer, Ruof, & Smeets, 2019) or show more willingness-to-pay in venture capital funds (Barber, Morse, & Yasuda, 2019). Asset managers have experienced that the introduction of the Morningstar Sustainability Rating has had a significant impact on their mutual fund flows and performance (Ammann, Bauer, Fischer, & Müller, 2019; Hartzmark & Sussman, 2019). Following this line of reasoning, we add to existing studies and provide insight for investors into sustainable indices like the DAX 50 ESG. Such information can help them to make better investment decision to achieve a high sustainable performance within their portfolios in consideration of the associated financial performance.

The remainder of this paper is organized as follows: Chapter Two presents the data. Next, Chapter Three presents the analysis and results, including both the conduct and product dimensions of sustainability for the constituents of various indices. In the following Chapter Four the financial performance of these indices is compared. The paper concludes in Chapter Five with a short summary of the results and provides guidance for an investor who wants to invest sustainably.

7.2 Data

We use various data sources for our analyses. The index and financial data is provided by Refinitiv Datastream and MSCI ESG Indices. The sustainability data on the index constituents is from the two major ESG databases Refinitiv ESG and ISS ESG.[48]

[48] Refinitiv Datastream is formerly known as Thomson Reuters Datastream and Refinitiv ESG as Thomson Reuters ESG. ISS ESG includes also all data from oekom research through its acquisition.

Furthermore, we use the Carhart factors for Germany from AQR.[49]

In addition to the index prices, Refinitiv's Datastream also provides information on the constituents of all German indices: DAX 50 ESG, DAX, MDAX, TecDAX, SDAX, and HDAX. We use from MSCI ESG indices data on index prices and information on the constituents of the following MSCI ESG universal indices for different regions: MSCI ESG Universal Germany, MSCI ESG Universal EMU, MSCI ESG Universal Europe, MSCI ESG Universal World, and MSCI ESG Universal ACWI.[50] This index family is best suited for a comparison with the DAX 50 ESG, because MSCI builds these indices for investors who look to enhance their exposure to ESG while maintaining a broad and diversified universe to invest in. These indices exclude only firms found to be in violation of international norms (for example, facing very severe controversies related to human rights, labor rights or the environment) and firms involved in controversial weapons (landmines, cluster munitions, depleted uranium, and biological and chemical weapons). The indices increase exposure to firms that have both a higher MSCI ESG rating and a positive ESG trend by reweighting free float market capitalization weights based on ESG indicators that are moving away from free float market capitalization weights. The MSCI ESG Germany, e.g., contains 41 constituents of the DAX 50 ESG that accounts for 75% of its constituents.

The information on the conduct dimension of a firm's sustainability includes ratings and scores of ISS ESG and of Refinitiv ESG. The ESG Corporate Rating from ISS ESG provides highly relevant material and forward-looking environmental, social and governance data and performance evaluations. A firm's ESG performance is assessed using a standard set of cross-sector indicators, supplemented by sector-specific indicators to address a firm's key ESG challenges. An international methodology panel ensures high

[49] https://www.aqr.com/Insights/Datasets.

[50] In the following, the MSCI ESG Universal is shortened to MSCI ESG for reasons of better readability.

quality analysis, indicators, evaluation structures and results. An external rating committee (consisting of ESG and SDG experts) supports the design of the sector-specific criteria and carries out a final review of the results. Refinitiv's ESG results are designed to objectively measure a firm's relative ESG performance, commitment and effectiveness in 10 key areas (emissions, eco-innovation, resource use, human rights, community, workforce, product responsibility, management, shareholders and CSR strategy) based on reported data. They also provide an overall ESG score, which is discounted for significant ESG controversies affecting a firm's sustainable performance. In our analyses, we use data points from both databases, which can be very alike or are specific to one database.

In order to be able to make additional assessments about the product dimension of sustainability, we use a unique SDG dataset from ISS ESG to assess the impact of a firm's product and service portfolio on the UN Sustainable Development Goals (SDGs). The SDG performance of a firm is gathered from public sources (e.g. international media), from interviews with independent experts on corporate sustainability (e.g. international NGOs and scientific institutions) and from the firms evaluated (e.g. annual report, CSR report and website).

All data from all databases refers to the same reporting date: 31 December 2019. The data collection took place in May 2020 in order to achieve the largest possible number of coverage and to ensure high data quality through correspondingly time-consuming checks in the databases. A brief overview of all indices analyzed can be found in Table 1.

[Insert Table 1 here.]

Table 1 shows that data from ISS ESG is available for more than 90% of the index constituents in most cases. In the case of Refinitiv ESG, the coverage is limited to between 50% and 70% of the constituents of the various indices. It should be noted that, particularly in the case of Refinitiv ESG, new data points or changes in the data for 2019 may still occur in 2020 and, possibly, even 2021. We work with the available information in all sustainability databases, which means that not all variables are available for all constituents. However, it is ensured that not a few firms can drive the results of the index by not including the corresponding variables in the analysis. Overall, both databases contain a sufficient number of constituents to allow an assessment of the sustainability performance of the indices.

7.3 Sustainability performance

In this paper, we measure the sustainability performance of an index at the conduct (ESG) and the product (SDGs) dimension of its constituents. First, we look at ESG ratings and scores. We then provide the results for each of the three individual pillars E(nviromental), S(ocial) and G(overnance), as well as of selected sub-categories. Finally, we compare the SDGs performance, i.e. the extent to which a firm's products and services are aligned with the SDGs.

7.3.1 Conduct dimension of sustainability

When an investor wants to investigate the sustainability of a firm or an index, he usually looks at related ESG ratings and scores. Within an ESG rating framework, a firm is usually assessed using a standard set of cross-sector indicators, supplemented by sector-specific indicators to address the firm's key ESG challenges. In addition to an overall ESG rating, the sustainability performance for each of the individual pillars, E, S and G, can also be analyzed. All these ratings and scores are made up of numerous key figures that can be very important for investors. In this section, we would like to measure the sustainability performance of the DAX 50 ESG as well as of comparable indices, both at the top level of the ESG ratings, within the individual pillars, and for selected key figures.

a.) ESG

First, we examine the ESG ratings of ISS ESG and Refinitiv ESG in Table 2. It shows that the constituents of the DAX 50 ESG have on average the second highest ESG rating of all German indices in both databases. The DAX has the highest ESG rating, but it is not statistically significantly different from the DAX 50 ESG. This can also be explained by the fact that 23 of the 30 DAX firms are included in the DAX 50 ESG. Even if additional controversies are included, this result remains stable.[51] If we also look at the other MSCI ESG Universal indices, the ESG performance score of ISS ESG is always lower, but the ESG score of Refinitiv ESG is higher for the MSCI ESG Germany compared to the DAX 50 ESG.

[Insert Table 2 here.]

