Carbon Risk*

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Abstract. The risks and opportunities arising from the transition process to a low-carbon economy affect firms' business. We quantify this "carbon risk" via a "Brown-Minus-Green factor" derived from 1,600 firms with data from four major ESG databases. This factor allows estimating an applicable measure of carbon risk: "carbon beta". We compute carbon betas for 39,000 firms and report them for countries and sectors. Firms can use carbon beta to understand their own carbon risk, regulators to gauge the impact of policy changes, and investors to directly manage carbon risk in their portfolios without hurting performance or preferences.

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

JEL Classification: G12, G15, Q51, Q54

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Climate change is real and threatens human well-being. This has led to numerous national and international initiatives[1] and legislation[2] aiming at reducing emissions of carbon and other greenhouse gases in order to combat climate change. One of the most far-reaching initiatives is the 21st Conference of the Parties 2015 (COP21), which resulted in the "Paris Agreement", signed by 195 nations, to limit global warming to below 2°C (United Nations, 2015). In other words, the world has agreed on the transition from a brown, high-carbon economy to a green, low-carbon economy.

However, how fast this transition will be and which path it will take is uncertain. In the nearer term, changes in environmental-economic policy like the introduction or repeal of carbon taxes or Donald Trump's support of carbon-intensive firms (Ramelli et al., 2018) affect the exposure of investors to the transition from a high-carbon economy to a low-carbon economy. Firms are also directly exposed to risks because of technological changes and advances in renewable energy sources leading to "stranded assets". These risks are long-term and cannot be diversified away in mean-variance efficient portfolios. This new kind of risk includes all positive and negative impacts on firm values that arise from uncertainty in the transition process from a brown to a green economy, suggesting that all firms including brown firms and green firms are exposed to carbon risk. We refer to these political, technology, and regulatory risks simply as "carbon risks."

If carbon risk is a risk factor, meaning that it is behind the comovement of assets, it is possible to develop a factor-mimicking portfolio that isolates this exposure. We develop a carbon risk mimicking portfolio, the "Brown-Minus-Green portfolio" (BMG) and add it to common asset pricing models. BMG is long in "brown" firms that are likely negatively affected by an unexpected shift to a low-carbon economy and short in "green" firms that are likely postively affected by an unexpected shift to a low-carbon economy. Green firms' equity prices will respond positively to unexpected changes towards a low-carbon economy, whereas brown firms' equity prices will respond negatively. Both brown and green firms are exposed to changes in the transition making them per se risky.

To construct BMG, we use detailed carbon and transition-related information for over 1,600 globally listed firms filtered from four major ESG databases and categorize these firms

[1] For example: EU Action Plan on Financing Sustainable Growth, Sustainable Development Goals (SDGs), Greenhouse Gas Protocol Corporate Accounting and Reporting Standards, Recommendations of the Task Force on Climate-related Financial Disclosures (TCFD).

[2] For example: Implementation 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.

as brown or green using an annual "Brown-Green-Score" (BGS).[3] The BGS is a composite measure of three indicators designed to separately capture the sensitivity of firms' "value chains" (e.g., current emissions), of their "public perception" (e.g., response to perceived emissions), and of their "adaptability" (e.g., mitigation strategies) to carbon risk. Tests show that the BMG significantly increases the explanatory power of common asset pricing models and suggest that it is equally important in explaining variation in global equity prices as the size factor.[4] The cumulative BMG portoflio returns are negative in the second half of our sample period meaning green firms are outperforming brown firms. This is consistent with casual observations that the focus on tackling climate change has increased over the past years; green firms that support these goals are likely to outperform brown firms that thwart them when the globe is looking for solutions.

Our approach is the first to study carbon risk globally. One of the key problems associated with measuring carbon risk in equities is the lack of data for most firms. Our markets based approach uses the information aggregation power of financial markets to identify how firms are exposed to carbon risk. We estimate carbon betas, a proxy for carbon risk, for more than 39,000 globally listed firms and show how they can be used by investors, portfolio managers, policy-makers, and firms.

