Carbon Risk*

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Keywords: Carbon risk, climate finance, economic transition, climate change, asset pricing
JEL Classification: G12, G15, Q51, Q54

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Abstract. The costs of addressing climate change will be borne by firms through their investments, supply-chains, and products and services. Financial markets play a role in aggregating firm-level information on the costs of the transition but also on pricing these risks. We construct a carbon risk factor for 1,600 global firms with carbon risk data from four major ESG databases. This factor can be used as a straightforward measure of carbon beta absent firm-specific carbon emissions information. We compute the carbon beta of 39,000 global firms. Our factor can be used by firms, regulators and investors to better understand carbon risk.

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Climate change is affecting human well-being and is costly to mitigate. Firms will be exposed to the costs of investing in new, clean and expensive technology and divesting old, cheap and dirty technology (e.g., Acemoglu et al., 2016; Haszeldine, 2009). Customers will demand new products and services with lower environmental impacts. And, suppliers will be required to reduce the environmental impacts of the supply chain. These changes represent a new source of risk, but also a new source of reward for firms. Financial markets play an important role as aggegrators and processors of information and by continuously producing information on firms' exposures to climate risk. *Carbon risk*[1], that contains any influence on a firm of the transition to a green, low carbon economy process, is the most important part of climate risk and the focus of our paper.

There are numerous national and international initiatives[2] and legislation[3] addressing climate change. One of the most far-reaching initiatives is the 21st Conference of the Parties (COP21) in Paris 2015, which resulted in an agreement of 195 nations to limit global warming to below 2°C above pre-industrial levels (United Nations, 2015). The global commitment to achieving emission targets was reaffirmed with the Katowice Climate Change Package (United Nations, 2018). Such agreements underline the worldwide commitment to actively pursue the transition to a green, low carbon economy. Initiatives such as the EU Action Plan on Financing Sustainable Growth, assign a key role to the financial system in order to achieve the goals and make financial flows consistent with a low-carbon economy. Unfortunately, there is little comprehensive information on carbon risks in asset prices. Our paper fills this gap and represents the first comprehensive study of carbon risk and reward in equities.

Numerous recent papers suggest that climate risk, of which carbon emissions are an important factor, are priced. Climate risk is costly to hedge and systematic (Engle et al., 2018) making understanding it central to the pricing of assets. Choi, Gao, and Jiang (2018) show that high carbon firms underperform low carbon firms during extreme heat events. Hong, Li, and

[1] For instance: The EPA reports that CO_2 makes up 81% of emitted Green House Gases that are responsible for trapping heat in the atmosphere (https://www.epa.gov/ghgemissions/overview-greenhouse-gases).
[2] For example: EU Action Plan on Financing Sustainable Growth, Sustainable Development Goals (SDGs), Greenhouse Gas (GHG) Protocol Corporate Accounting and Reporting Standards, Recommendations of the Task Force on Climate-related Financial Disclosures (TCFD).
[3] For example: Implementations of several cap and trade emission trading schemes, e.g. in the European Union, Canada, USA, or China, as well as national legislation, e.g. the French Energy Transition Law.

Xu (2019) demonstrate that food firms exposed to climate risks underperform in the long-run. Delis, de Greiff, and Ongena (2018) show that banks price climate policy risks in their loans and banks have started to develop broader policies on the financing of brown businesses (e.g., Rainforest Action Network et al., 2017). Ortega and Taspinar (2018), Murfin and Spiegel (2018) and Rehse et al. (2018) all report that climate risk is priced in the real estate market. Barnett, Brock, and Hansen (2018) demonstrate theoretically how climate uncertainty, including climate risk, can be priced in a dynamic stochastic equilibrium model. Krüger, Sautner, and Starks (2018) results suggest that climate concerns are an important factor in the investment decisions of large institutional investors. Divestment movements, like the Portfolio Decarbonization Coalition (PDC) promote the divestiture of high carbon firms making it more difficult and costlier for firms to acquire funding (e.g., Cheng et al., 2014).

Measuring carbon risk comprehensively is a challenge because systematic and fundamental information on firms' carbon exposure is non-existent and disclosure is neither universally mandatory nor standardized. We define carbon risk as the role carbon plays in a firms' value chain, the public perception of a firms carbon emissions and the ability of a firm with respect to regulatory and technology changes.[4] The main contribution of this paper is to develop a rigorous and straightforward capital-markets measure of firms' carbon risk, carbon beta, which can be estimated absent any carbon risk information. We construct a carbon risk factor "brown minus green" (*BMG*) from over 1,600 globally listed firms with detailed carbon risk information compiled from four major ESG databases. We categorized firms as brown or green using yearly carbon risk scores (*CRS*). This *CRS* is a composite measure of three carbon risk indicators capturing the impact of the transition process on the value chain of firms (e.g., current emissions), but also on the public perception (response to perceived emissions), and on the adaptability of a firm (such as future carbon emissions and mitigation strategies). We test the *BMG* factor in common asset pricing models and show that it significantly increases their explanatory power. The factor will be made freely accessible so that financial market participants will be able to measure the carbon risk of their portfolio thereby closing the gap in

[4] Our carbon risk scoring methodology was created in cooperation with data providers, climate consultancies, NGOs, asset managers and central banks in a series of workshops https://carima-project.de/en/experten-workshop/ and https://carima-project.de/en/2-experten-workshop/.

measuring carbon risk in asset prices. Importantly our appraoch does not rely on climate change being real or a hoax, it merely depends on how investors perceive the associated risks.

As the transition from a high carbon economy to a low carbon economy is ongoing and climate models and policy responses are unclear, capital markets may not yet agree on new equilibrium prices. Daniel, Litterman, and Wagner (2018) present a model in which climate uncertainty is resolved over time leading to transition periods between equilibriums making traditional risk factor premium arguments difficult to interpret. Hence, we are not proposing a new priced risk factor. Instead, we document the time-series and cross-section of market-perceived carbon risk in equity prices. We use the carbon risk factor to estimate annual carbon betas for more than 39,000 globally listed firms. We show that carbon betas increase over time and are high in South Africa, Brazil, and Canada and lower in European countries and Japan. As expected, tech firms have the lowest carbon beta, while basic material and energy firms have the highest carbon beta.

We also show that investors can achieve similar Sharpe Ratios with similar exposures to traditional systematic risks, such as the Fama and French (1993) factors or to specific industries while eliminating high carbon beta firms from their portfolios. From an analyst's perspective, we show that carbon beta is related to a firm's characteristics. Independent of their industry, firms investing in innovation and clean technology, proxied by R&D expenditures, face lower carbon risk while firms with dirty or "stranded" assets, proxied by property, plant and equipment (PPE) assets, face higher carbon risk. Taking the perspective of the financial industry, we show that valuations of banks and other financial services firms are strongly related to the carbon risk of domestic firms they are likely to finance.

An interesting question is what is driving carbon betas. We employ the methodology used in Campbell (1991) and Campbell and Vuolteenaho (2004) to decompose the market beta of carbon beta sorted portfolios into cash-flow news (fundamental) and discount-rate news (risk premium). We show that carbon beta is determined predominantly by the cash-flow component rather than the discount-rate component. This suggests that during our sample period carbon risk is driven by expectations about future cash-flows rather than an increase in the discount rate investors apply to these cash-flows.

The remainder of the paper is structured as follows: Section 1 shortly reviews the literature. Section 2 describes our methodology to quantify carbon risk via the carbon risk factor. Section 3 presents the data. In Section 4, we describe and test our carbon risk factor on relevance using common asset pricing tests. Section 5 reports the carbon beta over time, across countries and industries and analyzes the drivers of carbon beta via risk decomposition. Section 6 provides practical implications of the carbon beta. Section 7 concludes.

1 Related literature

Literature concerned with climate finance takes on different perspectives. Strands of literature may be concerned with climate science, policy impacts, financial stability, investor perspectives, and return implications.

Climate change will affect the entire economy and is a general source of uncertainty for society as a whole (Stern, 2008; Weitzman, 2014; IPCC, 2018). Despite extensive analyses on unprecedented climate events (e.g., Diffenbaugh et al., 2018) and on possible climate change scenarios (Rogelj et al., 2018), the transition path of the economy remains highly uncertain. A variety of models exist that assess the effects of global warming on the global economy, see for instance Stern (2007) and Nordhaus (2013). Most models translate economic activity into greenhouse gas emissions and transform these via various functions into an estimate of damages and mitigation costs (Nordhaus 1991a, 1991b, 1993; Rogelj et al., 2013). The models treat the atmosphere as an exhaustible resource with a fixed carbon holding capacity. In order to link science, economics, and policies of climate change, several integrated assessment models emerge; the most popular and Nobel Prize-winning model is the Dynamic Integrated model of Climate and the Economy (DICE; Nordhaus, 1993) and the Regional (RICE; Nordhaus and Yang, 1996) one, respectively. The social planner's role in these models is to find an optimal climate policy that trades off current and future consumption in the face of climate change effects and uncertainty.

Optimal policy generally reduces to providing tax incentives for clean technologies and taxing greenhouse gas (GHG) emissions efficiently (Goulder and Mathai, 2000; Acemoglu et al., 2016, Lemoine and Rudik, 2017). The effectiveness of market-based policies (Fowlie et al., 2016), demand-side solutions (Creutzig et al., 2018), or CO_2 taxes (Mardones and Flores,

2018) is still undetermined. That these policy incursions will leave firm cash-flows unchanged is unlikely. The uncertainties surrounding the economics of climate change are central to the design of climate policies (Hsiang et al., 2017) and are a key component driving climate and carbon risk.

Dietz et al. (2016) estimate a climate value at risk model for global financial assets with average climate risks of 1.8% (US$ 2.5 trillion) and a 99th percentile of 16.9% (US$ 24.2 trillion). Campiglio et al. (2018) highlight the relationship between climate change and global financial stability.

Institutional investors have been shown to increase their allocations towards sustainable portfolios after climate change induced natural disasters (Brandon and Krüger, 2018). Some investors are inclined to forgo financial performance to satisfy their social preferences (Riedl and Smeets, 2017) and active-ownership engagement and long-term investing can even lead to improved shareholder value (Dimson et al., 2015; Nguyen et al., 2017). Krüger (2015) demonstrates that equity prices fall when firms report negative corporate social responsibility news of which environmental news is an important subset. Flammer (2013) shows that stock prices increase for environmentally responsible firms and Heinkel et al. (2001) in turn demonstrate that polluting firms have lower stock prices and thus higher cost of capital due to ethical investing.

Lastly, 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 Emission Trading Scheme (ETS) which display positive returns during those time periods. De Haan et al. (2012) examine the relationship between corporate environmental performance (CEP) and stock returns and find a negative relationship between CEP and stock returns. Chava (2014) and El Ghoul et al. (2011) show that firms with higher carbon emissions also have higher costs of capital. Real estate prices have been shown to be directly and negatively related to climate change induced flooding and storms (Bernstein et al., 2018; Rehse et al., 2018).

Our study is closely related to the last strand of literature and measures carbon risk with a capital markets-based approach. We show that carbon risk can be quantified by a traditional asset pricing model and derive important implications for the use of the carbon beta as a risk measure.

2 Carbon risk factor construction

In this section, we describe in detail how we quantify carbon risk by our scoring concept via three distinct risk indicators: *(i)* value chain, *(ii)* public perception, and *(iii)* adaptability. By combining these three risk indicators, we calculate the carbon risk score (*CRS*) enabling us to distinguish firms into brown and green. Finally, we derive the carbon risk factor from these two types of firms using a long-short portfolio construction.

2.1 Carbon risk scoring concept

To create a long-short carbon risk factor portfolio from the returns of brown and green firms, we calculate the carbon risk of individual firms by calculating a carbon risk score (*CRS*). The score is based on the three main components of carbon risk: value chain, public perception, and adaptability. Value chain comprises production, processes, technology, and the supply chain and accounts for the current carbon emissions of a firm. Public perception covers how carbon emissions and a firm's carbon policy are perceived by its stakeholders (customers, investors, creditors, and suppliers). 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.

We review the financial impacts of related risk indicators in the carbon, corporate social responsibility, and ESG literature to provide further economic intuition for our concept. A firm's value chain is highly affected by changes in the economic transition process. Production processes as well as applied technologies cannot be transformed instantly and without high conversion costs (İşlegen and Reichelstein, 2011; Lyubich et al., 2018). 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).

A firm's public perception can create value by establishing a comprehensive reporting system (Krüger, 2015). On the one hand, a firm's performance may be affected by a crisis or negative events, in the form of reputational risks.[5] On the other hand, firms are valued higher if they can showcase their status and further action in the transition process and are thus able to make use of positive media coverage (Cahan et al., 2015; Byun and Oh, 2018).

Stakeholders and shareholders are concerned with a firm's ability to adapt quickly to deviations in the transition process, which may prevent underperformance due to current 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). A firm's adaptability is therefore a key indicator whether and to what extent it is affected by unexpected deviations from various carbon risk sources (Deng et al., 2013; Fatemi et al., 2015). In this framework, adaptability functions as a mediator for the positioning in the value chain and public perception category. Figure 1 illustrates these components of carbon risk reflected in the carbon risk factor.

[Insert Figure 1 here.]

To compute the *CRS* we first calculate the medians of each of the 55 carbon risk proxy variables.[6] We assign a value of 0 if the variable is below the median, and a value of 1 if it is above the median. Our logic of linking brown and green with high and low *CRS* is as follows. Facing the uncertainties surrounding the transition process, both brown and green firms are risky per se. However, if we are on the presumed path towards a green economy then brown firms are worse off than green firms and thus, have a higher carbon risk and vice versa. As a consequence, 0 represents low carbon risk whereas 1 indicates high carbon risk for each variable.[7] In the next step, we assign all 55 variables to their appropriate carbon risk indicator. By averaging all values within each risk indicator category, we obtain three different subscores.

[5] One recent example to be named here is the Volkswagen emissions scandal.

[6] A more detailed description on the dataset used can be found in chapter 3.1. For a full list of all variables and their codes see the Internet appendix Table IA.1.

[7] Each variable has been labelled in such a way that a high value represents high carbon risk and vice versa. Some variables have been standardized, for further information see Section 3.

By combining them, following Eq. (1), we finally arrive at a *CRS* of each firm *i* in each year *t*.[8]

$$CRS_{i,t} = \left(0.7\ Value\_Chain_{i,t} + 0.3\ Public\_Perception_{i,t}\right) - \left(0.7\ Value\_Chain_{i,t} + 0.3\ Public\_Perception_{i,t}\right)\ \frac{1 - Adaptability_{i,t}}{3} \tag{1}$$

The value chain subscore has a weight of 70% in the *CRS* reflecting its relative importance.[9] The public perception subscore carries 30% weight in the *CRS*.[10] In order to take into account the mediating role of adaptability, we subtract the sum of the two previous subscores up to a third of their value depending on the firm's adaptability subscore. An adaptability subscore of 0 implies that a firm is in an excellent position to deal with the transition process, however, a firm may still have current and perceived carbon risk reflected in the two other carbon risk indicators.[11] As a result, the *CRS* ranges between 0 and 1, where 0 denotes low and 1 denotes high carbon risk in the logic stated above. While the selection of variables, the determination of risk indicators, and the aggregating weights of the subscores may seem arbitrary, the outcome is *i)* the result of a workshop with acknowledged sustainability and finance experts from international institutions, consultancies, universities, and NGOs we hosted for this purpose and *ii)* subject to data availability and the correlation structure. Moreover, the weighting scheme has been intensively tested for robustness and our results remain economically the same.