If we consider the ESG score alone as the key indicator of how an investor should evaluate the sustainability performance of an investment, an investment in the DAX is the best choice. Nevertheless, the ESG rating is an aggregation of numerous sustainability indicators. Taking them into account, we get a holistic, yet much more complex picture of the sustainability of an investment.

b.) Environmental

In this first section, we analyze the environmental performance of the different indices. There are numerous studies on measuring corporate environmental performance and its relationship to financial performance (Chava, 2014; De Haan, Dam, & Scholtens Bert, 2012; Horváthová, 2010). However, there is an unclear relationship here, which depends, inter alia, on which figures are used to determine environmental performance.

To measure our environmental performance, we first review the Environmental Rating of ISS ESG and the Environmental Pillar Score of Refinitiv ESG in Table 3. The highest

[51] When considering the controversies, a higher value here represents a higher number and worse impact of controversies on the sustainability performance.

value in both databases for a German index is assigned to the DAX, followed by the DAX 50 ESG and the HDAX. Firms that are not part of the DAX 50 ESG have an average 17% to 28% significant lower environmental performance. Compared to global indices, the DAX 50 ESG has the highest Environmental Rating, but only the third highest Environmental Pillar Score after the MSCI ESG EMU and the MSCI ESG Germany. However, the mean values do not differ statistically singularly from one another. However, we find some evidence of the disagreement between the two databases on the environmental performance of their constituents.

[Insert Table 3 here.]

In both databases, the environmental performance is divided into three sub-categories: (1) for ISS ESG: Environmental Management, Products and Services and Eco-Efficiency; (2) for Refinitiv ESG: Emission Score, Environmental Innovation Score and Resource Use Score. We detect the same ranking of the indices for all six sub-categories, which indicates an overall higher environmental performance of the DAX compared to the DAX 50 ESG. Despite this result, the DAX 50 ESG constituents are on average more sustainable in these environmental categories than non-included German firms or compared to the firms of the MSCI ESG Universal ACWI.

In the following, we would like to take a closer look at one key issue of environmental sustainability. The role of carbon emissions is widely discussed in the literature. Studies, e.g., show that it is cost-effective to minimize emissions, thereby reducing, inter alia, the level and likelihood of physical and transitory risks (Görgen et al., 2020; Matsumura, Prakash, & Vera-Muñoz, 2014). Our results show that the DAX 50 ESG have lower carbon emissions than the DAX constituents. However, the larger firms in the DAX, as they usually emit more carbon emissions, distort the results. Furthermore, a global comparison shows that the carbon emissions caused by DAX 50 ESG firms are on average the second lowest.

Although carbon emissions will have to be significantly reduced in the future to combat climate change, it is evident that DAX 50 ES firms are better prepared due to their high scores regarding their GHG emission reduction targets & action plans and their disclosure of their climate change risks & mitigation strategies.

c.) Social

In this second section, we are going to discuss the social performance of the constituents of each index. Corporate social performance is important, as it can also be a driver of financial performance. Previous studies have found a U-shaped relationship, i.e. low social performance delivers higher and high social performance delivers the highest financial performance compared to moderate social performance (Barnett & Salomon, 2012).

[Insert Table 4 here.]

Table 4 provides the results for several social performance measures. First, we look at the two aggregated social ratings. Regarding ISS ESG, it should be noted that the social rating is combined with the governance rating. The highest values are found for the DAX, closely followed by the DAX 50 ESG constituents. The values do not differ statistically here. The DAX 50 ESG firms have a 20% higher social performance compared to the other firms in the HDAX universe. The differences remain if we look at the ISS ESG category Staff and Suppliers. A higher value for Staff and Suppliers can indicate a higher future financial performance, e.g., through a higher employee satisfaction (Edmans, 2011).

At Refinitiv ESG, the Social Score consists of four different sub-categories: Workforce, Human Rights, Community and Product Responsibility. Our results show that DAX and DAX 50 ESG firms have very high scores in the first two categories, followed by lower scores in the second two categories. Overall, it can be seen that the DAX 50 ESG has a very similar social performance to its next two indices, the DAX and the MSCI ESG Universal Germany.

d.) Governance

In this third section, we are going to discuss the governance performance of the constituents of each index. Most of the existing evidence points to a positive association between corporate governance and various performance indicators. Yet this line of research suffers from endogeneity problems that are difficult to solve. The emerging conclusion is that corporate governance is likely to evolve endogenously and from specific characteristics of the firm and its environment (Love, 2011).

[Insert Table 5 here.]

Table 5 presents the results for numerous governance performance measures. As social and governance performance are determined together at ISS ESG, we find here the same results as in the previous chapter: The DAX 50 ESG has the second highest performance after the DAX. In the case of Refinitiv ESG, a Governance Pillar Score is explicitly collected. The constituents of the DAX 50 ESG have an average governance performance that is almost 50% higher than that of firms that are not included. However, the DAX also has the highest governance performance by this measure compared to the DAX 50 ESG. Taking the MSCI ESG indices into account, only the MSCI ESG Germany Index has a higher Governance Pillar Score than the DAX 50 ESG.

Governance performance in ESG can only be examined more closely in the sub-category Corporate Governance and Business Ethics. Here it can be seen that the DAX 50 ESG and the DAX are on a par. In Refinitiv, the Governance Pillar Score is split into three sub-categories: Management Score, Shareholders Score and CSR Strategy Score. Our results shows that the difference between DAX 50 ESG and DAX in their governance performance according to Refinitiv ESG is mainly due to the different Management Score. Compared to the MSCI ESG Germany, the DAX 50 ESG also has a lower Management Score, but a higher Shareholder and CSR Strategy Score. Overall, the DAX 50 ESG can achieve a comparable governance performance.

7.3.2 Product dimension of sustainability

If an investor wants to look at the sustainability of a firm's products and services, SDGs can enable him to measure a product's impact on the achievement of sustainability goals. However, in many cases, the pursuit of social goals is often associated with higher environmental impacts. Studies have shown, e.g., that the eradication of extreme poverty and the reduction of income inequalities often leads to higher environmental impact. (Scherer et al., 2018).

Our ISS SDG dataset comprises information on the impact of a firm's product and service portfolio on the UN Sustainable Development Goals (SDGs). As the UN SDGs primarily target states and the public sector, not all the goals are relevant for firms. For this reason, ISS rates firms according to its own 15 specified firm-relevant Sustainability Objectives that are closely aligned with the UN's 17 SDGs; the ISS SDG objectives belong to either the environment pillar or the social pillar as shown in Table 6.

[Insert Table 6 here.]

ISS conducts a qualitative analysis for each individual sustainability objectives: (1) whether a product or service category makes a significant or limited net contribution to the achievement of the objective; (2) whether it has neither an explicitly positive nor an explicitly negative impact; (3) or whether the product or service actually represents a limited or significant obstacle to the achievement of the objective. The relevant share of net sales is indicated for each of the classified categories of products and services for which a net sales share of 1% or higher can be reasonably estimated.