We report average carbon betas by country and industry. Carbon betas are high and positive in countries like South Africa, Brazil, and Canada, which means they are likely negatively affected if the world speeds up the transition to a low-carbon economy. Contrarily, average carbon betas are negative in European countries and Japan. On industry level, tech firms have carbon betas near zero on average, while basic material and energy firms have the highest positive carbon betas as expected. There are, however, significant differences in carbon betas within industries suggesting that carbon risk is not simply a proxy for certain industries.

We show that investors can achieve comparable expected returns and Sharpe ratios for their portfolios with similar exposures to other systematic risks, e.g., to the Fama and French (1993) factors, or to specific industries, while reducing carbon beta via "best-in-class" approaches. We also show that carbon risk is related to firm characteristics independent of their industry. Firms investing in innovation and clean technology, proxied by R&D expenditures, have lower carbon betas while firms with dirty or "stranded" assets, proxied by property, plant and equipment

[3] The BGS was designed in cooperation with data providers, climate consultancies, NGOs, asset managers, and central banks in a series of workshops. See https://carima-project.de/en/.

[4] The factor will be made freely accessible so that financial market participants will be able to measure the carbon risk of their portfolio via the carbon beta and close the gap in measuring carbon risk in asset prices.

(PPE) assets, have higher carbon betas. Analyzing the carbon risk of the financial industry, we show that banks' and other financial firms' carbon risk is strongly related to the carbon risk of the domestic firms they are likely to finance.

To develop an understanding of the mechanism driving carbon risk, we apply the decomposition methodology developed by Campbell (1991) and Campbell and Vuolteenaho (2004). We decompose the market betas of carbon beta sorted test portfolios into components related to cash-flow news and discount-rate news. According to the model, the systematic risk of carbon risk sensitive portfolios is predominantly driven by the fundamental cash flow component and not the discount rate component.

As the transition from a high-carbon to a low-carbon economy is ongoing and uncertain, capital markets may not yet agree upon new equilibrium equity prices. In this context, Daniel et al. (2018) present a model in which climate uncertainty is resolved slowly over time leading to transition periods between equilibriums. Systematic return differences between brown and green firms may thus reflect ongoing re-evaluations of firm fundamentals rather than changing expectations regarding discount rates. Our results are consistent with Daniel et al. (2018) and suggest a transition between an old brown and a new green equilibrium.

The remainder of the paper is structured as follows: Section 1 reviews the literature. Section 2 describes our carbon risk measurement methodology. Section 3 presents the data. Section 4 tests the relevance of BMG. Section 5 reports the carbon betas across countries and industries and provides practical applications of carbon betas and its implications for investors, analysts, and regulators. Section 6 analyzes the drivers of BMG and carbon beta portfolios via a risk decomposition approach. Section 7 concludes.

1 Related literature on climate change in finance and economics

The literature on the economic impacts of climate change can be broadly grouped into five strands of research focusing on the macroeconomic assessment of climate change, policy impacts, investor perspectives, physical risks, and equity pricing implications.

Recent studies show how climate change affects an economy and is a general source of uncertainty for society (Stern, 2008; Weitzman, 2014; IPCC, 2018). Despite evidence of increases in extreme weather (e.g., Diffenbaugh et al., 2018) and on possible climate change scenarios (e.g., Rogelj et al., 2018), the transition path of the economy remains difficult to predict. Most models predict negative relationships between global warming and 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 its Regional version (RICE; Nordhaus and Yang, 1996), 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. 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. Overall, macro models suggest that macroeconomic risk and impacts are higher when climate change is not addressed.

Research on optimal policies focuses on the provision of fiscal incentives for clean technologies and the efficient taxation of greenhouse gas emissions (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), and CO_2 taxes (Mardones and Flores, 2018) is still undetermined. However, it is unlikely that these policy incursions will leave firms' cash flows unchanged. 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.