2.2 Long-short factor construction

For the construction of the carbon risk factor, we first determine the annual carbon risk score *CRS* for each firm. Subsequently, we follow the approach of Fama and French (1993) and

[8] We calculate the *CRS* only if at least 10% of all variables are available for a firm during a month to guarantee that it is meaningful and suitable to assess a firm.
[9] We assume value chain to be the most important risk indicator, since production, process, and supply chain management constitute the core of a firm. Moreover, governmental climate change related regulations are focused predominantly on current emissions, which are part of this indicator.
[10] Our results remain robust by changing the weights to 90% and 10% or 75% and 25%.
[11] As a robustness check, we allow firms to reduce their combined value chain and public perception subscores up to a half by their ability to adapt to the transition process. We can state that all results remain qualitatively similar.

unconditionally allocate all firms each year into six portfolios based on their market equity (size) and *CRS* using the median and terciles as breakpoints, respectively. Similar to Fama and French's (1993) value factor *HML*, we use the value-weighted average monthly returns of the four portfolios "small–high carbon risk" (*SH*), "big–high carbon risk" (*BH*), "small–low carbon risk" (*SL*), and "big–low carbon risk" (*BL*) to calculate our brown minus green carbon risk factor (*BMG*) following Eq. (2). Thus, BMG_t is the return in month t of a zero-investment portfolio which is long in high carbon risk (brown) firms and short in low carbon risk (green) firms:

$$BMG_t = 0.5\ (SH_t + BH_t) - 0.5\ (SL_t + BL_t) \tag{2}$$

Figure 2 plots cumulative returns of the carbon risk factor *BMG* and the corresponding long and short positions for the sample period from January 2010 to December 2016. The figure shows a strong contrast in the performance of the portfolios over time. While the cumulative return of the carbon risk 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 carbon risk factor drops from around +6% to around –30%, followed by an increase to around –20% in 2016. Hence, we conclude that firms with high carbon risk performed worse in the last years than firms facing lower carbon risk.

[Insert Figure 2 here.]

3 Data

For the construction of the carbon risk factor, we use a distinct dataset covering 1,600 firms and 55 variables with carbon risk information. We apply this factor to a sample of more than 39,000 global firms without any firm specific carbon risk information.

3.1 Carbon risk score sample

For the construction of the carbon risk factor, we use data from a unique dataset compiled from four major ESG databases; *(i)* the Carbon Disclosure Project (CDP) Climate Change questionnaire dataset, *(ii)* the MSCI ESG Stats[12] and the IVA ratings, *(iii)* the Sustainalytics

[12] Formerly KLD Stats.

(SUST) ESG Ratings data and carbon (GHG) emissions datasets, and *(iv)* the Thomson Reuters (TR) ESG dataset[13] to form a carbon risk score (*CRS*) data sample. This sample is used to construct our *CRS* and thereafter the carbon risk factor. By integrating the respective variables into one consistent dataset, we create a unique dataset with firms that are part of at least one of the datasets. The overall combined sample consists of 41,752 firms. By merging four databases each with different approaches in collecting data we ensure that little self-reporting bias enters our sample. We are aware that some selection bias may exist, a possibility we explore in a later section. However, by making use of databases that also engage analysts in their data collection procedure we address this bias as best as possible.

To quantify a firm's carbon risk we select relevant variables from a total of 785 ESG variables available in the combined dataset. 363 variables thereof are potentially relevant for describing environmental issues leaving out social and governance aspects. In a next step, we identify variables relevant for describing carbon risk. This leaves a sample of 131 variables. After checking for data availability and informational redundancy, i.e. high correlations between variables, the final variable set is comprised of 55 carbon risk proxy variables.[14]

We exclude all firms that are not identified as equity or which are not primary listed and delete all observations of zero returns at the end of a stock's time series. We do not take into account firms operating in the financial sector.[15] In the transition process, these firms behave quite differently from conventional ones. For example, the current practice of assigning carbon emissions does not apply to equity financing or loans leading financial institutions to appear to be less prone to carbon risk.[16] We conduct an analysis of the carbon risk of the financial industry in Section 6.3 using carbon betas to provide further insights on their true carbon risk exposure. Furthermore, to ensure that the pricing of the stocks used to construct the common carbon risk factor is relatively information efficient, we set as a condition that firms must be part of all four datasets and provide detailed information for the majority of the carbon risk

[13] Formerly ASSET4 ESG database.
[14] We checked for empirical exclusionary criteria and used the expertise of the participants of the workshop to derive our final variable set.
[15] Technically, we exclude all firms classified with a TRBC code equal to 55.
[16] There exists a separate strand of literature focusing on CSR particularly for the banking sector (e.g., Wu and Shen, 2013; Barigozzi and Tedeschi, 2015; Cornett et al., 2016).

proxy variables. This is a hard condition but gives us the possibility to overcome potential biases typical within one dataset. Overall, this leads to our final *CRS* data sample of 1,637 globally listed firms.

We obtain monthly returns as well as further financial information such as the monthly market value of equity and net sales from Thomson Reuters Datastream. The preparation of the financial data follows the recommendations of Ince and Porter (2006). Further, we get monthly risk factors from the Kenneth R. French Data Library.[17] Table 1 reports summary statistics for financial and environmental variables of our *CRS* data sample. The average market capitalization of a firm is roughly US$ 21 billion while the median is roughly US$ 8.5 billion. Thus, the dataset includes many small and a few very large firms.[18] The same applies for net sales. To avoid penalizing large firms concerning absolute carbon emissions, energy use, and expenditures, we standardize all continuous variables by a firm's net sales.[19]

[Insert Table 1 here.]

Besides continuous variables, the sample contains a number of discrete and binary variables, or variables ranging within a predefined bandwidth, such as the dataset specific scores. For all discrete variables, we align the direction of the variable values with a higher value standing for a higher exposure to carbon risk.

3.2 Full sample

Apart from the *CRS* data sample, we use a full sample absent any fundamental carbon risk related information to show carbon risk via the carbon beta in a broad universe of stocks.[20] Therefore, we obtain data on the primary, major equity listings of all global firms as of May 2018 from Morningstar Direct. We obtain a final selection of 39,537 listed firms. A geographic

[17] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research.
[18] Compared to the NYSE breakpoint of French, our sample consists of four times larger firms regarding the median.
[19] Standardized variables fall in the following categories: CO_2e emissions, energy use, environmental expenditures, and provisions, and are marked in Table 1.
[20] Note that the full dataset partially coincides with the *CRS* data sample. The level of coincidence, however, is low at 3.82%. Alternatively, we eliminate all stocks that are included in the *CRS* data sample from the full sample. The results remain basically the same.

and sectoral breakdown can be found in appendix A.1. covering both the *CRS* data sample and the full sample.

4 Relevance of the carbon risk factor

In this section, we provide first of all *(i)* descriptive statistics and correlations of common risk factors. In the next two subsections, we demonstrate that the unique characteristics of the carbon risk factor are able to explain *(ii) CRS* decile portfolios as well as *(iii)* single stock returns measured by an increase in the adjusted R^2.

4.1 Carbon risk factor summary statistics

To gain an economic understanding of the carbon risk factor, Table 2 shows summary statistics and correlations with traditional risk factors during our sample period. The average monthly return of the carbon risk factor is negative at −0.25%. The correlations between the carbon risk factor and the market factor, the Fama and French (1993) factors, and the Carhart (1997) momentum factor are relatively low. The correlations are low enough to assume that the carbon risk factor possesses unique return-influencing characteristics that enhance the explanatory power of common factor models of systematic variations in stock returns.

[Insert Table 2 here.]

4.2 *CRS*-decile portfolio analysis

To test if the carbon risk factor is able to enhance the explanatory power of common factor models, we construct annually rebalanced *CRS*-decile portfolios from the firms in the *CRS* data sample such that decile 1 contains the firms with the lowest *CRS* and decile 10 contains the firms with the highest *CRS*. We run time-series regressions of the deciles' equal-weighted[21] monthly excess returns on the Carhart model (Eq. 3) and on a five factor Carhart + *BMG* model (Eq. 4).

$$er_{p,t} = \alpha_p + \beta_{p1}\, er_{M,t} + \beta_{p2}\, SMB_t + \beta_{p3}\, HML_t + \beta_{p4}\, WML_t + \varepsilon_{p,t} \qquad (3)$$

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

$$er_{p,t} = \alpha_p + \beta_{p1}\, er_{M,t} + \beta_{p2}\, SMB_t + \beta_{p3}\, HML_t + \beta_{p4}\, WML_t + \beta_{p5}\, BMG_t + \varepsilon_{p,t} \quad (4)$$

$er_{p,t}$ is the monthly return of portfolio p in month t in excess of the risk-free rate, $er_{M,t}$ is the monthly excess return on the global market portfolio at time t, SMB_t and HML_t are the monthly returns on the global size and value factors (Fama and French, 1993), WML_t is the global momentum factor (Carhart, 1997), and $\varepsilon_{p,t}$ is a zero-mean error term.

In order to test whether *BMG* is able to increase the explanation of the variation of excess stock returns we apply the F-test on nested models (Kutner et al., 2005).[22] The results of the global *CRS*-decile analysis are shown in Table 3 with our five factor model on the left and differences to the Carhart model on the right. The market betas are significant and close to 1 for all deciles.

[Insert Table 3 here.]

A comparison of the adjusted R^2s and the results of the F-test confirm that the new carbon risk factor significantly enhances the explanatory power of the standard Carhart model, especially for the high carbon risk portfolios. In the case of *CRS*-decile 10, the adj. R^2 increases by more than 12 percentage points. Regarding the carbon betas, the table shows the expected pattern, i.e. the loading increases strictly monotonically from the low *CRS*-decile, which displays a significantly negative loading of −0.328, to the high *CRS*-decile with a significantly positive loading of 1.019, being on the same level as the market factor loading. Thus, our new carbon risk factor delivers the expected results and significantly enhances the explanatory power of standard common factor models. For additional details on the *CRS*-deciles, all differences in the alpha and the coefficients compared to the Carhart model are shown.

4.3 Carbon risk in single stocks

To test the relevance of the carbon risk factor we compare the results of a variety of factor models using the full sample.[23] Table 4 shows the results. For example, in row (4) of Panel A

[22] Two models are "nested" if one of them is a subset of the other.

[23] For our regressions we use only firms with a time-series of at least 12 months to obtain robust results. Also, we conduct this analysis for the *CRS* data sample only, which can be found in the Internet appendix (Table IA.2). Results remain basically the same.

we test if adding the carbon risk factor to the three factor Fama and French (1993) model enhances the regression's adjusted R^2 according to the F-Test (H_0: $\beta_{p5} = 0$). The four factor Fama and French + *BMG* model yields an on average 0.71 percentage points higher adjusted R^2 than the standard three factor model. In contrast, the Carhart model yields an increase of solely 0.10 percentage points compared to the three factor model (row 3), illustrating the importance of the carbon risk factor.

[Insert Table 4 here.]

To assess the economic importance, we present comparisons across various model specifications with and without the carbon risk factor. For example, the three factor model has an on average 1.02 percentage points higher adjusted R^2 than the CAPM model, whereas a CAPM + *BMG* model has an on average 0.84 percentage points higher adjusted R^2. Adding the Pástor and Stambaugh (2003) traded liquidity factor[24] to the Carhart model enhances the adjusted R^2 on average by 0.01 percentage points whereas adding the carbon risk factor instead yields an average 0.69 percentage points increase in R^2.

On single stock level, adding the carbon risk factor to the factor models significantly enhances the explanatory power in about 11% to 12% of all stocks in the various factor models according to the F-tests. For a more detailed assessment of the impact of the carbon risk factor on the stock returns of single firms, Panel B of Table 4 reports the number of significant factor betas from our global five factor model. Based on two-sided t-tests, 4,493 firms (11.91%) show a significant carbon beta on a 5% significance level. This is comparable to the number of significant *SMB* betas (4,420) and higher than the number of significant *HML* (2,590) and *WML* betas (2,381). The average carbon beta is positive with 0.19. Overall, compared to traditional factor benchmarks, our carbon risk factor performs well highlighting its relative importance.[25]

[24] Obtained from Pástor's webpage: http://faculty.chicagobooth.edu/lubos.pastor/research/. We use the US traded illiquidity factor for the global sample knowing that there is a significant number of US firms in the respective sample. (Pastor and Stambaugh, 2003)

[25] We have carried out numerous further investigations, including a factor spanning test, a comparison of the carbon risk factor with further prominent factors as well as latest asset pricing tests for different single and combined test assets. Additionally, we apply a democratic orthogonalization to make our factor perfectly uncorrelated to the Carhart model. We provide descriptive statistics, a decile table and a comparison of common factor models with our orthogonalized risk factors. All results remain robust and the carbon risk factor is essential in asset pricing. For all those analyses see Tables IA.3 – IA.9.

5 Carbon beta as a risk measure

In this section, we highlight descriptive properties and inferences about the BMG factor and carbon betas.

5.1 Development over time, country and industry exposures

We estimate firms' yearly carbon betas from their daily return data using our five factor model.[26] We demonstrate that the carbon beta varies over time, countries, and industries and thereby identify countries as well as industries that are positively and negatively exposed to carbon risk.

Figure 3 displays average carbon betas of firms covered in our two samples over time. The results show that firms in the full sample have on average a higher carbon beta than firms covered by the *CRS* sample. Whether or not this is driven by strategic non-disclosure or by other characteristics of reporting versus non-reporting firms is an open question. Generally, firms disclosing their emissions and environmental agenda might have an incentive to report their actions in a more positive light. Carbon betas in both samples increase in magnitude over time. For the *CRS* sample the average carbon beta increases from −0.17 at the beginning of the sample period to −0.03 in 2016. In the full sample, the carbon beta increases from −0.08 in 2010 to 0.08 in 2016. This positive trend potentially mirrors the increased awareness of the capital market, the importance of carbon risk, and the increase in the price of carbon.[27]

[Insert Figure 3 here.]

For the country breakdown using the full sample, we aggregate the carbon beta of a country as the average of all firms operating in the respective country. As illustrated in Figure 4, carbon betas are high in most countries except in Europe and Japan. This is consistent with the intuition that the European Union is following an ambitious climate policy, e.g. with its 2030 climate and energy framework and the EU Action Plan. The countries with the most negative exposure to carbon risk are European countries like Italy (−0.663), Spain (−0.591), and Portugal (−0.505). The country with the highest average carbon beta is South Africa (0.433), consistent

[26] We use the daily carbon risk factor to estimate more stable yearly carbon betas.
[27] We can state this due to the fact that the carbon risk factor volatility remains stable over time.

with the fact that the country delays climate action on a political level (Climate Action Tracker, 2018). South Africa is closely followed by Brazil (0.410) and Canada (0.401). The result of this analysis is not obviously correlated with GDP.