We first look at the ISS Sustainability Solutions Score. It is a single score that evaluates the aggregated contribution of a firm's product portfolio to the achievement of SDGs - in short; it represents the overall performance of a firm's SDGs. The Sustainability Solutions Scores only considers the most pronounced sustainable objectives (i.e. the highest positive and/or the lowest negative score). For firms without negative target scores, it is determined by the highest positive SOS and vice versa. For firms that have both positive and negative impacts on sustainability targets, the score is calculated as the sum of the highest positive and lowest negative sustainable objectives. The score is on a scale of -10.0 to 10.0. The Social and Environmental Pillar Scores follow the same general idea, but only consider the social or environmental target scores.

A look at the results shows that the TecDAX has the highest Sustainable Solutions Score, followed by firms in the SDAX and in the HDAX universe that are not included in the DAX 50 ESG. In the following, we will break down how this ranking emerged.

a.) Social

The social pillar comprises seven sustainable objectives: alleviating poverty, combating hunger and malnutrition, ensuring health, delivering education, attaining gender equality, providing basic services, and safeguarding peace. The social pillar score is highest on average for the TecDAX and lowest for the SDAX in Germany. The main driver for the high SDG performance of the TecDAX is the high contribution to the sustainable objectives ensuring health and providing basic services. This means that TecDAX firms manufacture products or provide services in these two areas that are beneficial to the assigned SDGs. Across all indices, included firms provide on average unhealthy food (combating hunger and malnutrition) or are involved in the production of weapons or weapons (safeguarding peace) systems. This reduces the overall social SDG performance among German indices. Viewed globally, the MSCI ESG Universal Germany has the highest and the MSCI ESG Universal ACWI the lowest social pillar score. Global indices show a lower contribution to ensuring health and even higher damage to combating hunger and malnutrition. In addition, a few firms also contribute or harm the SDGs in other social sustainable objectives to a minor degree.

b.) Environmental

The environmental pillar comprises of seven sustainable objectives: achieving sustainable agriculture & forestry, conserving water, contributing to sustainable energy use, promoting sustainable buildings, optimizing material use, mitigating climate change, preserving marine ecosystems and terrestrial ecosystems. On average, the environmental pillar score is highest for the SDAX, followed by the TecDAX and firms that are not included in the DAX 50 ESG. A closer look at the SDAX shows that the constituents in particular offer products and services that provide sustainable & climate-friendly energy. In addition, they promote sustainable business and are resource efficient by optimizing their material use. The contribution to these sustainable objectives and yet no significant negative impact leads to this high environmental SDG performance. However, the DAX 50 ESG has firms that provide non-sustainable energy, facilitate climate change, and threaten the marine and terrestrial ecosystem. The largest contribution to sustainable objectives across many indices lies in the promotion of sustainable buildings. All single results indicates an overall negative contribution to SDGs. Compared to the DAX or even the international indices, however, this influence is less negative.

Overall, it can be said that the DAX 50 ESG shows a good sustainable performance in many areas, but is not always better than comparable indices. It should, however, take particular account of firms' products in terms of their impact on the environment related

SDGs. Besides, the data providers disagree on some data points as to which index is more sustainable. In order to create a holistically sustainable index, it is not enough (1) to use only ESG and thereby neglect SDGs data and (2) to use sustainability data from only one data provider.

7.4 Financial performance

We assess the financial performance of each index in two steps. First, we look at raw returns and risk-adjusted performance measures. Second, we analyze three different risk measures. To explain the relatively poor performance of the DAX 50 ESG, we third examine the factor exposures of the various indices. Fourth, we divide our time period into the period before and during the COVID-19 crisis and consider these periods separately. Fifth, we apply an event study approach to show whether firms are rewarded or penalized when they are included in the DAX 50 ESG.

7.4.1 Performance indicators

Besides the sustainability performance of a sustainable index, it is also important for an investor to be aware of the associate financial performance. Hence, we look at performance indicators such as raw returns, the Sharpe Ratio and both CAPM and Carhart Alpha in the following analysis. The time period for the German indices starts on the first trading day of the DAX 50 ESG on 24 September 2012 and for the MSCI ESG Universal Indices on 28 May 2015 and ends in both cases on 30 April 2020.

a.) Return

First, we look at raw returns of all indices in Table 7. The average annual return of the DAX 50 ESG since its inception is 3.37%. This is the lowest value compared to the other German indices. In a comparison with the MSCI ESG indices, the DAX 50 ESG achieves a return of -2.52% for the shorter period from 28 May onwards.

[Insert Table 7 here.]

b.) Sharpe Ratio

In the next step, we consider the Sharpe Ratio as a risk-adjusted performance indicator. We calculate the Sharpe Ratio as the average return earned in excess of the risk-free rate per unit of volatility. We see the same ranking as for the raw returns. The DAX 50 ESG index performs worst, while the TecDAX still performs best.

c.) Alpha

We use alpha as our third performance indicator to indicate if an index manages to beat the market return. We use both the alpha estimated by a CAPM and a Carhart Four Factor Model (Carhart, 1997). We use the German market factor of AQR capital management, which includes all common German stocks. For the estimation of the Carhart Alpha, we also include the three usual risk factors: SMB (Size), HML (Value) and WML (Momentum). Our results show that the DAX 50 ESG cannot beat the market measured by a positive alpha in either period. In summary, the DAX 50 ESG has a relatively poor performance according to all performance indicators.

7.4.2 Risk indicators

In the following, we calculate risk indicators such as standard deviation, market beta and maximum drawdown to be able to assess the risk of the DAX 50 ESG and all other indices.

a.) Standard Deviation

As a first risk measure, we consider the annualized standard deviation and the annualized downside standard deviation in Table 8. The latter takes only the standard deviation of negative returns into account in its calculation. The TecDAX has the highest standard deviation of all German indices, while the DAX has the highest downside standard deviation. The DAX 50 ESG has in both indicators an average value compared to the other indices. A similar picture is also evident worldwide. Here the MSCI ESG EMU has the highest standard deviation and the MSCI ESG Germany the highest downside standard deviation while the DAX 50 ESG ranks for both indicators in the middle.

[Insert Table 8 here.]

b.) Market Beta

Our next risk indicator is the market beta estimated from a CAPM model. The market beta of an investment is the measure of the risk arising from exposure to general market movements as opposed to idiosyncratic factors. It therefore covers the systematic risk of an investment. The market beta of the DAX 50 ESG is close to one, which means that the market and the index move similarly. In comparison to the German indices, this is the second highest systematic risk, only exceeded by the DAX.

c.) Maximum Drawdown

As a last risk indicator, we consider the maximum drawdown MDD. We calculate the MDD as the maximum loss from a peak to a trough of an index before a new peak is attained. The DAX 50 ESG had the highest maximum loss within the period with 44.75% loss in the COVID-19 stock crash. Comparably high values can also found for all other indices.