Krüger et al. (2018) suggest that climate concerns are important factors 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 costly for firms to acquire funding (e.g., Cheng et al., 2014). 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).

Numerous recent papers suggest that physical risks impact asset prices. Physical risks are costly to hedge and systematic (Engle et al., 2018) making understanding them central to the pricing of assets. Choi et al. (2018) show that high-carbon firms underperform low-carbon firms during extreme heat events. Hong et al. (2019) demonstrate that food firms exposed to physical risks underperform in the long-run. Delis et al. (2018) show that banks price climate policy risks in their loans and 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) report that physical risks influence prices in the real estate market. Barnett et al. (2018) demonstrate theoretically how climate uncertainty, including physical risks, can be priced in a dynamic stochastic equilibrium model.

Finally, 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. Oestreich and Tsiakas (2015) construct European country-specific “dirty-minus-clean” portfolios based on the number of free emission allowances during the first two phases of the EU Emissions Trading Scheme (ETS) which display positive returns during those time periods. 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. Our study is closely related to this strand of literature but is the first to measure carbon risk in global asset prices via a capital market-based approach.

2 Carbon risk measurement methodology

In this section, we present our methodology to measure carbon risk. First, we describe how to identify green and brown firms using the “Brown-Green-Score” (BGS) using three indicators: value chain, public perception, and adaptability. Second, we use the BGS to build BMG as a mimicking portfolio for carbon risk. Third, we describe how we measure carbon risk of firms using carbon beta. Figure 1 provides an overview of our methodology.

[Insert Figure 1 here.]

2.1 BGS methodology

We determine the fundamental characteristic of brown or green firms by calculating the BGS for each individual firm. This is based on three main indicators: value chain, public perception, and adaptability, capturing the impact of the transition process on a firm. Value chain comprises production, processes, technology, and the supply chain and accounts for the current emissions of a firm. Public perception covers how carbon emissions and a firm's carbon policy are perceived by its stakeholders (e.g., 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 and mitigation strategies. We review the related carbon, CSR, and ESG literature to provide further economic intuition for our indicators.

Production processes as well as applied technologies cannot be transformed instantly and without costs (İşlegen and Reichelstein, 2011; Lyubich et al., 2018). However, regulatory interventions may provide support for required technological changes (Acemoglu et al., 2012) and prevent carbon leakage (Martin et al., 2014). Worldwide supply chains and their environmental impact are difficult to analyze, highly interrelated, and therefore extraordinarily vulnerable to climate related risk sources (Faruk et al., 2001; Xu et al., 2017). Therefore, a firm's value chain is highly affected by changes in the transition process towards a green economy.

A firm's public perception can affect valuation. For instance, value can be created by establishing a comprehensive reporting system (Krüger, 2015). Value of firms with low social capital or trust can be destroyed during a crisis (Lins et al., 2017) or during negative events in the form of reputational risks. Firms may be valued higher if they can demonstrate their activities in support of the climate and are thus able to make use of positive media coverage (Cahan et al., 2015; Byun and Oh, 2018). Thus, public perception of a firm's support of the transition process may impact its respective value.

Finally, a firm's ability to adapt quickly to changes in the transition process may prevent underperformance due to risks in its own value chain or public perception (Lins et al., 2017). Investors already value environmental corporate policies as a necessary risk prevention measure (Fernando et al., 2017). A firm's adaptability is therefore a key indicator whether and to what extent it is affected by unexpected developments (Deng et al., 2013; Fatemi et al., 2015). In our framework, adaptability functions as a mediator between the value chain and the public perception category.