[Insert Figure 4 here.]

On industry level, the carbon betas are as expected and illustrated in Figure 5. We find low and negative carbon betas in financial services and technology firms, and positive carbon betas in industries with extraordinarily high carbon emissions and which are proclaimed to be sensitive to climate change and mitigation policies, i.e. the basic materials and energy sector.[28]

[Insert Figure 5 here.]

Overall, the breakdown of the carbon betas over time, countries, and industries is consistent with our expectation on how carbon risk is likely to be priced. We show that carbon betas of individual firms have increased in our sample period. Moreover, energy and basic materials firms are more positively exposed to carbon risk, i.e. exhibit a higher carbon beta than the technology sector. Furthermore, the boxplots demonstrate that within industries, it is possible to cover a large bandwidth of carbon betas, e.g., in the Basic Materials sector we find negative as well as positive carbon betas.

5.2 Risk decomposition of carbon beta

In this section, we analyze the economic mechanisms driving the BMG factor and the market factor broken down into carbon beta portfolios. We follow the beta decomposition approach of Campbell (1991) and Campbell and Vuolteenaho (2004). The analysis is geared towards understanding whether or changes in expectations about firm cash-flows or changes in discount rates is driving the BMG factor and the correlation of firms returns with market returns.

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-

[28] Both country and industry breakdown of betas show basically the same results for the *CRS* data sample which can be found in Figures IA.1 and IA.2 of the Internet appendix.

evaluations towards a new equilibrium. 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 VAR model.[29] For the variance decomposition, we modify Campbell's (1991) approach using the *BMG* 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 per Campbell and Vuolteenaho (2004). In Table 5, we report the absolute and normalized results of the variance decomposition of *BMG* as well as correlations between the components. 11.86% of the total *BMG* variance can be attributed to discount rate news whereas the remaining 88.14% are driven by cash-flow news. This suggests that the carbon risk factor is mainly determined by expectations about future cash-flows and not about changes in the discount rate that investors apply to these cash-floes. This is consistent with the transition from a brown towards a green economy that is highly senstive to changes in technologies (investments) and customers preferences for goods and services (revenues).[30]

[Insert Table 5 here.]

In a second test, we follow Campbell and Vuolteenaho (2004) more closely and decompose market betas of carbon beta sorted portfolios into a cash-flow and a discount-rate beta.[31] 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 carbon beta and size sorted test asset portfolios by sorting the over 39,000 stocks of the full sample into 20 5%-quantiles based on their individual carbon beta and splitting each portfolio by the stocks' median market capitalization.

[Insert Figure 6 here.]

[29] For further details on the model specification see Appendix A.1.

[30] Campbell, Polk, and Vuolteenaho (2010) explain that movements in stock prices are either driven by the characteristics of cash flows (fundamentals view) or by investor sentiment (sentiment view).

[31] For this analysis, we stick to the model specification of Campbell and Vuolteenaho (2004) using the excess market return as first state variable. Details are given in Appendix A.1. Results for the decomposition using the carbon risk factor as first state variable can be found in Figure A.1.

As shown in Figure 6, 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 betas show a U-shaped pattern. This suggests that the extreme portfolios, i.e. green and brown firms, have higher cash-flow betas and are thus more exposed to fundamental re-evaluations of firm values.[32]

Motivated by this finding, 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 than for transitory discount-rate shocks. In Table 6, we provide evidence in favor of this argument by applying the asset pricing models described in Campbell and Vuolteenaho (2004) to our 40 carbon beta/size sorted test asset portfolios. The price for cash-flow beta risk in the cross-section is almost ten times higher than for discount-rate beta risk (15.9% vs. 1.6% p.a. in the unrestricted factor model). When constraining the price for the discount-rate beta to the market variance (two-beta ICAPM) the results remain economically the same. Since carbon sensitive portfolios are predominantly prone to cash-flow news, we conclude that conservative investors demand a higher return for holding those portfolios due to their risk aversion for fundamental cash-flow risks.

[Insert Table 6 here.]

6 Practical applications of carbon beta

In this section we provide further insights into the relationship between balance sheet data that proxy for investment in clean technologies and stranded assets and the carbon beta of a firm. We also show that investors are not worse off in terms of their Sharpe Ratios (SRs) when investing in low carbon risk portfolios holding other factor loadings and industry allocations constant. Finally, we make the case that financial services firms, and banks in particular, are

[32] In Figure IA.3, we find that the extreme portfolios display higher systematic risk per se, which is primarily driven by cash-flow risk as shown in Figure 6.

more involved in financing high carbon risk firms in high carbon risk countries than in low carbon risk countries, and thus more exposed to carbon risk.

6.1 Carbon beta from an investor's perspective

Investors weigh between risk and return in their portfolios. To show that it is possible to construct a portfolio with similar risk-adjusted returns and similar exposure to traditional risk factors but lower carbon risk, we first estimate the beta loadings of our five factor model for all stocks in the full sample. Then, we construct 5×5×5 conditionally sorted portfolios based on market beta quintiles, followed by *SMB* beta quintiles and subsequently by *HML* beta quintiles. The resulting 125 portfolios consist of firms with similar characteristics regarding the factors of the five factor model but potentially cover a broad range with respect to carbon beta. In the following, we keep only the firms with below average carbon betas (best-in-class) with respect to all carbon betas within the portfolio or only the firms with above average carbon betas (worst-in-class). For all three cases – all firms, best-in-class, and worst-in-class – we calculate equal-weighted portfolio returns as well as risk-adjusted performance measures over time.

The results are presented in Panel A of Table 7. The average portfolio has an annual SR of 0.44, while the low carbon risk portfolio generates a SR of 0.8. This represents an eight percentage points significantly higher SR for the low carbon risk portfolio than for the high carbon risk portfolio. The low carbon risk portfolio also exhibits lower volatility of −0.04. More importantly, the carbon beta difference between the low carbon risk and the high carbon risk portfolios is −0.91, which means that an investor's portfolios changed from being highly positively correlated with carbon risk to being negatively correlated. Even though investors change their exposure to carbon risk, their exposure to the market, *SMB*, and *HML* remains roughly the same.

[Insert Table 7 here.]

In Panel B, we conduct a similar analysis using industry portfolios to demonstrate that it is possible to construct industry portfolios of low (best-in-class) carbon beta firms within a sector without having significant lower returns but significantly lower volatility than that of high carbon beta firms (worst-in-class). Panel B presents the results for equal-weighted portfolio returns and risk-adjusted performance measures. An investor can construct a portfolio with a significantly lower carbon beta of −1.03 and without changing the sector allocation of his or her portfolio, but with the same SR and a significantly lower volatility of −0.04.[33] Overall, the results suggest that investors can change their carbon exposure without sacrificing exposure to traditional risk factors or industry preferences.

6.2 Carbon beta from an analyst's perspective

To determine influencing factors of firms' carbon betas, we conduct panel regressions. For the *CRS* data sample, we explain the annual carbon beta using the three carbon risk subscores value chain, public perception, and adaptability used to compute the *CRS*. Further, we use specific firm fundamentals as well as country, industry, and time fixed effects.[34] The results presented in Panel A of Table 8 show that all subscores are positively and significantly correlated with carbon betas. This suggests for instance that firms with higher value chain subscores also have higher carbon betas. The same interpretation holds for public perception and adaptability. Moreover, higher R&D expenditures lead to lower carbon betas. This reinforces the assumption that more innovative firms exhibit lower carbon betas. On the other hand, the Property, Plant, and Equipment (PPE) variable suggests that firms with high PPE asset values, which might represent legacy production equipment as well as stranded assets,[35] have higher carbon betas.

[Insert Table 8 here.]

Panel B shows the results for the full sample without the carbon risk score indicators, as this data is not available for all firms. The results hold across both samples in that we find that R&D reduces the carbon beta, and PPE increases it. These panel regressions show that the carbon beta is partially explained by firm characteristics related to a firm's exposure to carbon risk. Thus, analysts can consider carbon beta as a measure to redefine their forecasts for firms and take into account carbon risks for their valuation strategy.

[33] The results remain robust for value-weighted portfolios.
[34] The analysis with solely the carbon risk indicators can be found in the appendix (Table A.3).
[35] For a definition of stranded assets have a look at Carbon Tracker Initiative (2013).

6.3 Carbon betas in the financial industry

Firms operating in the financial services sector do not generally emit carbon in their daily operations and thus are not directly exposed to carbon risk. However, they can be highly involved in the financing of local firms with high carbon risk making a bank's loan portfolio correlated with carbon risk. To study this relationship, we conduct an analysis of the carbon beta of banks and other financial services firms in our full sample, conditional on the carbon beta of the country in which they are domiciled. By dividing countries according to the average carbon beta of all their firms into two groups, we identify high and low carbon risk countries (*CRC*). In Table 9 Panel A, results of a *CRC* division by terciles is shown.

[Insert Table 9 here.]

A bank in a low *CRC* has on average a carbon beta of -0.337. In comparison with a high CRC, it has a significantly lower carbon beta of -0.587. A bank in a middle *CRC* has a lower carbon beta than in a high *CRC*, but a higher carbon beta than a low *CRC* (significant negative difference between low and middle *CRC* betas). In Panel C, we use quartiles to highlight the fact that the results are not conditional on data sub-setting. These results remain robust if we use financial services firms in general including banks (see Panel B and D). Through their financing decisions, even the financial industry is strongly affected by carbon risk.

7 Conclusion

The global economy is transitioning from a high carbon past to a low carbon future. Some firms are well positioned to deal with the risk associated with the transition process, whereas others are not. The risk in this transition process is present at the firm, industry, and country level.

We introduce a new measure for this kind of risk, the carbon risk, which we name carbon beta. The carbon risk factor *BMG*, necessary to measure the carbon beta, will be made freely available for everybody to use. The information contained in the carbon beta can be used by, e.g., analysts, investors, and regulators. Analysts can use the carbon betas to integrate readily available information and sharpen their forecasts. Investors can assess the carbon risk in their portfolio and make portfolio allocation decisions to change their exposure to carbon risk. We show that this is possible without hurting performance. The carbon betas can also be used by portfolio managers to show investors the steps they can take with respect to climate change. Investors, pension funds, and insurance firms can use this information to hedge carbon risk in their portfolios and their operations. Finally, regulators and national governments can use the carbon beta to assess the carbon risk in the economy as a whole. This information will allow for more directed policy and for an external assessment of the carbon risk of an individual firm.

The decomposition of carbon betas into cash-flow and discount-rate components reveals that brown and green firms, respectively, have higher cash-flow betas and are thus more exposed to fundamental re-evaluations of firm values than to discount-rate changes. Furthermore, the price for cash-flow betas is higher than for discount-rate betas, since investors demand a higher premium for fundamental risks.

Carbon risk and the transition process may impact cash flows by increasing current expenses, investments, and discount rates via changes in public perception. Assessing changes in carbon risk (betas) around regulatory and policy changes is a fruitful avenue of future research. For instance, simple carbon beta event studies can be used to assess the impact of the introduction of carbon pricing, taxation, cap-and-trade, R&D credit, or similar policies for the whole economy, within an industry and for individual firms. A broadening of carbon and environmental disclosure to make disclosure mandatory and make disclosure comparable across jurisdictions is important.

The quantification of carbon risk is thus a step towards a low carbon future by aligning the incentives of investors, firms, regulators, and everyone that is impacted by climate change.

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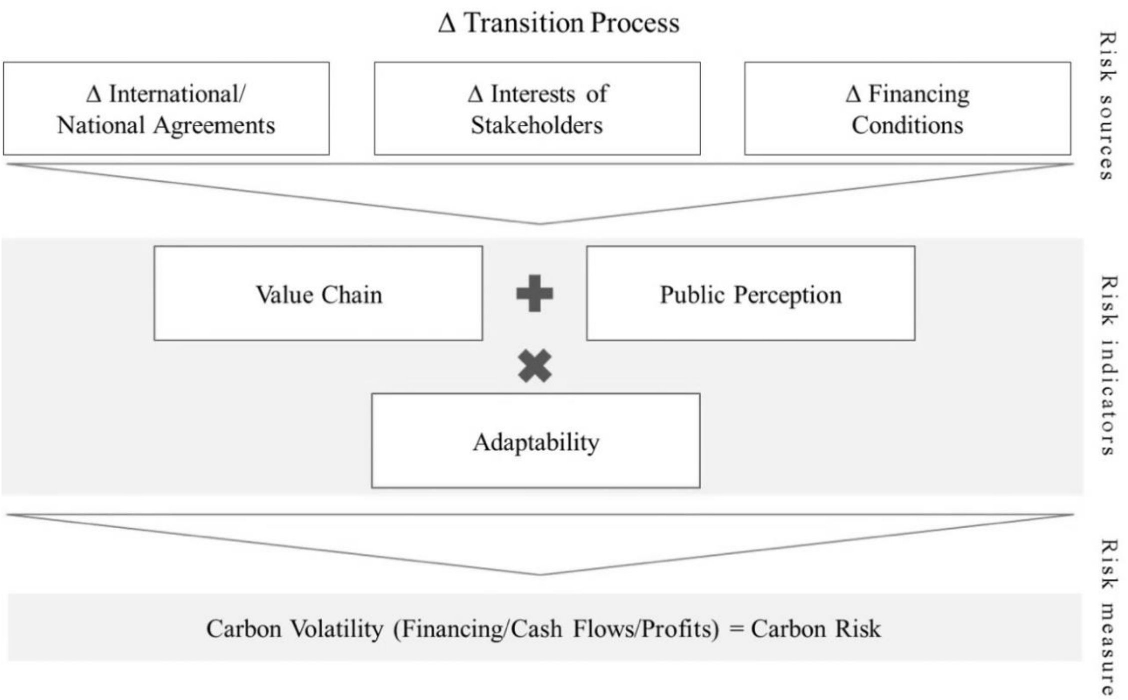
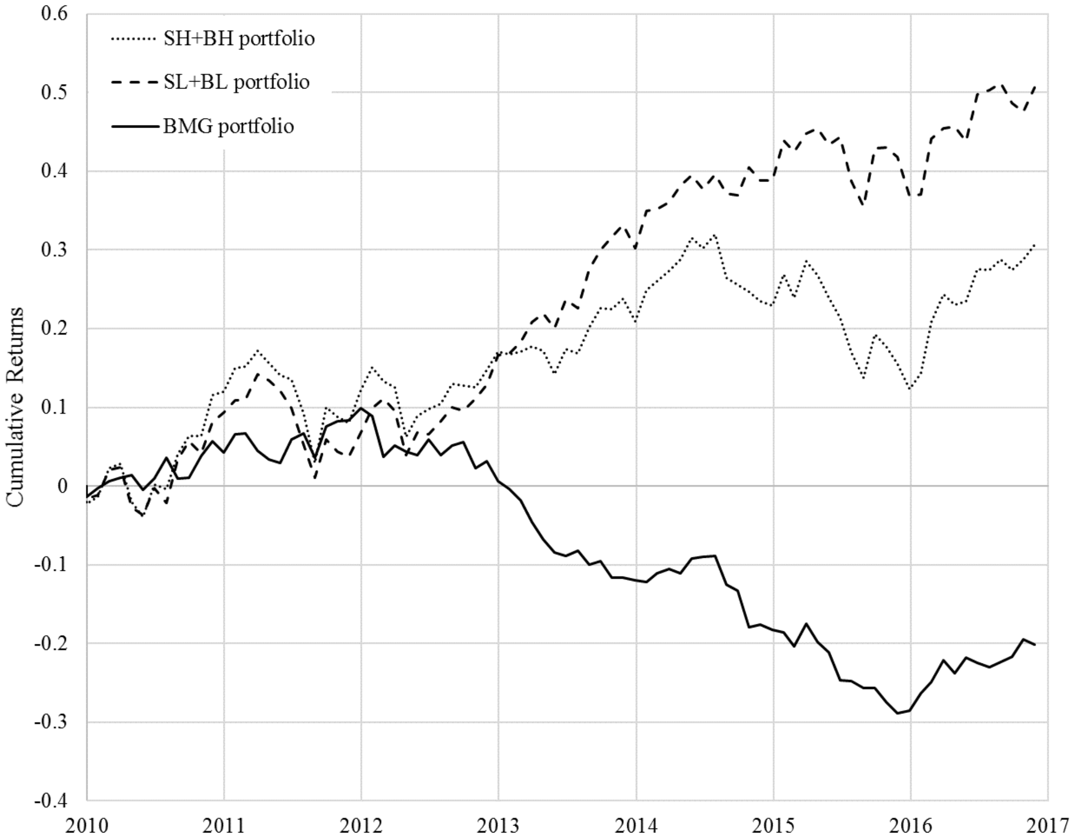
Figures and Tables