Overall, it can be stated that the DAX 50 ESG ranks in the middle by the various risk indicators. It should be noted, however, that our results are significantly influenced by the COVID-19 stock market crash. We therefore carry out an explicit investigation in the second-next section.

7.4.3 Factor exposures

In order to be able to examine the differences in the performance of the various indices in more detail, we look at the factor exposures to size, value and momentum in Table 9. For this purpose, we use German factors from the AQR Database and estimate constant betas the entire period. If we look at the DAX 50 ESG, we have a notable negative exposure on the size factor. This was to be expected, since the largest firms in Germany are a component of this index. With regard to the value and momentum factor, the DAX 50 ESG as well as other major German indices do not show any exposure. Therefore, the lower financial performance of the DAX 50 ESG cannot be attributed to differences in factor exposures.

[Insert Table 9 here.]

7.4.4 Financial performance during the COVID-19 crisis

In order to examine the financial performance differences in times of a crisis, we divide our time series into three periods using the COVID-19 crisis in line with previous papers (Albuquerque, Koskinen, Yang, & Zhang, 2020; Ramelli & Wagner, 2020). First, we consider the period prior to 2020. Second, we analyze a long crisis period defined as first quarter of 2020. Third, we investigate a short and more pronounced crisis period starting from February 24 to March 31. We would like to examine here whether the sustainable DAX 50 ESG is more resilient in times of crisis than an index that is not explicitly sustainable, such as the DAX or the HDAX.

First, we note that in the period before COVID-19, the DAX 50 ESG was the worst performing of all German indices, both in terms of return and Sharpe Ratio. The lower risk in this period measured by the standard deviation is not be sufficiently compensated. In addition, the DAX 50 ESG has the highest maximum drawdown in this period. If we look at the second period, which includes the first quarter of 2020, the TecDAX performs best. During this COVID-19 period, the sustainable index cannot outperform the other indices. This is due in particular to the fact that the DAX 50, as can be seen from Chapter 3, does not have a significantly higher sustainability performance, which could allow being more resilient. The same result also occurs when we look at the third period. Even in this most pronounced period of the COVID-19 crisis, we do not find any significant differences between the DAX 50 ESG and other German indices. However, a similar picture emerges when we look at the MSCI ESG Germany. This sustainability index is also not able to outperform the DAX or the HDAX. A superior performance of sustainable stocks measured by ES policies during the crisis period, as Albuquerque, Koskinen, Yang, and Zhang (2020) find for the American market, cannot be confirmed in our study for the German market.

[Insert Table 10 here.]

7.4.5 Short-term performance effect of the inclusion in the DAX 50 ESG

In order to further investigate the performance of the DAX 50 ESG, we analyze the impact of the inclusion of a firm into this index. There are two different competing theoretical perspectives here, namely the revisionist view, which suggests a positive impact on the inclusion into a sustainable index, and the traditional view, which suggests a negative impact. The revisionist view says that considering sustainability enhances a firm's reputation, especially by avoiding negative headlines, as well as by reducing conflicts between a firm and its stakeholders, both leading to a higher financial performance. In contrast, the traditional view states that policies increasing a firm’s sustainability performance are not productive. The respective operational costs of, e.g., environmental or social activities are higher than the resulting financial benefits leading to an overall lower performance.

To figure out which theory applies to the DAX 50 ESG, we use a similar approach like Oberndorfer, Schmidt, Wagner, and Ziegler (2013) and conduct an event study for the inclusion in the DAX 50 ESG. Our study is based on the analysis of abnormal returns estimated by asset pricing models. We employ two of the most well-known models; the Capital Asset Pricing Model (CAPM) and the Fama and French Three-Factor Model; to estimate normal returns. The so-called abnormal returns are defined as the difference between actual and normal returns. By aggregating these abnormal returns both over time and in a cross section, we obtain cumulative average abnormal returns (CAARs). Using the

CAARs, we can determine the average effect of the inclusion into the DAX 50 ESG for a firm over several days.

A key task of an event study is to test the null hypothesis that the event has no impact on returns. In this respect, we consider three different tests. First, we assume that the CAARs are normally distributed and test their statistical significance. Second, we use the BMP test (Boehmer, Masumeci, & Poulsen, 1991), which improves the Patell test by taking into account the possible cross-sectional increase in the variance of returns that may occur within the event window. Third, we use the adjusted Patell test (Kolari & Pynnönen, 2010) to respond to the fact that the previous two tests suffer from the cross-sectional correlation of abnormal returns. It heavily affects their outcome in the case of event-day clustering that verifies when a single event simultaneously affects all firms included in the analysis.

As usual in literature, our estimation window covers 100 trading days and ends 25 days before the event. Our event window includes the event day [0] and five days after the event day, as is common in corresponding short-term event studies. To support our results, we have additionally analyzed CAARs for several time intervals prior to the event. If the new information on inclusion in a sustainability stock index is not expected before the event but is relevant for investors, the CAARs should be insignificant before the event but significantly different from zero in the event window. Therefore, we additionally investigate the time intervals [-24,-19], [-18,-13], [-12,-7] and [-6,-1] before the event. As a robustness test, we also implement a portfolio approach, which is an alternative method for calculating CAARs (Kothari & Warner, 2007).[52]

[Insert Table 11 here.]

[52] Portfolio CARs (instead of CAARs) may be calculated on the basis of an equally weighted portfolio combining all the firms under review (before the calculation of the abnormal returns), whereby the portfolio is considered as a single firm.

Table 11 reports the CAARs and the portfolio CAR for the different time interval. The table additionally reports the p-values of the three different test statistics to evaluate the significance of the results. It shows that the CAAR in the complete event window [0,5] is significantly negative. In contrast, the CAARs in the time intervals [−24,−19], [−18,−13], [−12,−7], and [−6,−1] before the event are not only insignificantly different from zero. We find a similar result when we compare the results in panel B with the Fama and French three-factor model. Consequently, it can be concluded that the inclusion of German firms in the DAX 50 ESG index had a negative impact on their stock returns. This result is also in line with the findings of Oberndorfer, Schmidt, Wagner, and Ziegler (2013) that firms there were also penalized if they joined a sustainability index. The result of our event study approach may explain why the index has performed relatively poorly. However, a statement on the long-term performance of the DAX 50 ESG can only be made to a limited extent at the present time and should be part of future research.

7.5 Conclusion

In our study we provide an in depth analysis of the sustainability performance of the DAX 50 ESG index. We examine both the conduct (ESG) and the product (SDGs) dimensions of sustainability. We also address the problem of ESG disagreement by using two different major databases. Our results show that the DAX 50 ESG has a relatively high sustainability performance compared to most indices, but is not significantly different from, e.g., the DAX. The results of the financial analysis show that the DAX 50 ESG has performed relatively poorly. The low performance compared to comparable indices does not seem to be driven by a difference in factor exposures. Even when looking at different time periods before and during the COVID-19 crisis, no significant outperformance of the DAX 50 ESG can be found. One explanation for the relatively poor performance may be that the inclusion of a firm in the index is currently penalized.