To compute BGS we use 55 variables containing firm specific information related to one of the three broader indicators described above.[5] For each variable, we assign zero to firms below the median in a given year and one to firms above the median. In the next step, we average the 55 values assigned to a firm in a given year separately within the three indicators which results in subscores for value chain, public perception, and adaptablity. Finally, we calculate BGS for each firm *i* in each year *t* by combining the subscores using Eq. (1).

$$BGS_{i,t} = \left(0.7\ Value\ Chain_{i,t} + 0.3\ Public\ Perception_{i,t}\right) - \left(0.7\ Value\ Chain_{i,t} + 0.3\ Public\ Perception_{i,t}\right)\ \frac{1 - Adaptability_{i,t}}{3} \quad (1)$$

The value chain subscore has a weight of 70% in the BGS to reflect its relative importance.[6] The public perception subscore carries 30% weight in the BGS.[7] 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 zero implies that a firm is in an excellent position to deal with an alteration of the transition process. However, a firm may still have high current and perceived emissions reflected in the two other risk indicators.[8] As a result, the BGS ranges between zero and one, where zero denotes a green and one denotes a brown firm in the logic stated above.

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

2.2 BMG – A mimicking portfolio for carbon risk

The BMG portfolio is constructed to mimic a factor related to carbon risk, similar in intuition to the Fama and French (1993) size and book-to-market factors. For the construction of BMG,

[5] A description of the dataset follows in Section 3.1. For a full list of variables and their codes see the Internet appendix Table IA.1.
[6] We assume value chain to be the most important indicator, since production, processes, and supply chain management constitute the core of a firm. Moreover, governmental climate change related regulations are focused predominantly on current emissions, which are part of this indicator.
[7] Our results remain robust to changes in weights.
[8] 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.

we determine the annual BGS for each firm. Subsequently, we unconditionally allocate all firms each year into six portfolios based on their market equity (size) and BGS using the median and terciles as breakpoints, respectively. We use the value-weighted average monthly returns of the four portfolios “small/high BGS” (SH), “big/high BGS” (BH), “small/low BGS” (SL), and “big/low BGS” (BL) to calculate BMG following Eq. (2). Thus, BMG_t is the return in month t of a self-financing portfolio which is long in brown firms and short in green firms:

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

Figure 2 plots cumulative returns of BMG and the corresponding long and short portfolios for the sample period from January 2010 to December 2016. The figure shows a strong contrast in the performance of the brown and the green portfolio over time. While the cumulative return of BMG 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 BMG drops from around +3% to around –30%, followed by an increase to around –20% in 2016. Hence, brown firms performed worse than green firms on average during our sample period.

[Insert Figure 2 here.]

2.3 Carbon beta – A capital market-based measure of carbon risk

To measure the carbon risk of firms without primary carbon or transition-related information, we run time-series regressions explaining firms’ excess returns using an extended Carhart model (1997) following Eq. (3), where $er_{i,t}$ is the monthly return of firm i in month t in excess of the risk-free rate, α_i is the firm’s mean abnormal return, β_i are the sensitivities of the firm’s excess return to the risk factor returns, $er_{M,t}$ is the excess return on the global market portfolio, SMB_t and HML_t are the global size and value factors, WML_t is the global momentum factor, BMG_t is the global carbon risk mimicking portfolio, and $\varepsilon_{i,t}$ is a zero-mean error term.[9]

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

The carbon beta β_i^{BMG} is thus a capital market-based measure of carbon risk that captures the sensitivity of a firm to carbon risk. Positive values represent “brown” firms which are likely negatively affected relative to others by unexpected shifts of the transition. Vice versa, negative carbon betas represent “green” firms which are likely negatively affected relative to others by unexpected shifts of the transition.

[9] We thank Kenneth French for providing the data of the risk factors.

3 Data

In this section, we describe the two data samples used. The "BGS data sample" of 1,637 global firms with detailed fundamental carbon and transition-related information is used to construct BMG and to conduct first tests of BMG. The "full sample" with return data for more than 39,000 global firms is used for further tests of BMG and to analyze carbon risk on global equity prices.

3.1 BGS data sample

For the construction of BMG, we compile a unique dataset from four major ESG databases; *(i)* the Carbon Disclosure Project (CDP) Climate Change questionnaire dataset, *(ii)* the MSCI ESG Stats[10] and the IVA ratings, *(iii)* the Sustainalytics ESG Ratings data and carbon emissions datasets, and *(iv)* the Thomson Reuters ESG dataset.[11] We name this data sample "BGS data sample" and use it to compute BGS and to construct BMG. By merging four databases with different approaches in collecting data including estimations by analysts we minimize a potential self-reporting bias.