Figure 1
Carbon risk scoring concept



This figure shows our carbon risk score (*CRS*) concept. It reflects the change in the climate change transition process, which can be expressed in three risk sources, namely a change in international and national agreements, an alteration of the interests of stakeholders, and a transformation of the financing conditions. The risk sources have an impact on the value chain as well as on the public perception of a firm, but it is mediated by the ability to adapt to the transition process. The exposure to carbon risk can be measured in the volatility of a transition-linked change in financing costs, cash flows, or profits.

Figure 2
Cumulative returns of the *BMG* factor and the long and short positions



This figure shows cumulative returns of the *BMG* factor and the weighted underlying long (*SH*+*BH*) and short positions (*SL*+*BL*) for the sample period from January 2010 to December 2016.

Table 1
Descriptive statistics of variables

Variable	N	Mean	SD	Median	Variable	N	Mean	SD	Median
Panel A. Thomson Reuters Financials					**Panel C. Sustainalytics**				
Returns (%)	76,700	0.74	9.01	0.69	Carbon Intensity	59,492	45.07	39.03	50.00
Market equity (US$ mio.)	76,700	20,959	38,749	8,557	Renewable Energy Use	59,492	85.08	34.78	100.00
Net sales (US$ mio.)	76,405	18,528	35,278	7,643	Supplier Environmental Programmes	29,321	64.37	34.59	70.00
R&D (US$ mio.)	51,153	82	512	5	Sustainable Products & Services	33,978	73.55	30.90	75.00
PPE (US$ mio.)	120,554	1,068	5,782	95	Scope of GHG Reporting	58,948	28.85	37.87	0.00
Leverage ratio	120,274	0.22	0.23	0.18	Environmental Policy	72,552	39.84	33.38	50.00
Book-to-market ratio	121,508	0.80	3.56	0.59	Green Procurement Policy	72,552	55.99	33.16	60.00
Cash (US$ mio.)	104,558	288	2,481	29	Renewable Energy Programmes	59,428	78.94	27.49	75.00
Return on Assets	121,481	0.04	7.07	0.03	Environmental Management System	72,552	25.52	30.78	20.00
Net sales full sample (US$ mio.)	121,532	2,351	10,998	294	Air Emissions Programmes	26,915	67.59	33.23	75.00
Panel B. Thomson Reuters ESG					Overall ESG Score	72,552	34.22	8.66	34.38
Energy Use Total (std.)	51,480	119,343	6,682,551	630.74	**Panel D. CDP**				
CO_2 Equivalents Emission Total (std.)	63,959	7,672	465,116	59.69	Greenhouse Gas Emissions (std.)	61,760	47,611	1,541,905	61.29
Clean Technology	72,991	0.76	0.43	1.00	Regulatory Opportunities Sources	70,670	2.64	2.37	2.00
Emission Reduction Prod. Process	72,806	0.49	0.50	0.00	Climate related Opport. Sources	70,670	1.18	1.04	1.00
Sustainable Supply Chain	72,806	0.23	0.42	0.00	Regulatory Risks Sources	70,670	1.85	1.87	1.00
Renewable Energy Use	72,806	0.32	0.47	0.00	Climate related Risks Sources	70,670	1.22	1.25	1.00
Climate Change Risks/Opportunities	72,806	0.23	0.42	0.00	Regulatory Opportunities	62,675	0.08	0.27	0.00
Energy Efficiency Policy	72,806	0.11	0.31	0.00	Climate related Opportunities	62,648	0.14	0.34	0.00
Emission Reduction Target/Objective	52,780	0.03	0.16	0.00	Regulatory Risks	62,792	0.94	0.24	1.00
Energy Efficiency Target/Objective	36,525	0.05	0.22	0.00	Climate related Risks	62,720	0.81	0.39	1.00
Environmental Investments Initiatives	75,350	0.33	0.47	0.00	Emission Reduction Target	6,871	0.72	1.18	0.00
Environmental Exp. Investments	75,350	0.51	0.50	1.00	Disclosure Score	55,676	22.31	18.80	19.00
Environmental Expenditures (std.)	29,999	0.01	0.04	0.00	Performance Band	58,595	4.30	2.12	3.00
Environmental Partnerships	75,350	0.76	0.43	1.00	**Panel E. MSCI ESG**				
Environmental Provisions (std.)	17,677	0.04	0.16	0.01	Opportunities in Clean Tech	21,758	0.66	0.47	1.00
Policy Emissions	75,350	0.89	0.32	1.00	Energy Efficiency	7,039	0.57	0.50	1.00
Environmental R&D Exp. (std.)	8,881	0.09	0.01	0.09	Opportunities Renewable Energy	2,280	0.57	0.49	1.00
Emission Reduction Score	72,806	16.18	19.76	7.64	Carbon Emissions	51,357	0.48	0.50	0.00
Resource Reduction Score	72,806	16.11	19.59	7.93	Regulatory Compliance	13,137	0.10	0.30	0.00
Environmental Score	72,806	16.14	19.66	7.41	Climate Change Controversies	58,358	0.03	0.18	0.00
Innovation Score	75,330	38.21	26.05	33.86	Industry-adjusted Overall Score	75,171	4.25	2.30	4.20
Emissions Score	75,330	26.26	20.74	21.52	Carbon Emissions Score	63,802	2.87	2.46	2.67
					Climate Change Theme Score	46,298	2.83	2.67	2.30
					Environmental Pillar Score	75,146	4.32	2.03	4.40
					Panel F. Morningstar				
					Returns (%)	2,686,759	1.13	17.08	0.00

This table reports the descriptive statistics for all variables of the *CRS* data sample as well as for the full sample for the period from January 2010 to December 2016. Variables with (std.) are standardized by net sales. A country and sector breakdown can be found in appendix A.1. A list of all variable codes can be found in internet appendix IA.1.

Table 2
Risk factor descriptive statistics and correlations

Factor	Mean excess return (%)	SD (%)	T-stat.	Correlations				
				BMG	er_M	*SMB*	*HML*	*WML*
BMG	-0.25	1.95	-1.17	1.00				
er_M	0.76	4.02	1.74	0.09	1.00			
SMB	0.06	1.39	0.37	0.20	-0.02	1.00		
HML	0.00	1.68	-0.02	0.27	0.19	-0.06	1.00	
WML	0.57	2.53	2.06	-0.24	-0.20	0.00	-0.41	1.00

This table displays descriptive statistics and correlations of the monthly risk factors of the *4F Carhart model* and the *BMG* factor for the sample period from January 2010 to December 2016. The factors er_M, *SMB*, *HML*, *WML*, and the risk-free rate are provided by Kenneth French.

Table 3
CRS-decile portfolio performance

	Median *CRS*	*5F Carhart + BMG model*							Δ *Carhart 4F model*					
		Alpha	er_M	*SMB*	*HML*	*WML*	*BMG*	Adj. R^2 (%)	Δ *Alpha*	Δ er_M	Δ *SMB*	Δ *HML*	Δ *WML*	Δ Adj. R^2 (%)
Low *CRS*	0.24	-0.001	1.143***	0.142*	-0.062	-0.159***	-0.328***	95.32	-0.001[a]	-0.003[a],***	-0.099[a]	-0.083[a],*	0.036[a],**	1.60***
		(-0.44)	(39.59)	(1.71)	(-0.81)	(-3.20)	(-5.28)							
2	0.32	0.001	1.012***	0.105	0.018	-0.078*	-0.288***	95.61	-0.001[a]	-0.003[a],***	-0.087[a]	-0.073[a]	0.032[a]	1.58***
		(0.93)	(41.12)	(1.48)	(0.28)	(-1.84)	(-5.42)							
3	0.37	0.002**	1.028***	0.169**	-0.055	-0.116**	-0.143**	94.59	-0.001[a],**	-0.002[a],***	-0.043[a]	-0.037[a]	0.016[a],**	0.32**
		(2.10)	(36.86)	(2.10)	(-0.76)	(-2.40)	(-2.38)							
4	0.42	0.001	1.046***	0.171**	-0.023	-0.077	-0.096	94.06	0.000[a]	-0.001[a],***	-0.029[a],*	-0.025[a]	0.011[a]	0.09
		(0.45)	(35.14)	(1.99)	(-0.30)	(-1.49)	(-1.50)							
5	0.45	0.000	1.011***	0.142	0.006	-0.101*	-0.015	93.55	0.000[a]	0.000[a],***	-0.005[a]	-0.003[a]	0.002*	-0.08
		(-0.32)	(33.35)	(1.62)	(0.08)	(-1.92)	(-0.24)							
6	0.49	0.001	0.945***	0.200**	0.060	-0.094*	0.127**	93.99	0.000[a]	0.001[a],***	0.038[a],***	0.032[a]	-0.015[a],**	0.26**
		(0.67)	(34.03)	(2.49)	(0.82)	(-1.97)	(2.11)							
7	0.53	0.001	0.991***	0.212**	-0.007	-0.074	0.415***	94.06	0.001[a]	0.004[a],***	0.126[a],***	0.105[a]	-0.046[a],*	3.12***
		(0.57)	(33.55)	(2.49)	(-0.09)	(-1.45)	(6.52)							
8	0.58	0.000	1.084***	0.226**	0.022	-0.195***	0.448***	94.45	0.001[a]	0.005[a],***	0.136[a],***	0.114[a]	-0.050[a],***	2.93***
		(0.04)	(34.06)	(2.46)	(0.26)	(-3.54)	(6.54)							
9	0.64	-0.003**	1.078***	0.085	-0.035	-0.072	0.688***	93.06	0.002[a],**	0.007[a],***	0.209[a],**	0.175[a]	-0.077[a],*	6.88***
		(-2.34)	(30.07)	(0.83)	(-0.37)	(-1.16)	(8.90)							
High *CRS*	0.73	-0.001	1.092***	0.214*	-0.008	-0.165**	1.019***	91.52	0.002[a]	0.010[a],***	0.309[a],***	0.258[a]	-0.114[a],**	12.47***
		(-0.76)	(25.00)	(1.70)	(-0.07)	(-2.18)	(10.82)							

This table shows monthly median carbon risk scores (*CRS*), alpha performance and beta coefficients of the *5F Carhart + BMG model* for annually rebalanced, equal-weighted decile portfolios based on the *CRS* of the stocks in the *CRS* data sample for the sample period from January 2010 to December 2016. On the right panel, the table displays Δ alphas and coefficients between the *5F Carhart + BMG model* and the *4F 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: $\beta_{p5}=0$).

Table 4
Comparison of common factor models

Panel A. Significance tests for explanatory power of various models

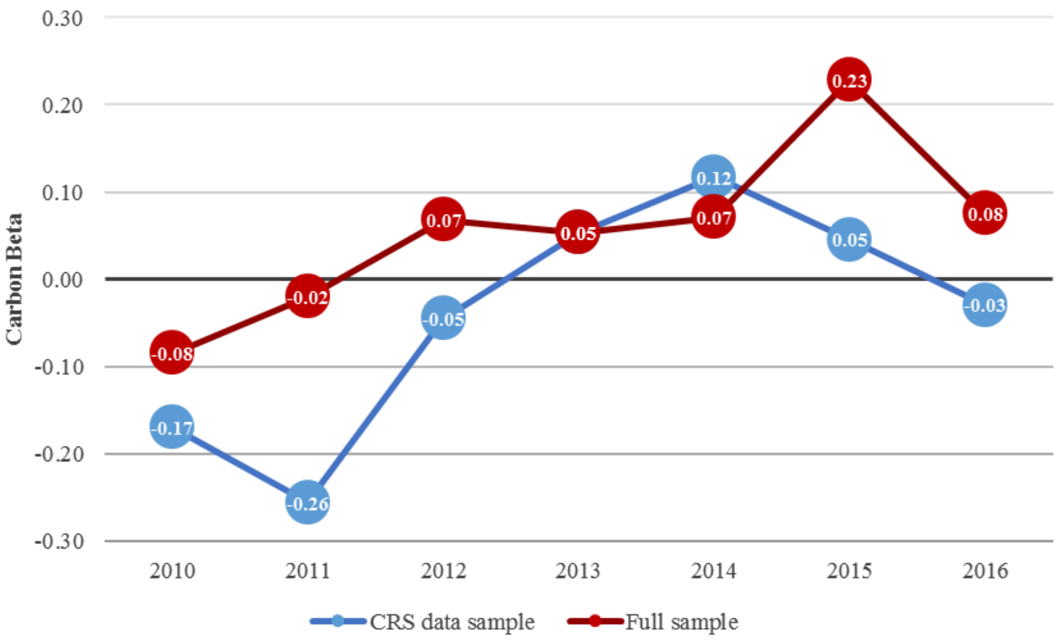
	Avg. Δ adj. R^2 (%)	F-test at sign. level 5% (%)
(1) CAPM - 3F FF	1.02	11.49
(2) CAPM - 2F CAPM + *BMG*	0.84	12.05
(3) 3F FF - 4F Carhart	0.10	5.98
(4) 3F FF - 4F FF + *BMG*	0.71	11.55
(5) 4F Carhart - 5F PS	0.01	5.01
(6) 4F Carhart - 5F Carhart + *BMG*	0.69	11.55