Our results can be discussed critically in relation to the press statement that the "DAX 50 ESG will be the standard for ESG investments in Germany" (Qontigo, 2020). Our results show that the DAX 50 ESG should take in particular account of firms' products in terms of their impact on environmental SDGs to provide a more holistic sustainable performance. In addition, as data providers disagree on the assessment of the sustainability of a firm, a sustainability index should incorporate ratings and scores from more than one sustainability data provider.

Furthermore, studies have shown that of all the different ESG investment styles, negative screening is considered the least advantageous for investment and is driven by product-related and ethical considerations. A full sustainability integration and engagement is considered more beneficial (Amel-Zadeh & Serafeim, 2018). A comparable "DAX Sustainable Impact" index could be another step further towards financing sustainability.

It is also important to make statements like "The real economy is facing a process of transformation and it is the responsibility of the financial sector to finance this process; indices such as the DAX 50 ESG offer an important base" understandable for investors, and to show what impact they can really have (Qontigo, 2020). Since the purchase of the DAX 50 ESG means that the shares for its constituents only change hands on the secondary market, there is initially no sustainable impact on them. It may be that, e.g., when a sustainable firm issues new shares, it can profit from a higher share price due to increased investor demand by sustainable indices. Subsequently, this firm can use this profit to expand its sustainable activities and achieve an impact.

In addition, a sustainable index can improve the conditions for socially responsible investors to impact firm behavior (Opp & Oehmke, 2020). A main condition is that a firm is subject to financing restrictions. Furthermore, the desired impact requires a broad mandate, as socially responsible investors must internalize the social costs whether they invest in a particular firm. It should be noted that in equilibrium, sustainable assets have negative alphas, whereas non-sustainable assets have positive alphas. Therefore, a sustainable investor has to be willing to accept a lower expected performance as the price for sustainability. A more sustainable asset is also more exposed to an ESG risk factor, which captures shifts in customers' tastes for sustainable products or investors' tastes for sustainable holdings. Finally, sustainable investments can lead to positive social impacts by inducing more investment by sustainable firms. A more sustainable firm invest more, especially when risk aversion is low, average ESG sensitivity is high, and when stock prices have a greater impact on firms' investments (Pástor, Stambaugh, & Taylor, 2019). An index provider who wants to make a sustainable contribution should transparently provide its investors with such considerations and offer a related broad sustainable product range.

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Tables and Figures

Table 1
Index Overview

Panel A. Germany	*DAX 50 ESG*	*DAX*	*MDAX*	*TecDAX*	*SDAX*	*HDAX*
Constituents	50	30	60	30	70	99
Coverage ISS ESG (%)	100.00	100.00	95.00	93.33	62.86	96.97
Coverage Refinitiv ESG (%)	54.00	53.33	61.67	76.67	71.43	61.62

Panel B. World	*DAX 50 ESG*	*MSCI ESG Germany*	*MSCI ESG EMU*	*MSCI ESG Europe*	*MSCI ESG World*	*MSCI ESG ACWI*
Constituents	50	55	238	426	1,614	2,921
Coverage ISS ESG (%)	100.00	96.36	98.32	96.95	97.03	83.40
Coverage Refinitiv ESG (%)	54.00	52.73	56.72	64.55	56.26	50.12

Table 2
ESG Performance Measures

Panel A. Germany	*DAX 50 ESG*	*Ex DAX 50 ESG*	*DAX*	*MDAX*	*TecDAX*	*SDAX*	*HDAX*
ISS ESG							
ESG Performance Score	51.25	38.38***	53.53	41.40***	39.08***	38.75***	44.26***
Refinitiv ESG							
ESG Score	72.12	46.83***	80.09*	57.69***	45.92***	41.81***	60.72**
ESG Controversies Score	55.42	79.81***	41.29	69.53	79.00**	86.58***	63.40
ESG Combined Score	56.58	44.21***	58.49	51.48	44.83**	40.94***	51.29

Panel B. World	*DAX 50 ESG*	*Ex DAX 50 ESG*	*MSCI ESG Germany*	*MSCI ESG EMU*	*MSCI ESG Europe*	*MSCI ESG World*	*MSCI ESG ACWI*
ISS ESG							
ESG Performance Score	51.25	31.70***	49.70	49.32*	47.95**	36.17***	32.05***
Refinitiv ESG							
ESG Score	72.12	56.67***	73.03	71.76	70.00	59.21***	56.94***
ESG Controversies Score	55.42	71.53***	49.83	56.62	62.38	75.52***	71.21***
ESG Combined Score	56.58	52.03	57.40	60.30	59.77	53.63	52.12

The stars indicate the significance of the difference between the mean of an index and the mean of the DAX 50 ESG measured using an unpaired t-test: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3
Environmental Performance Measures

Panel A. Germany

	DAX 50 ESG	*Ex DAX 50 ESG*	*DAX*	*MDAX*	*TecDAX*	*SDAX*	*HDAX*
ISS ESG							
Environmental Rating	2.20	1.83***	2.27	1.88***	1.81***	1.88***	1.98***
Environmental Management	2.51	1.83***	2.63	2.00***	1.83***	1.80***	2.16***
Products and Services	2.00	1.81**	2.05	1.81**	1.81*	1.86	1.87*
Eco-efficiency	2.70	1.82***	2.77	1.98***	1.65***	1.96***	2.17***
Refinitiv ESG							
Environment Pillar Score	70.48	50.46***	76.25	57.32**	44.85***	46.61***	58.70**
Emission Score	74.64	45.10***	76.06	56.68***	45.70***	42.58***	59.41**
Environmental Innovation Score	57.83	36.68***	68.14	48.94	39.23*	30.04***	49.62
Resource Use Score	80.89	49.33***	86.22	62.28***	48.98***	44.99***	64.66**
CO_2 Total (10.000 t)	301.35	98.60*	394.08	174.47	20.22	57.01*	245.55

Panel B. World

	DAX 50 ESG	*Ex DAX 50 ESG*	*MSCI ESG Germany*	*MSCI ESG EMU*	*MSCI ESG Europe*	*MSCI ESG World*	*MSCI ESG ACWI*
ISS ESG							
Environmental Rating	2.20	1.72***	2.16	2.19	2.14	1.82***	1.73***
Environmental Management	2.51	1.86***	2.45	2.50	2.43*	1.99***	1.88***
Products and Services	2.00	1.63***	1.98	1.99	1.95	1.72***	1.64***
Eco-efficiency	2.70	1.89***	2.58	2.71	2.64	2.06***	1.90***
Refinitiv ESG							
Environment Pillar Score	70.48	54.30***	71.36	73.37	68.83	55.50***	54.58***
Emission Score	74.64	58.96***	72.56	79.38	75.60	60.91**	59.21**
Environmental Innovation Score	57.83	45.19**	60.30	62.23	55.79	44.77**	45.44**
Resource Use Score	80.89	58.20***	80.89	79.71	75.72	60.23***	58.57***
CO_2 Total (10.000 t)	301.35	454.05	306.92	423.95	354.03	297.61	451.46