We select variables from a total of 785 ESG variables available in the compiled dataset to quantify a firm's BGS. 363 variables thereof are potentially useful for describing environmental issues leaving out social and governance aspects. 131 of the broader environmental variables are directly related to carbon and transition-related issues as opposed to, e.g., waste or water pollution. The final variable set is comprised of 55 proxy variables that cover all aspects of carbon risk with little or no redundancy.[12] To our knowledge, this dataset contains the most comprehensive carbon and transition-related information in this research area.

Next, 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.[13] In the transition process, these firms behave quite differently compared to firms in other industries. As one example, the current practice of assigning carbon emissions does not apply to equity financing or lending, which makes financial institutions appear to be less prone to carbon risk.[14] Furthermore, we include

[10] Formerly KLD Stats.
[11] Formerly ASSET4 ESG database.
[12] We checked for empirical exclusionary criteria and used the expertise of the participants of our workshops to derive our final variable set.
[13] Technically, we exclude all firms classified with a Thomson Reuters Business Classification (TRBC) code equal to 55.
[14] 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). We conduct an analysis of the carbon risk of the financial industry in Section 5.4 using carbon betas to provide further insights on their exposure beyond their BGS.

only firms that are part of all four databases and provide detailed information for the majority of the BGS variables. This is a strict condition but gives us the possibility to overcome potential biases. We relax this condition in our carbon beta analysis in which we study all firms. Overall, this leads to our final BGS 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). Table 1 reports summary statistics for financial and environmental variables of the BGS data sample.

[Insert Table 1 here.]

To avoid penalizing large firms concerning absolute carbon emissions, energy use, and expenditures, we standardize all continuous variables by the firm's net sales.[15] Besides continuous variables, the sample contains a number of discrete and binary variables, and variables ranging within a predefined bandwidth, such as the database specific scores.

3.2 Full sample

In addition to the BGS data sample, we use a full sample obtaining all primary, major equity listings of global firms from Morningstar Direct. This final selection consists of 39,537 firms and is survivorship bias free. A comparison between the geographic and sectoral breakdown of both samples reported in Appendix A.2 shows that the BGS data sample is representative of the full sample.[16]

4 Relevance of BMG

In this section, we provide descriptive statistics for BMG and correlations between BMG and other common factors. Further, we test if BMG is a relevant determinant of variation in global equity prices by conducting sorted portfolio analyses within the BGS data sample as well as further tests for single firms using the full sample.

[15] Standardized variables fall in the following categories: CO_2e emissions, energy use, environmental expenditures, and provisions, and are marked in Table 1.

[16] Note that the full sample coincides with the BGS data sample. The level of coincidence, however, is low at 3.82%. Alternatively, we eliminate all stocks that are included in the BGS data sample from the full sample. The results remain basically the same.

4.1 BMG summary statistics

Table 2 reports summary statistics and correlations with common factors during our sample period. The average monthly return of BMG is negative at −0.25%, the standard deviation is 1.95%. The correlations between BMG and the market, size, value, and momentum factor are relatively low.[17] This suggests that BMG possesses unique return-influencing characteristics that are able to enhance the explanatory power of common factor models.

[Insert Table 2 here.]

4.2 BGS-decile portfolio analysis

We construct BGS sorted portfolios to test if BMG is able to enhance the explanatory power of common factor models. We sort firms in the BGS data sample into annually rebalanced deciles such that decile 1 contains the firms with the lowest BGS, i.e. the greenest firms, and decile 10 contains the firms with the highest BGS, i.e. the brownest firms. We run time-series regressions of the deciles' equal-weighted monthly excess returns on the Carhart (1997) model and on a five factor Carhart + BMG model (Eq. 3).[18]

The results of the global BGS-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 one for all deciles. In order to test whether BMG is able to significantly increase the explanation of the variation in excess stock returns we apply the F-test on nested models (Kutner et al., 2005). For additional details on the BGS-deciles, all differences compared to the Carhart model in the alpha and the beta coefficients are reported.