Panel B. Significance tests for risk factor betas for the *5F Carhart + BMG model*

		T-test of significance of coefficients					
	Avg. coeff.	10% level		5% level		1% level	
		#	%	#	%	#	%
er_M	0.935	24,627	65.30	21,587	57.24	15,957	42.31
SMB	0.674	7,113	18.86	4,420	11.72	1,475	3.91
HML	-0.011	4,652	12.34	2,590	6.87	685	1.82
WML	-0.023	4,312	11.43	2,381	6.31	586	1.55
BMG	0.190	6,824	18.09	4,493	11.91	1,892	5.02

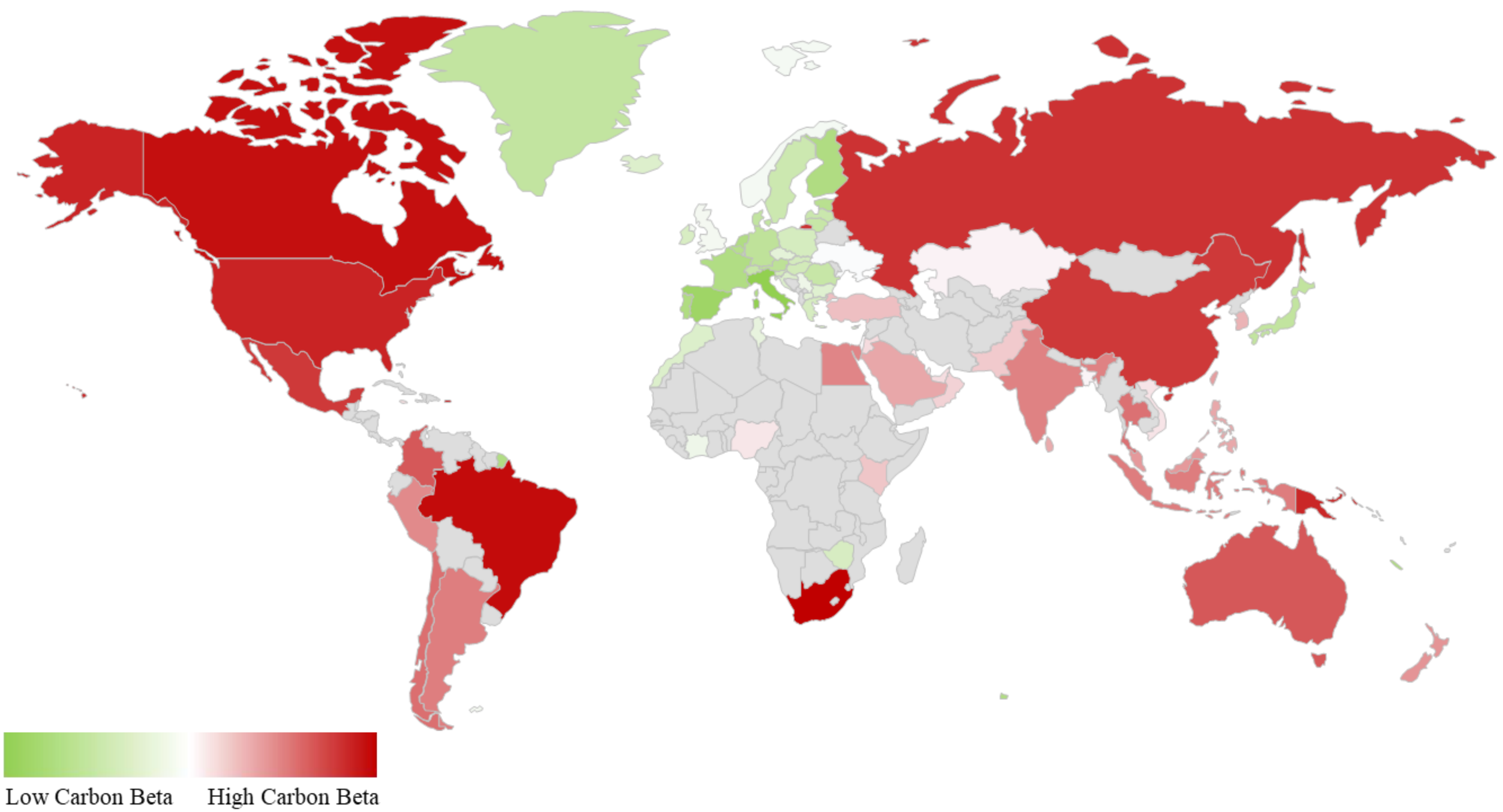
This table provides a comparison of common factor models. Panel A reports the average Δ adj. R^2 between different factor models run on single stocks from the full sample in the sample period from January 2010 to December 2016. Significance statistics are based on one-sided F-tests for nested models (H_0: $\beta_{p5}=0$). Panel B shows average coefficients as well as the absolute (#) and relative (%) number of statistically significant beta coefficients from *5F Carhart + BMG model* regressions run on single stocks from the full sample in the sample period. Statistical significance is based on two-sided t-tests. The factors er_M, *SMB*, *HML*, and *WML* are provided by Kenneth French, the Pástor - Stambaugh (PS) liquidity factor is provided by Ľuboš Pástor.

Figure 3
Carbon beta in time



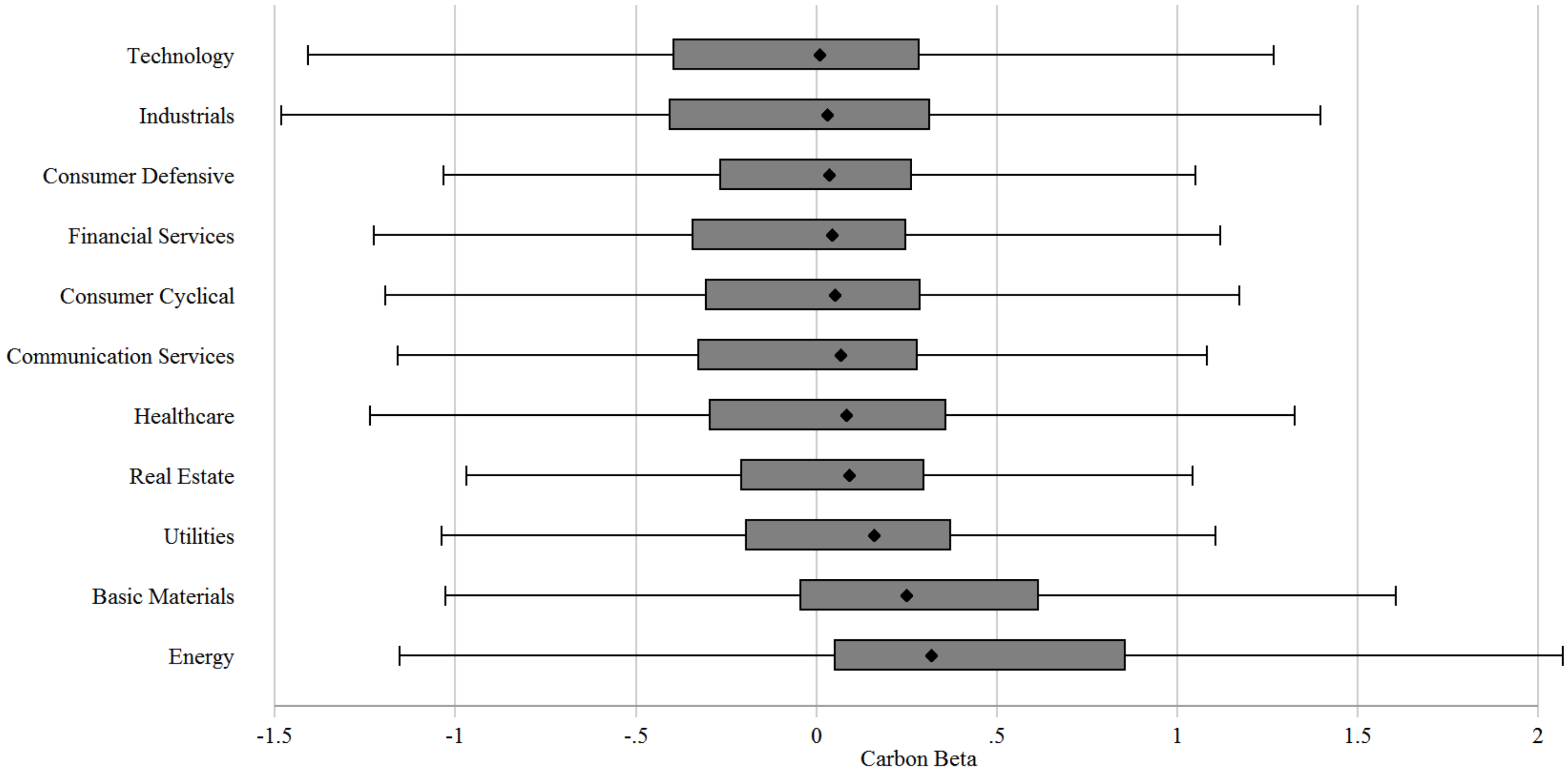
This figure shows the average annual carbon beta of the *CRS* data sample and the full sample for the period from January 2010 to December 2016. All firm carbon betas are estimated based on daily return data.

Figure 4
Carbon beta landscape



This figure shows the carbon beta of the full sample across the world. We include all countries with at least 30 firms in our full sample to correct for outliers. A greenish color indicates a low average carbon beta of the country, whereas a deep red color states that, on average, the countries' firms have high carbon betas.

Figure 5
Carbon beta industry breakdown



This figure shows a boxplot of the carbon beta of the full sample across sectors. The sectoral breakdown is based on the super sectors of the Morningstar Global Equity Classification Structure (MGECS). The sectors are sorted in ascending order by their carbon beta.

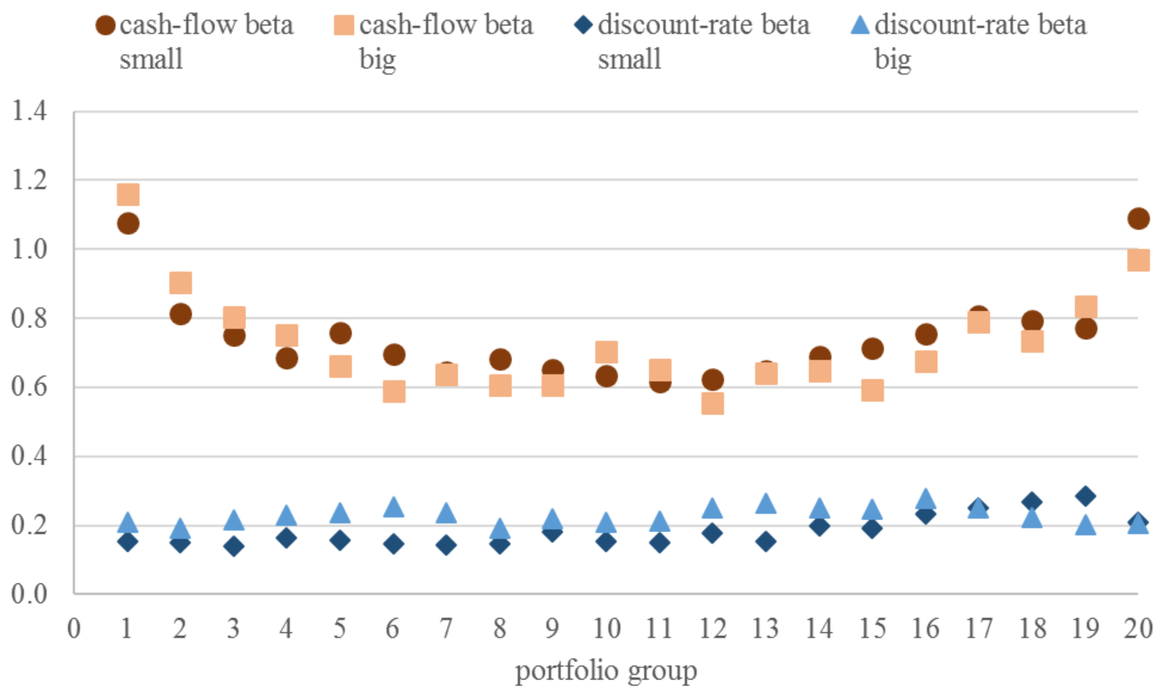
Table 5

Variance decomposition

	variance components			
	$Var(N_{CF})$	$Var(N_{DR})$	$-2\ Cov(N_{CF}, N_{DR})$	$Corr(N_{CF}, N_{DR})$
Absolute (%)	0.0394	0.0045	-0.0057	21.44
	(0.00)	(0.00)	(0.00)	(0.01)
Normalized (%)	103.13	11.86	-14.99	21.44
	(0.17)	(0.02)	(0.04)	(0.01)

This table shows the results of the variance decomposition of the carbon risk factor for the sample period from January 2010 to December 2016. We report both the absolute and normalized values of variances and covariance of the cash-flow news and discount-rate news for the carbon risk factor. The standard errors in parentheses are calculated using a jackknife method.

Figure 6
Beta decomposition of 40 test assets



This figure shows the beta decomposition of the 40 test assets built out of the full samples. Firms are sorted into 20 portfolios based on their individual carbon beta (portfolio group) and then split into small and big subsamples with the median of the size as breakpoint. The cash-flow and discount-rate betas are obtained by following the methodology of Campbell and Vuolteenaho (2004).

Table 6

Asset pricing tests

	unrestricted factor model		two-beta ICAPM	
	unrestricted	α=0	unrestricted	α=0
R_{zb} less R_{rf} (g_0)	0.003	0	0.003	0
% pa	3.837	0	3.763	0
std. error	(0.004)		(0.003)	
$\hat{\beta}_{CF}$ premium (g_1)	0.013	0.016	0.013	0.017
% pa	15.934	18.687	15.941	20.881
std. error	(0.004)	(0.002)	(0.003)	(0.001)
$\hat{\beta}_{DR}$ premium (g_2)	0.001	0.008	0.002	0.002
% pa	1.571	10.054	1.907	1.907
std. error	(0.012)	(0.008)	(0.000)	(0.000)
R^2	0.275	0.261	0.275	0.248

This table shows premia estimated in the sample period from January 2010 to December 2016. 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 based on carbon beta and size. Standard errors are from the respective cross-sectional regression.