The stars indicate the significance of the difference between the mean of an index and the mean of the DAX 50 ESG measured using an unpaired t-test: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4
Social Performance Measures

Panel A. Germany	*DAX 50 ESG*	*EX DAX 50 ESG*	*DAX*	*MDAX*	*TecDAX*	*SDAX*	*HDAX*
ISS ESG							
Social and Governance Rating	2.41	1.99^{***}	2.46	2.12^{***}	2.03^{***}	1.96^{***}	2.19^{***}
Staff and Suppliers	2.44	1.97^{***}	2.53	2.09^{***}	1.92^{***}	1.95^{***}	2.20^{***}
Society and Product Responsibility	2.27	1.89^{***}	2.34	2.01^{***}	1.99^{***}	1.85^{***}	2.08^{***}
Refinitiv ESG							
Social Pillar Score	77.60	56.03^{***}	83.23	66.92^{**}	52.75^{***}	47.96^{***}	68.01^{**}
Workforce Score	87.63	63.25^{***}	90.55	75.04^{***}	68.67^{***}	58.95^{***}	77.28^{**}
Human Rights Score	80.31	50.70^{***}	86.49	65.68^{**}	51.52^{***}	44.16^{***}	67.83^{*}
Community Score	68.09	41.98^{***}	73.76	56.16	34.30^{***}	35.41^{***}	56.65
Product Responsibility Score	74.53	51.87^{***}	80.54	62.40^{*}	51.24^{***}	47.14^{***}	65.17
Panel B. World	*DAX 50 ESG*	*EX DAX 50 ESG*	*MSCI ESG Germany*	*MSCI ESG EMU*	*MSCI ESG Europe*	*MSCI ESG World*	*MSCI ESG ACWI*
ISS ESG							
Social and Governance Rating	2.41	1.86^{***}	2.38	2.32^{**}	2.27^{***}	1.98^{***}	1.87^{***}
Staff and Suppliers	2.44	1.74^{***}	2.43	2.36^{**}	2.28^{***}	1.84^{***}	1.75^{***}
Society and Product Responsibility	2.27	1.79^{***}	2.25	2.18^{**}	2.14^{***}	1.88^{***}	1.79^{***}
Refinitiv ESG							
Social Pillar Score	77.60	56.65^{***}	77.99	75.01	72.72^{**}	59.84^{***}	57.01^{***}
Workforce Score	87.63	63.67^{***}	86.21	80.76^{**}	79.19^{**}	65.08^{***}	64.04^{***}
Human Rights Score	80.31	50.36^{***}	83.31	80.70	77.31^{*}	53.08^{***}	50.89^{***}
Community Score	68.09	53.27^{***}	68.77	69.16	67.68	60.56^{*}	53.52^{***}
Product Responsibility Score	74.53	55.52^{***}	72.26	68.32	65.56	58.40^{***}	55.83^{***}

The stars indicate the significance of the difference between the mean of an index and the mean of the DAX 50 ESG measured using an unpaired t-test: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5
Governance Performance Measures

Panel A. Germany

	DAX 50 ESG	*EX DAX 50 ESG*	*DAX*	*MDAX*	*TecDAX*	*SDAX*	*HDAX*
ISS ESG							
Social and Governance Rating	2.41	1.99***	2.46	2.12***	2.03***	1.96***	2.19***
Corporate Governance and Business Ethics	2.63	2.22***	2.63	2.40***	2.20***	2.17***	2.44**
Refinitiv ESG							
Governance Pillar Score	67.48	45.52***	79.25	52.33***	41.71***	39.14***	56.72*
Management Score	68.00	41.84***	85.88**	49.17**	41.83***	36.44***	56.71
Shareholders Score	62.31	45.18**	62.56**	56.16	38.95***	40.75***	54.04
CSR Strategy Score	71.89	36.73***	73.98	50.37***	34.82***	33.70***	53.26***

Panel B. World

	DAX 50 ESG	*EX DAX 50 ESG*	*MSCI ESG Germany*	*MSCI ESG EMU*	*MSCI ESG Europe*	*MSCI ESG World*	*MSCI ESG ACWI*
ISS ESG							
Social and Governance Rating	2.41	1.86***	2.38	2.32**	2.27***	1.98***	1.87***
Corporate Governance and Business Ethics	2.63	2.23***	2.59	2.55	2.56	2.45**	2.24***
Refinitiv ESG							
Governance Pillar Score	67.48	57.24***	68.78	65.63	67.11	60.12**	57.43***
Management Score	68.00	59.77**	72.54	69.26	70.87	64.18	59.95*
Shareholders Score	62.31	51.69	58.88	54.87	54.19	52.15	51.79
CSR Strategy Score	71.89	53.42***	65.90	64.90*	68.77	52.51***	53.75***

The stars indicate the significance of the difference between the mean of an index and the mean of the DAX 50 ESG measured using an unpaired t-test: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6
Sustainable Products Performance Measures

Panel A. Germany	*DAX 50 ESG*	*EX DAX 50 ESG*	*DAX*	*MDAX*	*TecDAX*	*SDAX*	*HDAX*
ISS ESG							
Sustainable Solutions Score	0.91	1.74	0.56	1.46	2.66**	1.96	1.20
Social Pillar Score	1.12	1.22	1.45	1.31	2.07	0.83	1.25
Alleviating poverty	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Combating hunger and malnutrition	-0.02	-0.06	0.00	-0.01	0.00	-0.10	-0.01
Ensuring health	0.74	1.00	1.09	0.85	1.69	0.83	0.85
Delivering education	0.01	0.01	0.00	0.01	0.00	0.00	0.01
Attaining gender equality	0.01	0.00	0.01	0.00	0.00	0.01	0.00
Providing basic services	0.47	0.37	0.62	0.46	0.41	0.20	0.49
Safeguarding peace	0.00	-0.06	0.00	-0.06	-0.01	-0.03	-0.05
Environmental Pillar Score	-0.16	0.52	-0.80*	0.12	0.63*	1.16**	-0.04
Achieving sustainable agr. & forestry	-0.02	0.00	-0.05	0.01	0.00	0.01	-0.01
Conserving water	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Contributing to sustainable energy use	-0.17	0.24*	-0.79	0.03	0.63**	0.74*	-0.09
Promoting sustainable buildings	0.09	0.15	0.03	0.08	0.00	0.25	0.06
Optimizing material use	0.01	0.13	0.01	0.04	0.00	0.19	0.03
Mitigating climate change	-0.16	0.30	-0.64	0.03	0.63**	0.76*	-0.05
Preserving marine ecosystems	-0.06	-0.01	-0.04	-0.04	0.00	-0.01*	-0.03
Preserving terrestrial ecosystems	-0.05	-0.02	-0.08	-0.04	0.00	0.00*	-0.05