[Insert Table 3 here.]

A comparison of the adjusted R^2s and the results of the F-test confirm that BMG significantly enhances the explanatory power of the standard Carhart model, especially for the high BGS portfolios. In the case of BGS-decile 10, the adj. R^2 increases by more than 12 percentage points. The table reports carbon beta loadings that increase strictly monotonically from the low BGS-decile, which displays a significantly negative loading of −0.328, to the high BGS-decile with a significantly positive loading of 1.019, similar to the market factor loading. The medium

[17] We also conducted correlation and regression analyses on potentially related influencing factors including the oil price (oil spot and futures prices) as well as oil industry equity and commodity indices and carbon price (carbon certificates and respective derivatives). There are no remarkable results affecting our factor.

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

BGS-deciles show carbon betas close to zero. Overall, BMG delivers the expected results and significantly enhances the explanatory power of common factor models in BGS-deciles.

4.3 Comparison of common factor models

We compare the results of common factor models with and without BMG using the full sample. Panel A of Table 4 shows the results of more than 39,000 single stock regressions. The first two models compares how (1) SMB and HML versus (2) BMG change the explanatory power of the CAPM. The average increase of model (1) in the adj. R^2 is 1.02 percentage points. This increase is significant for 11.49% of the firms in the sample. In comparison, BMG alone increases the adj. R^2 by 0.84 percentage points and significantly for 12.05% of the regressions. The following two models contrasts how (3) the Carhart (1997) momentum factor vs. (4) BMG changes the explanatory power of the Fama and French (1993) model. This comparison shows a seven times increase in the adj. R^2 for BMG than for the momentum factor. Finally, the last model (5) provides further evidence that the BMG increases the explanatory power of common factor models, for example the Carhart (1997) model.

[Insert Table 4 here.]

For a more detailed assessment of the impact of BMG on the stock returns of single firms, Panel B of Table 4 reports the number of significant factor betas from the Carhart + BMG 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 at 0.19.[19] Overall, compared to common factors, BMG performs well highlighting its relative importance for explaining variation in global equity returns. We continue to confirm this conclusion by conducting a broad range of further asset pricing tests.[20]

5 Carbon beta as a risk measure

In this section, we highlight the variation of carbon betas in countries and industries. We also show that investors can manage the carbon beta of their portfolios without sacrificing

[19] A similar analysis conducted with the BGS data sample can be found in the Internet appendix (Table IA.2). The results are economically the same.

[20] We have carried out numerous further investigations, including a factor spanning test, a comparison of BMG with further prominent factors, a maximum Sharpe ratio approach 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 other risk factors. We provide descriptive statistics, a decile table, and a comparison of common factor models with our orthogonalized factors. All results remain robust and BMG is essential in asset pricing. For all those analyses see Tables IA.3 – IA.9.

performance, exposure to common factors or to industry preferences. Taking an analyst's perspective, we relate firm characteristics to carbon beta to analyze what influences firms' sensitivity to the transition process. Finally, we take a closer look at the carbon risk of the financial industry.

5.1 Carbon beta variation in countries and industries

The carbon beta varies over countries and industries. For the country breakdown of 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 3, 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, for example with its 2030 climate and energy framework and the EU Action Plan. The countries with the most negative carbon betas are European countries, such as Italy (−0.663), Spain (−0.591), and Portugal (−0.505). The country with the highest average carbon beta is South Africa (0.433), consistent 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).

[Insert Figure 3 here.]

At industry level, the carbon betas are illustrated in Figure 4. 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 known to be sensitive to climate change and mitigation policies, i.e. the basic materials and energy sector.[21]

[Insert Figure 4 here.]