Table 7
Matching exposures

	SR	Excess return	SD	Carbon beta	*MKTRF* beta	*SMB* beta	*HML* beta
Panel A. 125 Portfolios							
All firms	0.44	0.18	0.41	-0.02	0.65	0.88	0.21
High carbon beta	0.40	0.18	0.44	0.47	0.65	0.87	0.20
Low carbon beta	0.48	0.19	0.39	-0.44	0.65	0.89	0.22
Low-High carbon beta	0.08***	0.01	-0.04***	-0.91***	0.00	0.02	0.03
Panel B. 11 Industry Portfolios							
All firms	0.41	0.17	0.41	0.01			
Worst-in-class	0.40	0.17	0.43	0.52			
Best-in-class	0.43	0.17	0.39	-0.50			
Best-worst	0.04	0.00	-0.04***	-1.03***			

This table shows the yearly average of the Sharpe ratio (SR), excess returns, and volatility as well as the carbon beta, and the *MKTRF*, *SMB*, and *HML* beta of 125 portfolios in Panel A. The portfolios are conditionally constructed on the *MKTRF*, *SMB*, and *HML* beta of all stocks in the full sample and aggregated equal-weighted. The high (low) carbon beta portfolios include only stocks of the original portfolio with a carbon beta above (below) its portfolio mean. For Panel B, a stock is categorized as worst-in-class (best-in-class) if its carbon beta is above (below) their respective industry's carbon beta mean. The industry classification is based on the super sectors of the Morningstar Global Equity Classification Structure (MGECS).*, **, *** denote significance on the 10%, 5%, and 1% level of the differences, respectively. Significance tests are based on two-sided t-tests.

Table 8
Panel regressions

	Panel A. *CRS* data sample				Panel B. Full sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Value Chain	0.49***	0.19***	0.32***	0.54***				
Public Perception	0.58***	0.23***	0.52***	0.60***				
Adaptability	0.74***	0.23**	0.64***	0.69***				
R & D	-0.035**	-0.026***	-0.060***	-0.034**	-0.020***	-0.020***	-0.021***	-0.021***
PPE	0.066**	0.080***	0.058	0.066**	0.036***	0.0084**	0.035***	0.036***
Leverage Ratio	0.040**	-0.029**	0.060***	0.040**	0.015***	-0.0075***	0.015***	0.015***
Book-to-market Ratio	-0.20***	0.013	-0.22***	-0.19***	-0.16***	-0.0037	-0.16***	-0.15***
Cash	0.011	0.013	-0.0039	0.013	-0.040***	-0.0069***	-0.040***	-0.038***
RoA	0.094***	-0.030**	0.073***	0.10***	-0.0033	-0.011***	-0.0043	-0.00019
Net Sales	-0.0053	-0.056***	0.033	-0.0043	-0.022***	0.0030	-0.020***	-0.021***
Country fixed effects	no	yes	no	no	no	yes	no	no
Industry fixed effects	no	no	yes	no	no	no	yes	no
Time fixed effects	no	no	no	yes	no	no	no	yes
R^2	0.16	0.59	0.21	0.17	0.12	0.39	0.12	0.15
Within R^2		0.064	0.14	0.16		0.0071	0.12	0.11
N	2,978	2,976	2,978	2,978	30,664	30,663	30,664	30,664

This table shows panel regressions with the carbon beta as the dependent variable. Standard errors are clustered on firm level. All accounting variables are logarithmized. For Panel B, we exclude all firms with a market capitalization of less than US$ 50 mio. *, **, *** denote significance on the 10%, 5%, and 1% level, respectively. Significance tests are based on two-sided t-tests.

Table 9
Carbon beta in the financial industry

	High CRC	Middle CRC	Low CRC	
Panel A. Bank terciles				
Average carbon beta	0.250	0.135	-0.337	
Δ middle CRC	-0.116**			
Δ low CRC	-0.587***	-0.472***		
Panel B. Financial services terciles				
Average carbon beta	0.267	0.121	-0.305	
Δ middle CRC	-0.147***			
Δ low CRC	-0.572***	-0.425***		
	High CRC	**Q3**	**Q2**	**Low CRC**
Panel C. Bank quartiles				
Average carbon beta	0.229	0.219	-0.014	-0.459
Δ Q3 CRC	-0.009			
Δ Q2 CRC	-0.242***	-0.233***		
Δ low CRC	-0.688***	-0.679***	-0.446***	
Panel D. Financial services quartiles				
Average carbon beta	0.269	0.188	-0.020	-0.418
Δ Q3 CRC	-0.081			
Δ Q2 CRC	-0.289***	-0.208***		
Δ low CRC	-0.688***	-0.606***	-0.399***	

This table shows the average carbon beta of banks and financial services firms depending on the carbon beta of their domiciles. Countries are divided in terciles in Panel A and B, and in quartiles in Panel C and D, respectively, based on their average carbon beta. Banks and financial services firms are identified using the Morningstar Global Equity Classification Structure (MGECS). *, **, *** denote significance on the 10%, 5%, and 1% level of the differences, respectively. Significance tests are based on two-sided t-tests.

Appendix

Appendix A.1

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:

$$z_{t+1} = a + \Gamma z_t + u_{t+1} \tag{5}$$

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 (5) generates the data, t + 1 cash-flow and discount-rate news are linear functions of the t + 1 shock vector:

$$N_{DR,t+1} = e1'\lambda u_{t+1} \tag{6}$$

$$N_{CF,t+1} = (e1' + e1'\lambda)u_{t+1} \tag{7}$$

where $e1$ is a vector with the first element equal to one and the others equal to zero and $\lambda = \rho\Gamma(I - \rho\Gamma)^{-1}$.[36]

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 the carbon risk factor (BMG). Second, we add the term yield spread (TY) as a weighted average of country specific interest rates by Thomson Reuters Datastream.[37] 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 small high-book-to-market portfolio and the log book-to-market value of the small low-book-to-market portfolio.[38]

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

$$Var(BMG_t - E_{t-1}BMG_t) = Var(N_{CF}) + Var(N_{DR}) - 2Cov(N_{CF}, N_{DR}) \tag{8}$$

[36] We set ρ close to one as defined in Campbell and Vuolteenaho (2004).
[37] We use the weighting scheme of the MSCI World index as of the end of our sample period.
[38] 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.

$$1 = \frac{Var(N_{CF})}{Var(BMG_t - E_{t-1}BMG_t)} + \frac{Var(N_{DR})}{Var(BMG_t - E_{t-1}BMG_t)} - 2\frac{Cov(N_{CF}, N_{DR})}{Var(BMG_t - E_{t-1}BMG_t)} \tag{9}$$

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):

$$\beta_{i,CF} = \frac{Cov\left(r_{i,t}, N_{CF}\right)}{Var(r_{M,t} - E_{t-1}r_{M,t})} \tag{10}$$

$$\beta_{i,DR} = \frac{Cov\left(r_{i,t}, -N_{DR}\right)}{Var(r_{M,t} - E_{t-1}r_{M,t})} \tag{11}$$

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

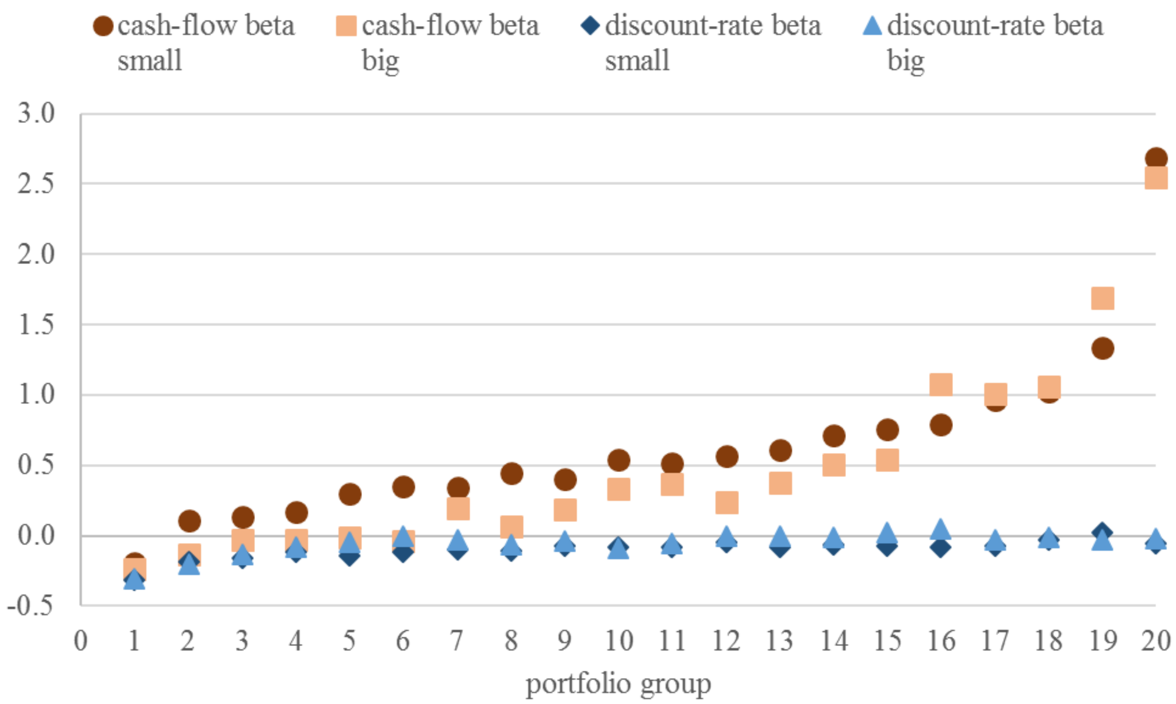
The decomposition for the 40 test assets based on carbon beta and size is shown in Table A.1. and graphically in Figure 6.

Table A.1
Beta decomposition of test assets

	CAPM Beta		β_{CF}		β_{DR}	
	Small	Big	Small	Big	Small	Big
Low	1.273	1.441	1.078	1.161	0.154	0.210
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
2	0.996	1.161	0.814	0.903	0.150	0.192
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
3	0.924	1.078	0.751	0.805	0.140	0.216
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
4	0.876	1.041	0.686	0.752	0.163	0.231
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
5	0.934	0.946	0.757	0.661	0.156	0.238
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
6	0.863	0.890	0.696	0.588	0.146	0.253
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
7	0.805	0.924	0.644	0.638	0.144	0.236
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
8	0.840	0.844	0.682	0.608	0.146	0.193
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
9	0.841	0.867	0.651	0.607	0.181	0.219
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
10	0.802	0.939	0.634	0.702	0.152	0.208
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
11	0.771	0.894	0.616	0.652	0.152	0.212
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
12	0.827	0.863	0.624	0.554	0.178	0.252
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
13	0.817	0.949	0.649	0.640	0.155	0.263
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
14	0.925	0.953	0.690	0.649	0.200	0.249
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
15	0.933	0.898	0.713	0.592	0.193	0.247
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
16	1.002	0.990	0.755	0.677	0.234	0.278
	(0.002)	(0.005)	(0.002)	(0.004)	(0.002)	(0.002)
17	1.072	1.098	0.807	0.789	0.252	0.249
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
18	1.096	1.028	0.795	0.734	0.267	0.223
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
19	1.082	1.098	0.773	0.834	0.285	0.201
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
High	1.348	1.238	1.091	0.971	0.209	0.204
	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)

This table shows the calculated cash-flow (β_{CF}) and discount-rate beta (β_{DR}) for the sample period of January 2010 to December 2016 for the 40 test assets built on carbon beta and size. Standard errors are in parentheses and calculated by a bootstrap method conditional on the estimated news series using 2,500 simulations.

Figure A.1
Beta decomposition of 40 test assets



This figure shows the *BMG* beta decomposition of the 40 test assets built out of the full samples. Firms are sorted into 20 portfolios based on their individual carbon beta (portfolio group) and then split into small and big subsamples with the median of the size as breakpoint. The cash-flow and discount-rate betas are obtained by following the methodology of Campbell and Vuolteenaho (2004).

Appendix A.2

Table A.2

Geographic and sectoral breakdown of global firms

Panel A. *CRS* data sample

a. Geographic

Country	#	%
United States	418	25.53
Japan	227	13.87
United Kingdom	193	11.79
Canada	97	5.93
Australia	75	4.58
France	66	4.03
South Africa	59	3.60
Germany	53	3.24
Taiwan	48	2.93
South Korea	36	2.20
Other Europe	237	14.48
Other Asia	78	4.76
Other Americas	37	2.26
Other Australasia	13	0.79
Total	1,637	100.00

b. Sectoral

Sector	TRBC	#	%
Industrials	52	368	22.48
Cyclical Consumer Goods & Services	53	277	16.92
Basic Materials	51	239	14.60
Technology	57	191	11.67
Non-Cyclical Consumer Goods & Services	54	167	10.20
Energy	50	118	7.21
Utilities	59	104	6.35
Healthcare	56	109	6.66
Telecommunications Services	58	64	3.91
Total		1,637	100.00

Panel B. Full sample

a. Geographic

Country	#	%
United States	5,106	12.91
China	4,104	10.38
Japan	3,800	9.61
India	3,569	9.03
Canada	2,998	7.58
South Korea	1,957	4.95
Taiwan	1,860	4.70
Australia	1,775	4.49
United Kingdom	1,711	4.33
Malaysia	951	2.41
Other Europe	5,830	14.74
Other Asia	4,197	10.6
Other Americas	774	1.96
Other Africa	691	1.74
Other Australasia	156	0.39
Other *(no country code available)*	58	0.15
Total	39,537	100.00

b. Sectoral

Sector	MGECS	#	%
Consumer Cyclical	102	6,343	16.04
Technology	311	6,276	15.87
Industrials	310	6,234	15.77
Basic Materials	101	5,637	14.26
Financial Services	103	4,208	10.64
Healthcare	206	2,854	7.22
Consumer Defensive	205	2,624	6.64
Real Estate	104	2,367	5.99
Energy	309	1,560	3.95
Utilities	207	873	2.21
Communication Services	308	561	1.42
Total		39,537	100.00

This table shows the geographic (a.) and sectoral breakdown (b.) in absolute numbers and percentages for the *CRS* sample (Panel A) and the full sample (Panel B) for the sample period from January 2010 to December 2016. The *CRS* data sample sectoral breakdown is based on the Thomson Reuters Business Classification (TRBC). The full sample sectoral breakdown is based on the super sectors of the Morningstar Global Equity Classification Structure (MGECS).

Table A.3
Panel regressions

	(1)	(2)	(3)	(4)
Value Chain	0.88***	0.47***	0.53***	0.86***
Public Perception	0.50***	0.043	0.56***	0.55***
Adaptability	1.76***	0.92***	1.30***	1.74***
Country fixed effects	no	yes	no	no
Industry fixed effects	no	no	yes	no
Time fixed effects	no	no	no	yes
R^2	0.16	0.52	0.23	0.18
Within R^2		0.054	0.100	0.17
N	6,681	6,680	6,681	6,681

This table shows panel regressions with the carbon beta as dependent variable in the *CRS* data sample. Standard errors are clustered on firm level. *, **, *** denote significance on the 10%, 5%, and 1% level, respectively. Significance tests are based on two-sided t-tests.