Panel B. World

	DAX 50 ESG	*EX DAX 50 ESG*	*MSCI ESG Germany*	*MSCI ESG EMU*	*MSCI ESG Europe*	*MSCI ESG World*	*MSCI ESG ACWI*
ISS ESG							
Sustainable Solutions Score	0.91	0.01	1.07	0.35	0.36	0.34	0.02
Social Pillar Score	1.12	0.51	1.47	0.59	0.59	0.69	0.52
Alleviating poverty	0.00	-0.03	0.00	-0.02	-0.02	-0.03	-0.03
Combating hunger and malnutrition	-0.02	-0.28	-0.02	-0.33	-0.34	-0.26	-0.27
Ensuring health	0.74	0.36	1.08	0.47	0.46	0.51	0.37
Delivering education	0.01	0.03	0.00	0.01	0.05	0.03	0.03
Attaining gender equality	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Providing basic services	0.47	0.26	0.56	0.33	0.28	0.29	0.26
Safeguarding peace	0.00	0.01	0.00	-0.03	-0.01	0.01	0.01
Environmental Pillar Score	-0.16	-0.50	-0.35	-0.18	-0.20	-0.33	-0.49
Achieving sustainable agr. & forestry	-0.02	0.02	0.00	0.07	0.07	0.02	0.01
Conserving water	0.00	-0.01	0.00	0.03	0.05	-0.03	-0.01
Contributing to sustainable energy use	-0.17	-0.53	-0.41	-0.42	-0.41	-0.44	-0.53
Promoting sustainable buildings	0.09	0.09	0.08	0.15	0.12	0.12	0.09
Optimizing material use	0.01	0.03	0.01	0.06	0.05	0.03	0.03
Mitigating climate change	-0.16	-0.49	-0.33	-0.34	-0.38	-0.38	-0.48
Preserving marine ecosystems	-0.06	-0.06	-0.05	-0.02	-0.06	-0.06	-0.06
Preserving terrestrial ecosystems	-0.05	-0.11	-0.07	0.00	-0.03	-0.08	-0.11

The stars indicate the significance of the difference between the mean of an index and the mean of the DAX 50 ESG measured using an unpaired t-test: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7
Performance Measures

Panel A. Germany

	DAX 50 ESG	*DAX*	*MDAX*	*TecDAX*	*SDAX*	*HDAX*
Return	3.37	5.44	10.12	16.29	9.99	6.51
Sharpe Ratio	0.20	0.33	0.62	0.91	0.62	0.39
CAPM Alpha	-2.05	0.38	5.62	12.90	5.73	1.51
Carhart Alpha	-0.01	2.37	5.06	10.60	6.30	2.81

Panel B. World

	DAX 50 ESG	*MSCI ESG Germany*	*MSCI ESG EMU*	*MSCI ESG Europe*	*MSCI ESG World*	*MSCI ESG ACWI*
Return	-2.52	-1.38	-0.85	-1.49	3.33	3.08
Sharpe Ratio	-0.18	-0.12	-0.10	-0.15	0.20	0.18
CAPM Alpha	-5.57	-4.11	-3.52	-4.19	2.42	2.03
Carhart Alpha	-2.41	-2.22	-1.70	-3.20	2.95	2.50

Table 8
Risk Measures

Panel A. Germany	*DAX 50 ESG*	*DAX*	*MDAX*	*TecDAX*	*SDAX*	*HDAX*
Standard Deviation	19.00	19.34	17.12	19.93	16.68	18.80
Downside SD	15.12	15.48	13.69	15.30	14.04	15.23
Market Beta	1.01	1.02	0.86	0.92	0.81	1.00
Maximum Drawdown	44.75	38.78	38.99	33.18	38.81	39.49

Panel B. World	*DAX 50 ESG*	*MSCI ESG Germany*	*MSCI ESG EMU*	*MSCI ESG Europe*	*MSCI ESG World*	*MSCI ESG ACWI*
Standard Deviation	20.43	19.57	19.15	18.02	17.27	16.85
Downside SD	16.76	16.36	16.78	15.69	15.21	14.84
Market Beta	1.03	0.99	0.96	0.87	0.59	0.58
Maximum Drawdown	44.75	40.69	37.75	34.59	33.22	32.98

Table 9
Factor Exposures

Panel A. Germany	*DAX 50 ESG*	*DAX*	*MDAX*	*TecDAX*	*SDAX*	*HDAX*
Size	-0.56	-0.64	-0.20	0.02	0.20	-0.54
Value	0.01	-0.01	-0.05	-0.31	-0.01	-0.03
Momentum	-0.04	-0.03	0.05	0.11	-0.06	0.00

Panel B. World	*DAX 50 ESG*	*MSCI ESG Germany*	*MSCI ESG EMU*	*MSCI ESG Europe*	*MSCI ESG World*	*MSCI ESG ACWI*
Size	-0.55	-0.53	-0.47	-0.42	-0.30	-0.28
Value	0.04	-0.02	0.01	0.01	0.07	0.07
Momentum	-0.04	0.03	0.02	0.06	0.06	0.06

Table 10
Financial Performance during the COVID-19 crisis

Panel A. Germany

	DAX 50 ESG	*DAX*	*MDAX*	*TecDAX*	*SDAX*	*HDAX*
Return						
2012-2019	6.19	8.37	13.71	18.99	13.39	9.73
2020 Q1	-19.17	-18.02	-18.61	-15.32	-17.26	-19.27
COVID-19	-27.35	-26.83	-27.40	-19.74	-28.15	-27.70
Sharpe Ratio						
2012-2019	0.39	0.52	0.90	1.05	0.91	0.61
2020 Q1	-1.23	-1.13	-1.41	-0.26	-1.22	-1.28
COVID-19	-4.11	-4.02	-4.61	-3.31	-4.84	-4.28
Standard Deviation						
2012-2019	16.80	17.18	15.25	18.58	14.53	16.69
2020 Q1	45.74	45.87	40.19	39.42	41.87	44.72
COVID-19	69.02	69.03	62.65	58.92	61.82	67.59
Maximum Drawdown						
2012-2019	29.40	29.27	22.41	21.28	26.84	27.14
2020 Q1	39.62	38.78	38.99	33.18	38.81	39.49
COVID-19	36.09	35.24	35.77	29.30	34.72	36.03