Internet Appendix

Table IA.1

Descriptions of environmental variables of the four ESG databases

Variable name	Code	Variable name	Code
Panel A. Thomson Reuters		**Panel C. CDP**	
Energy Use Total	ENRRDP033	Greenhouse Gas Emissions	CC8.
CO_2 Equivalents Emission Total	ENERDP023	Regulatory Opportunities Sources	CC6.1a.
Clean Technology	ENPIDP066	Climate related Opp. Sources	CC6.1c.
Emission Reduction Prod. Process	ENERO05V	Regulatory Risks Sources	CC5.1a.
Sustainable Supply Chain	ENRRDP058	Climate related Risks Sources	CC5.1c.
Renewable Energy Use	ENRRDP046	Regulatory Opportunities	CC6.1.
Climate Change Risks/Opportunities	ENERDP089	Climate related Opportunities	CC6.1.
Energy Efficiency Policy	ENRRDP0122	Regulatory Risks	CC5.1.
Emission Reduction Target/Objective	ENERDP0161	Climate related Risks	CC5.1.
Energy Efficiency Target/Objective	ENRRDP0192	Emission Reduction Target	CC3.1.
Environmental Investments Initiatives	ENERDP095	Disclosure Score	Disclosure Score
Environmental Expenditures Investm.	ENERO24V	Performance Band	Performance Band
Environmental Expenditures	ENERDP091		
Environmental Partnerships	ENERDP070		
Environmental Provisions	ENERDP092		
Policy Emissions	ENERDP0051		
Environmental R&D Expenditures	ENPIDP023		
Emission Reduction Score	ENER		
Resource Reduction Score	ENRR		
Environmental Score	ENVSCORE		
Innovation Score	TRESGENPIS		
Emissions Score	TRESGENERS		
Panel B. Sustainalytics		**Panel D. MSCI ESG**	
Carbon Intensity	E.1.9	Opportunities in Clean Tech	ENV-str-A
Renewable Energy Use	E.1.11	Energy Efficiency	ENV-str-O
Supplier Environmental Programmes	E.2.1.1	Opportunities Renewable Energy	ENV-str-M
Sustainable Products & Services	E.3.1.1	Carbon Emissions	ENV-str-D
Scope of GHG Reporting	E.1.6	Regulatory Compliance	ENV-con-B
Environmental Policy	E.1.1	Climate Change Controversies	ENV-con-F
Green Procurement Policy	E.2.1	Industry-adjusted Overall Score	Industry-adjusted Score
Renewable Energy Programmes	E.1.8	Carbon Emissions Score	Carbon Emissions Score
Environmental Management System	E.1.2	Climate Change Theme Score	Climate Change Theme Score
Air Emissions Programmes	E.1.3.3	Environmental Pillar Score	Environmental Pillar Score
Overall ESG Score	Total ESG Score		

This table provides variable names and codes of the 55 environmental variables from the Thomson Reuters ESG (TR), Carbon Disclosure Project (CDP), MSCI ESG KLD (MSCI) and Sustainalytics ESG (SUST) datasets used to construct the stock specific carbon risk scores (*CRS*).

Table IA.2
Comparison of common factor models – *CRS* data sample

Panel A. Significance tests for explanatory power of various models

	Avg. Δ adj. R^2 (%)	F-test at sign. level 5% (%)
(1) CAPM – 3F FF	2.15	17.23
(2) CAPM - 2F *BMG*	2.80	22.13
(3) 3F FF - Carhart	0.21	8.61
(4) 3F FF - 4F *BMG*	2.55	21.07
(5) 4F Carhart - 5F PS	0.36	5.37
(6) 4F Carhart - 5F *BMG*	2.62	21.67

Panel B. Significance tests for risk factor betas for the 5*F Carhart + BMG model*

	Avg. coeff.	T-test of significance of coefficients					
		10% level		5% level		1% level	
		#	%	#	%	#	%
er_M	1.086	1,122	74.35	1,030	68.26	864	57.26
SMB	0.122	314	20.81	211	13.98	81	5.37
HML	-0.095	218	14.45	128	8.48	48	3.18
WML	-0.124	245	16.24	145	9.61	43	2.85
BMG	0.227	448	29.69	345	22.86	190	12.59

This table provides a comparison of common factor models. Panel A reports the average Δ adj. R^2 between different factor models run on single stocks from the *CRS* data sample in the sample period from January 2010 to December 2016. Significance statistics are based on one-sided F-tests for nested models (H_0: $\beta_{p5}=0$). Panel B shows average coefficients as well as the absolute (#) and relative (%) number of statistically significant beta coefficients from *5F Carhart + BMG model* regressions run on single stocks from the *CRS* data sample in the sample period. Statistical significance is based on two-sided t-tests. The factors er_M, *SMB*, *HML*, and *WML* are provided by Kenneth French, the Pástor - Stambaugh (PS) liquidity factor is provided by Ľuboš Pástor.

Table IA.3

Factor spanning tests

Dependent variable	(1) *BMG*	(2) er_M	(3) *SMB*	(4) *HML*	(5) *WML*
er_M	0.0095		-0.005	0.044	-0.074
	(0.18)		(-0.13)	(1.04)	(-1.15)
SMB	0.30**	-0.044		-0.12	0.012
	(2.07)	(-0.13)		(-0.96)	(0.07)
HML	0.25*	0.31	-0.098		-0.53***
	(1.88)	(1.04)	(-0.96)		(-3.30)
WML	-0.11	-0.22	0.004	-0.23***	
	(-1.25)	(-1.15)	(0.07)	(-3.30)	
BMG		0.044	0.17**	0.17*	-0.17
		(0.18)	(2.07)	(1.88)	(-1.25)
Intercept (%)	-0.21	0.90**	0.10	0.14	0.58**
	(-0.97)	(1.99)	(0.62)	(0.80)	(2.22)
adj. R^2 (%)	9.47	0.63	0.76	18.07	15.96

This table shows the results of using four factors in regressions to explain average returns on the fifth factor for the sample period from January 2010 to December 2016. The factors er_M, *SMB*, *HML*, and *WML* are provided by Kenneth French. *, **, *** denote significance on the 10%, 5%, and 1% level, respectively. The intercept and the adj. R^2 are given in percent, t-values are shown in brackets and based on two-sided t-tests.

Table IA.4

Comparing further prominent factors

Panel A. Correlations

	RMW	*CMA*	*I/A*	*ROE*	*QMJ*	*BAB*
BMG	-0.07	-0.16	0.10	-0.32	-0.28	-0.33

Panel B. Factor spanning tests

Dependent variable	(1) *BMG*	(2) *BMG*	(3) *BMG*	(4) *BMG*
er_M	0.049	0.010	-0.060	-0.026
	(0.83)	(0.16)	(-0.73)	(-0.50)
SMB	0.381**	-0.013	0.186	0.320**
	(2.35)	(-0.12)	(1.03)	(2.26)
HML	0.463***		0.203	0.253*
	(2.77)		(1.43)	(1.95)
WML			-0.097	-0.008
			(-1.08)	(-0.09)
RMW	0.350			
	(1.40)			
CMA	-0.233			
	(-0.95)			
I/A		0.078		
		(0.47)		
ROE		-0.363**		
		(-2.53)		
QMJ			-0.205	
			(-1.09)	
BAB				-0.469*
				(-2.63)
Intercept (%)	-0.345	-0.382	-0.051	0.213
	(-1.55)	(-1.64)	(-0.20)	(0.81)
adj. R^2 (%)	9.41	5.49	9.68	15.75

This table shows the results of using different factors in regressions to explain average returns of the *BMG* factor for the sample period from January 2010 to December 2016. The factors er_M, *SMB*, *HML*, *RMW*, and *CMA* are provided by Kenneth French, the *I/A* and *ROE* factors are provided by Lu Zhang and the *QMJ* and *BAB* factors are provided by AQR Capital Management. *, **, *** denote significance on the 10%, 5%, and 1% level respectively. The intercept and the adj. R^2 are given in percent, t-values are shown in brackets and are based on two-sided t-tests.

Table IA.5
Maximum Sharpe ratio approach

Rank	SR	Return (%)	SD (%)	Optimal weights				
				er_M	*SMB*	*HML*	*WML*	*BMG**
1	0.32	0.35	1.06	0.17	0.14	0.17	0.34	0.18
2	0.32	0.41	1.28	0.21		0.18	0.42	0.19
3	0.31	0.44	1.37	0.24	0.16		0.40	0.20
4	0.31	0.51	1.64	0.29			0.49	0.21
5	0.31	0.43	1.37	0.24	0.11	0.16	0.49	
…	…	…	…	…	…	…	…	…
22	0.17	0.68	4.01	1.00		0.00		
23	0.13	0.14	1.03		0.33	0.12		0.55
24	0.13	0.16	1.22		0.38			0.62
25	0.12	0.19	1.61			0.15		0.85
26	0.03	0.05	1.39		1.00	0.00		

This table shows the maximum ex post Sharpe ratios (SRs) by combining the four risk factors and the reverse *BMG** factor for the sample period from January 2010 to December 2016. The factor weightings in each row achieve the maximum SR. We report only the five best and worst cases according to the maximum SR. The factors er_M, *SMB*, *HML*, and *WML* are provided by Kenneth French.

Table IA.6
Asset pricing tests

Factor model	Mean α	GRS Test statistic	p-value	Mean adj. R^2	Mean |α|	SR	SR^2
Panel A. 5x5 Size/Value Portfolios							
CAPM	0.0004	1.447	0.124	0.892	0.001	0.804	0.646
CAPM + BMG	0.0006	1.359	0.169	0.896	0.001	0.794	0.630
3F	**0.0000**	1.701	0.050	0.964	0.001	**0.888**	**0.789**
4F + BMG	0.0001	1.612	0.071	0.964	0.001	0.882	0.778
4F	0.0001	1.438	0.131	0.964	0.001	0.854	0.729
5F + BMG	0.0001	1.382	0.159	0.965	0.001	0.850	0.722
5F	0.0001	1.242	0.249	0.965	0.001	0.831	0.691
6F + BMG	0.0001	1.120	0.355	0.966	**0.001**	0.809	0.655
6F	0.0001	1.178	0.302	0.966	0.001	0.825	0.680
7F + BMG	0.0001	**1.082**	0.394	**0.966**	0.001	0.807	0.652
Panel B. 5x5 Size/Momentum Portfolios							
CAPM	0.0009	5.185	0.000	0.874	0.003	1.522	2.315
CAPM + BMG	0.0012	4.984	0.000	0.880	0.003	1.520	2.310
3F	0.0006	4.995	0.000	0.931	0.003	**1.522**	**2.317**
4F + BMG	0.0007	4.774	0.000	0.931	0.003	1.518	2.306
4F	0.0007	4.491	0.000	0.967	0.002	1.509	2.276
5F + BMG	0.0008	4.351	0.000	0.967	0.002	1.507	2.272
5F	**0.0006**	3.930	0.000	0.935	0.002	1.479	2.188
6F + BMG	0.0006	3.719	0.000	0.936	0.002	1.475	2.174
6F	0.0006	3.832	0.000	0.967	0.002	1.488	2.213
7F + BMG	0.0007	**3.662**	0.000	**0.967**	**0.002**	1.485	2.206

Table IA.6 cont'd.

Factor Model	Mean α	GRS Test statistic	p-value	Mean adj. R^2	Mean |α|	SR	SR^2
Panel C. 5x5 Size/Operating Profitability Portfolios							
CAPM	0.0011	2.400	0.003	0.909	0.002	1.035	1.072
CAPM + BMG	0.0013	2.310	0.005	0.911	0.002	1.035	1.071
3F	0.0008	3.235	0.000	0.962	0.002	1.225	1.501
4F + BMG	0.0008	3.192	0.000	0.963	0.002	**1.241**	**1.541**
4F	0.0007	2.813	0.001	0.962	0.002	1.194	1.426
5F + BMG	0.0007	2.831	0.001	0.963	0.002	1.216	1.478
5F	0.0006	2.297	0.005	0.968	0.001	1.131	1.279
6F + BMG	0.0005	2.206	0.008	**0.969**	**0.001**	1.136	1.290
6F	0.0006	2.177	0.009	0.968	0.001	1.121	1.257
7F + BMG	**0.0005**	**2.123**	0.011	0.968	0.001	1.131	1.279
Panel D. 5x5 Size/Investment Portfolios							
CAPM	0.0008	2.050	0.013	0.909	0.002	0.957	0.916
CAPM + BMG	0.0010	1.940	0.020	0.912	0.002	0.948	0.899
3F	0.0005	2.286	0.005	0.966	0.002	**1.030**	**1.061**
4F + BMG	0.0005	2.159	0.009	0.966	0.001	1.021	1.043
4F	0.0004	1.956	0.020	0.966	0.001	0.996	0.991
5F + BMG	0.0004	1.886	0.026	0.966	0.001	0.992	0.985
5F	0.0003	1.580	0.080	0.971	0.001	0.938	0.880
6F + BMG	0.0003	1.449	0.128	**0.971**	0.001	0.920	0.847
6F	0.0003	1.519	0.101	0.971	0.001	0.937	0.877
7F + BMG	**0.0003**	**1.423**	0.141	0.971	**0.001**	0.926	0.857

This table shows the results of various asset pricing tests on four different global test assets. We include 25 global portfolios formed on Size/Value, Size/Momentum, Size/Operating Profitability, and Size/Investment 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 sample period ranges from January 2010 to December 2016. The factors er_M, *SMB*, *HML*, *WML*, *RMW*, and *CMA* are provided by Kenneth French.

Table IA.7

Descriptive statistics - orthogonalized risk factors

Factor	Mean excess return (%)	SD (%)	T-stat.	Correlations				
				BMG	er_M	*SMB*	*HML*	*WML*
$BMG^{\perp}$	-0.23	1.95	-1.10	0.9808				
$er_M^{\perp}$	0.84	4.02	1.92		0.9957			
$SMB^{\perp}$	0.08	1.39	0.55			0.9914		
$HML^{\perp}$	0.09	1.68	0.48				0.9537	
$WML^{\perp}$	0.64	2.53	2.31					0.9758

This table displays descriptive statistics of the monthly democratically orthogonalized risk factors of the *4F Carhart model* and the *BMG* factor for the sample period from January 2010 to December 2016. Correlations are reported between the orthogonalized risk factors and the original risk factors. The original factors er_M, *SMB*, *HML*, and *WML* are provided by Kenneth French.