Panel B. World

	DAX 50 ESG	*MSCI ESG Germany*	*MSCI ESG EMU*	*MSCI ESG Europe*	*MSCI ESG World*	*MSCI ESG ACWI*
Return						
2012-2019	6.19	5.76	7.12	1.66	5.91	5.73
2020 Q1	-19.17	-18.68	-19.89	-17.24	-9.60	-10.17
COVID-19	-27.35	-26.39	-26.38	-24.34	-22.95	-22.89
Sharpe Ratio						
2012-2019	0.39	0.38	0.48	0.06	0.40	0.39
2020 Q1	-1.23	-1.25	-1.40	-1.30	-0.50	-0.59
COVID-19	-4.11	-4.04	-4.08	-4.00	-3.20	-3.37
Standard Deviation						
2012-2019	16.80	16.03	15.88	15.31	13.33	13.19
2020 Q1	45.74	44.29	43.10	39.82	44.53	42.66
COVID-19	69.02	67.46	66.74	62.42	70.89	67.70
Maximum Drawdown						
2012-2019	29.40	29.32	26.46	24.45	20.47	20.94
2020 Q1	39.62	39.22	37.75	34.59	33.22	32.98
COVID-19	36.09	35.84	34.26	31.17	29.89	29.62

Table 11
Event Study for the Inclusion in the DAX 50 ESG

Panel A. CAPM

	[-24,-19]	[-18,-13]	[-12,-7]	[-6,-1]	[0,5]
CAAR	0.42	0.28	-0.47	-0.79	-1.42
Normal	*0.42*	*0.58*	*0.37*	*0.13*	*0.01*
BMP	*0.52*	*0.52*	*0.35*	*0.06*	*0.06*
Adj. Patell	*0.64*	*0.70*	*0.47*	*0.09*	*0.01*
PF CAR	0.45	0.28	-0.64	-0.96	-1.80
Adj. Patell	*0.61*	*0.75*	*0.48*	*0.29*	*0.06*

Panel B. Fama and French

	[-24,-19]	[-18,-13]	[-12,-7]	[-6,-1]	[0,5]
CAAR	0.18	0.00	-0.17	-0.88	-1.04
Normal	*0.71*	*1.00*	*0.72*	*0.07*	*0.03*
BMP	*0.86*	*0.98*	*0.65*	*0.04*	*0.17*
Adj. Patell	*0.89*	*0.98*	*0.70*	*0.05*	*0.04*
PF CAR	0.24	0.06	-0.44	-1.08	-1.50
Adj. Patell	*0.77*	*0.94*	*0.59*	*0.19*	*0.07*

8 Conclusion

This dissertation addresses relevant issues in Sustainable and Climate Finance. Up to now there have only been a few studies dealing with the quantification and management of carbon risk. The first article in this dissertation therefore investigates carbon risk in global equity prices using a capital market-based approach. The main finding is that our BMG factor is able to quantify carbon risk − though it is not yet priced. The second article reinforces these findings and provides insights on how to incorporate carbon risk into portfolio management. The portfolio strategies shown enable the portfolio manager to attain the desired exposure to carbon risk and to be aware of the associated risk and return implications. The third article reinforces the importance of considering carbon risk in the light of the current COVID-19 crisis. The findings show that green and brown business models are not suitable to fully mitigating crisis periods, however, being on the forefront of sustainability has proved to be more advantageous than being brown during the COVID-19 pandemic. The importance of analyzing carbon emissions in finance is supported by the results of the fourth article. The approaches shown here to improve the accuracy of the valuation of firms can be used by capital market participants and also applied to other non-financial information.

Even beyond climate change, considering non-financial information on sustainability plays an important role in the assessment of firms. The fifth article shows here that the contribution to specific SDGs has a value-enhancing impact on firms. Such insights can help to accelerate the transformation of the economy towards a more sustainable one. Various financial instruments, such as indices, can finance this transformation. The sixth article shows how sustainability and the financial performance of a selected index, the DAX 50 ESG, can provide incentives for investors to pursue this development.

The findings in this dissertation are new and highly relevant for various capital market participants. First, policy makers, regulators and supervisors can use the results to enact new rules and laws that take into account the impact of carbon risks and sustainability on capital markets. Especially due to the numerous initiatives currently launched to adapt global financial flows to combat climate change, it is important to consider the findings on carbon risks in order to facilitate an efficient transformation process towards a green economy. These results are also particularly relevant in the context of economic stimulus packages and green deals developed in response to the COVID-19 crisis, so that carbon risks and sustainability can be explicitly taken into account.

Second, the results of this dissertation are particularly relevant for investors, asset and portfolio managers, as they allow them to adequately integrate and manage carbon risk in asset and portfolio management and to make better-informed investment decisions. In addition, this dissertation contributes to a better holistic understanding of sustainability, which complements the existing ESG, CSR and impact frameworks of investors.

Third, these findings can also help analysts and firms to better develop strategies and business models that take into account carbon risk and sustainability aspects. Firm value can be increased through appropriate and efficient management of sustainability and risk. Doing so further supports the transformation process towards a green and sustainable economy desired by society.

There are still gaps in the research beyond the results of this dissertation that need to be filled. The findings presented here may enable other researchers to pursue study towards better understanding relevant non-financial information and exogenous sustainability-related risks from a financial perspective. The crucial question of whether it is profitable to be sustainable should also be examined in the framework of a holistic approach to sustainability. An approach to address this issue can be directly based on related studies (e.g., Hussain et al., 2018; Friede et al., 2015 or Busch et al., 2020) and the findings shown here on the impact of SDGs on firm values. Furthermore, studies dealing with the question “Do investors knowingly accept lower expected financial returns in exchange for nonpecuniary benefits from investing in assets with both social and financial objectives?" (Barber et al., 2019) can also benefit from the consideration of sustainability from a financial perspective described here.

In addition, the analysis of all articles shows that the reasons for publishing non-financial information should be thoroughly investigated. These findings help, on the one hand, to drive the necessary awareness for transparent and high-quality reporting and, on the other hand, to strengthen the quality of the data for future research. A few papers (e.g. Matsumara et al., 2014) have laid important foundations and combining them with the findings of the fifth article on the differences of SDGs data disclosure may help to make good advances here.

In the research area Carbon Risk, it is also essential to address the current discussion about suitable scenario analyses (e.g. TCFD, 2017). It is important to discuss the limitations of scenario analyses from a financial perspective in order to provide advice for policymakers and regulators. With these new findings, the crucial next steps towards a low-carbon and more sustainable economy can be determined in an economically meaningful direction.

Overall, it is important that new research in Climate and Sustainable Finance is meaningful, economically rational, and market efficient to support the transforming of the economy into a more sustainable one. This is aided by providing new awareness of what can either (1) reduce or increase the cost of capital for green/sustainable or brown/non-sustainable practices, (2) reduce or increase liquidity for green/sustainable or brown/non-sustainable practices, (3) support or enable the management of environmental-related physical and transition risks, (4) encourage or enable firms adopting sustainable practices, and (5) what can support systemic change through spill-over effects.

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