Table IA.8

CRS-decile portfolio performance – orthogonalized risk factors

	Panel A. *5F Carhart + BMG model*								Panel B. Decomposition of R^2 on deciles level						
									Decomposed-R^2 (%)					Systematic R^2 (%)	Idiosyncratic variance $(1-R^2)$ (%)
	$Alpha^{\perp}$	$er_M^{\perp}$	$SMB^{\perp}$	$HML^{\perp}$	$WML^{\perp}$	$BMG^{\perp}$	Adj. R^2 (%)	ΔAdj. R^2 (%)	$er_M^{\perp}$	$SMB^{\perp}$	$HML^{\perp}$	$WML^{\perp}$	$BMG^{\perp}$		
Low *CRS*	-0.001	1.138***	0.086	0.072	-0.247***	-0.241***	95.32	1.60***	92.76	0.06	0.06	1.73	0.99	95.60	4.40
2	0.001	1.007***	0.053	0.119**	-0.169***	-0.212***	95.61	1.58***	93.59	0.03	0.23	1.04	0.98	95.88	4.12
3	0.002**	1.025***	0.137*	0.076	-0.209***	-0.067	94.59	0.32**	93.00	0.20	0.09	1.54	0.10	94.92	5.08
4	0.001	1.043***	0.143*	0.106	-0.183***	-0.022	94.06	0.09	92.89	0.21	0.17	1.13	0.01	94.41	5.59
5	0.000	1.013***	0.123	0.147**	-0.215***	0.060	93.55	-0.08	91.73	0.16	0.34	1.63	0.08	93.94	6.06
6	0.001	0.953***	0.197**	0.206***	-0.223***	0.206***	93.99	0.26**	90.19	0.46	0.74	1.96	1.00	94.35	5.65
7	0.001	1.000***	0.247***	0.180**	-0.225***	0.482***	94.06	3.12***	86.78	0.64	0.49	1.74	4.76	94.42	5.58
8	0.000	1.104***	0.262***	0.252***	-0.362***	0.539***	94.45	2.93***	85.04	0.58	0.77	3.61	4.79	94.79	5.21
9	-0.003**	1.093***	0.155	0.204**	-0.256***	0.740***	93.06	6.88***	82.11	0.20	0.50	1.78	8.89	93.48	6.52
High *CRS*	-0.001	1.122***	0.322**	0.292***	-0.383***	1.091***	91.52	12.47***	71.27	0.71	0.85	3.29	15.92	92.03	7.97

Panel A shows the alpha performance and beta coefficients for annually rebalanced equal-weighted decile-portfolios based on the carbon risk score (*CRS*) of the stocks in the *CRS* data sample for the sample period. The risk factors are orthogonalized democratically. *, **, *** denote significance on the 10%, 5%, and 1% level, respectively. For the alphas and beta coefficients, significance statistics are based on two-sided t-tests. Significance symbols for the differences in adj. R^2 are based on the one-sided F-test for nested models (H_0: $\beta_{p5}=0$). Panel B shows the decomposed-R^2 of each democratically orthogonalized risk factor for the global *CRS*-deciles. 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 IA.9
Comparison of common factor models - orthogonalized risk factors

Panel A. Decomposition of R^2 with orthogonalized factors on single stock level

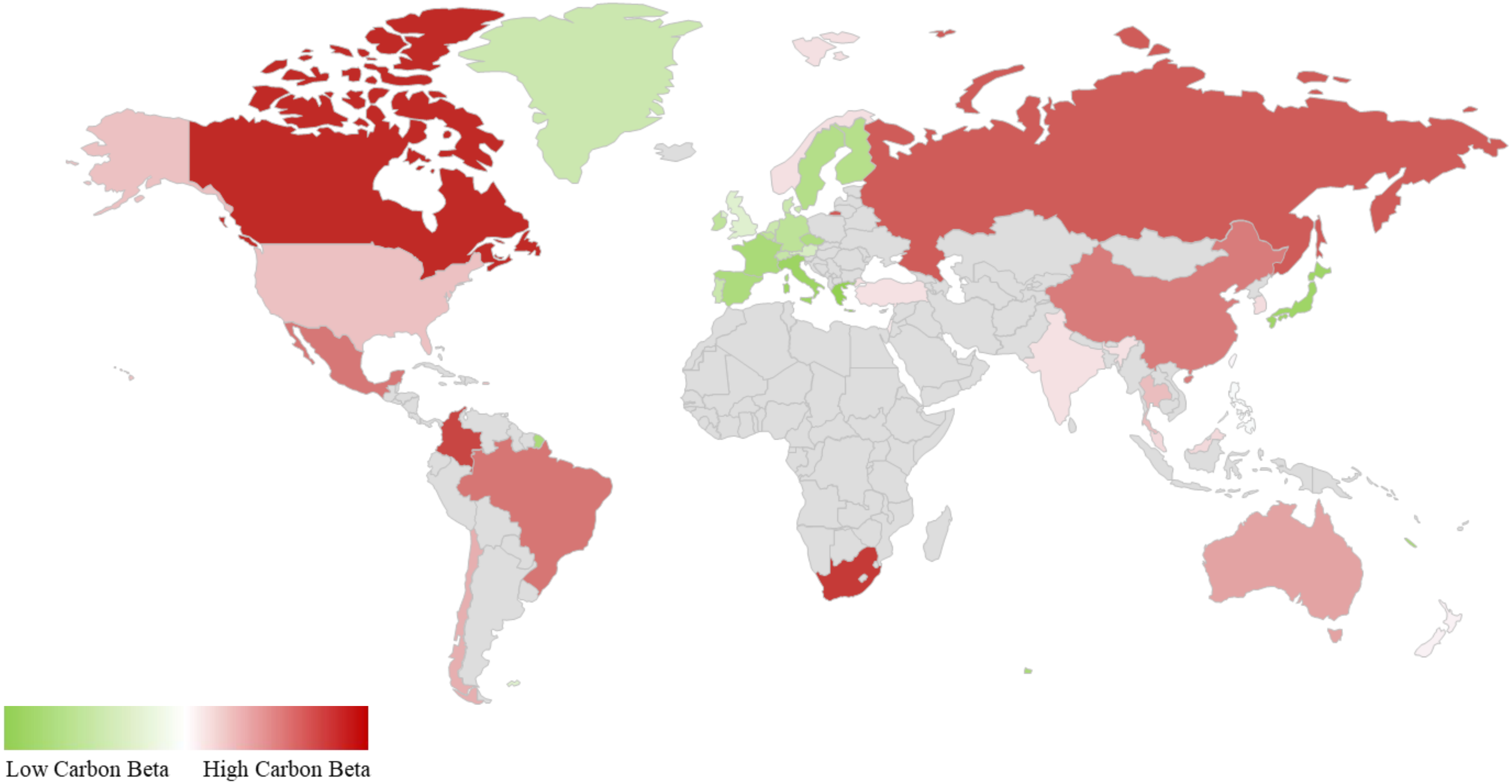
Avg. decomposed-R^2 (%)					Avg. systematic R^2 (%)	Avg. idiosyncratic variance (1-R^2) (%)
$er_M^{\perp}$	$SMB^{\perp}$	$HML^{\perp}$	$WML^{\perp}$	$BMG^{\perp}$		
12.31	2.30	1.73	1.87	2.42	20.63	79.37

Panel B. Significance tests for orthogonalized risk factor betas for the *5F Carhart + BMG model*

	Avg. coeff.	T-test of significance of coefficients					
		10% level		5% level		1% level	
		#	%	#	%	#	%
$er_M^{\perp}$	0.922	25,370	67.27	22,428	59.47	16,819	44.60
$SMB^{\perp}$	0.686	7,236	19.19	4,504	11.94	1,537	4.08
$HML^{\perp}$	0.086	4,876	12.93	2,754	7.30	786	2.08
$WML^{\perp}$	-0.168	5,656	15.00	3,434	9.11	984	2.61
$BMG^{\perp}$	0.287	7,424	19.69	4,924	13.06	2,192	5.81

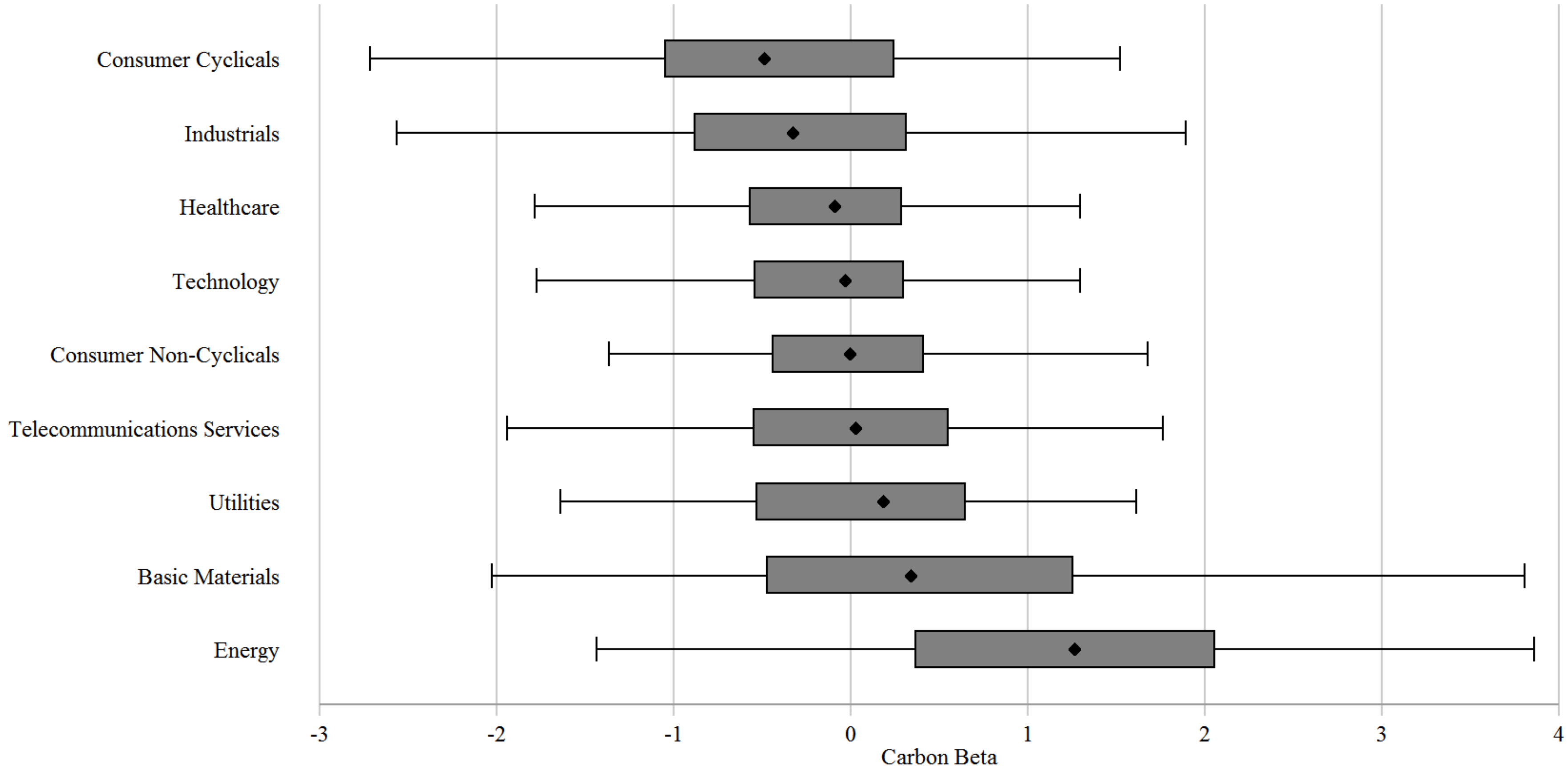
This table provides a comparison of common regression models with orthogonalized risk factors. Panel A shows the average decomposed-R^2 values of orthogonalized factors. Regressions are run based on the *5F Carhart + BMG model* with single stocks from the full sample. Furthermore, the average systematic R^2 and the average idiosyncratic variance obtained from the systematic variance are displayed. Panel B shows average coefficients as well as the absolute (#) and relative (%) numbers of statistically significant beta coefficients from the democratically orthogonalized *5F Carhart + BMG model* regressions run on single stocks from the full sample in the sample period from January 2010 to December 2016. Statistical significance is based on two-sided t-tests.

Figure IA.1
Carbon beta landscape



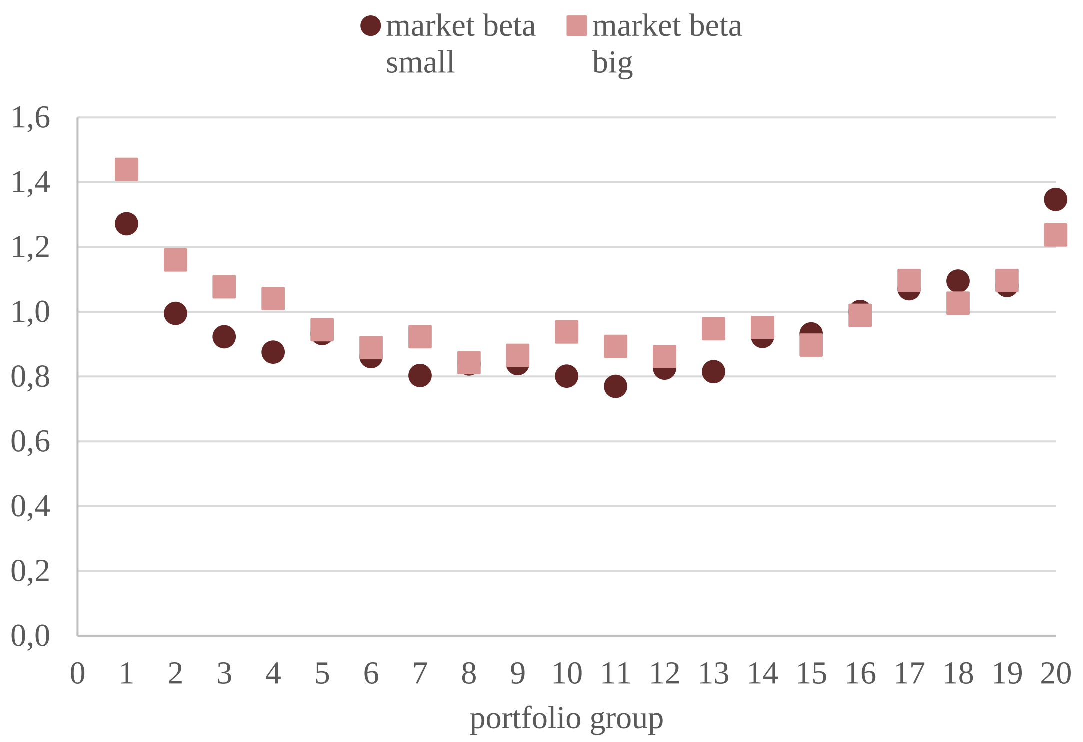
This figure shows the carbon beta of the *CRS* data sample across the world. A greenish color indicates a low average carbon beta of the country, whereas a deep red color states that, on average, the countries' firms have high carbon betas.

Figure IA.2
Carbon beta industry breakdown



This figure shows the carbon beta of the *CRS* data sample across sectors. The sectoral breakdown is based on the Thomson Reuters Business Classification (TRBC). The sectors are sorted in ascending order by their carbon beta.

Figure IA.3
CAPM beta of 40 test assets



This figure shows the market beta of the 40 test assets built out of the full samples. Firms are sorted into 20 portfolios based on their individual carbon beta (portfolio group) and then split into small and medium subsamples with the median of the size as breakpoint.