Overall, the breakdown of the carbon betas over countries and industries is consistent with our expectation of how carbon betas are distributed. Energy and basic materials firms are more positively exposed to an unexpected change in the transition process 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 highly negative as well as highly positive carbon betas. Thus, carbon risk is not merely an industry-specific phenomenon.

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

5.2 Carbon beta from an investor's perspective

We demonstrate how investors can take carbon risk into consideration via the inclusion of carbon beta into portfolio management. First, we use the distribution of carbon betas within industries to replicate common best-in-class strategies. We construct three globally diversified portfolios. The first represents the equal-weighted return of all firms in our full sample.[22] The second (third) includes only the best-in-class (worst-in-class) firms of each industry according to their carbon beta, i.e. having a carbon beta above (below) the median of the respective industry carbon beta. For all three portfolios, we calculate annualized mean excess returns, standard deviations, and Sharpe ratios (SR).

[Insert Table 5 here.]

Panel A of Table 5 shows that an investor can construct a portfolio with a significantly lower carbon beta of −1.03 without changing the industry allocation of his or her portfolio, but with the same SR and a significant change in volatility of −0.04. Hence, it is possible for investors to take carbon beta into account and construct portfolios that are broadly diversified across industries and without sacrificing risk-or-return considerations.

Some investors may be more interested in exposures to other common risk factors than in a diversified allocation across industries. We show that it is possible to construct a portfolio with similar risk-adjusted returns and similar exposure to common factors but lower carbon betas. First, we estimate the beta loadings of our Carhart + BMG model for all firms in the full sample. Second, we construct 5×5×5 conditionally sorted portfolios based on market, SMB, and HML beta quintiles. The resulting 125 portfolios consist of firms with similar characteristics regarding the factor exposures but potentially cover a broad range with respect to carbon beta. In the following, we apply the same methodology as for the industry best-in-class approach.

The results are presented in Panel B of Table 5. The average portfolio has an annual SR of 0.44, while the low carbon beta portfolio generates a SR of 0.48. This represents an eight percentage points higher SR for the low carbon beta portfolio than for the high carbon beta portfolio. The low carbon beta portfolio also exhibits a decrease in volatility by −0.04. More importantly, the carbon beta difference between the low and the high carbon beta portfolios is −0.91. This means that investors can change their exposure to carbon beta independent of their

[22] The results remain robust for value-weighted portfolios.

exposure to the market, SMB, and HML beta. Overall, the results show that investors can change their carbon beta without sacrificing performance, exposure to common factors, or to industry preferences.

5.3 Carbon beta determinants from an analyst's perspective

Analysts are interested in the financial impacts of the transition process on a firm's value. Thus, it is important for them to know the influencing factors of firms' carbon betas. We conduct panel regressions and apply country, industry, and time fixed effects to account for unobserved differences. The most interesting variables we use to explain carbon betas are R&D expenditures, which may proxy for innovation and investment in new, clean technologies, and property, plant, and equipment (PPE) assets, that proxy for legacy production equipment as well as "stranded assets".[23] As control variables, we use common firm fundamental variables. For the BGS data sample, we explain the annual carbon beta using the three subscores value chain, public perception, and adaptability that are used to compute the BGS.[24]

The results presented in Panel A of Table 6 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 as innovation and investment in new, clean technology may reduce firms' sensitivity to an unexpected change in the transition process towards a green economy. Conversely, higher PPE leads to higher carbon betas meaning that carbon beta is influenced by the presence of old technology and stranded assets.

[Insert Table 6 here.]

Panel B shows the results for the full sample without the risk 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 indicate that carbon beta is partially explained by firm characteristics related to a firm's exposure to carbon risk. Carbon risk should also be considered by analysts looking to improve their forecasts.

[23] The latter describes particular assets which may suffer from unanticipated or premature devaluations during the transition process towards a green economy.

[24] The analysis with only the risk indicators can be found in the appendix (Table A.3).

5.4 Carbon betas in the financial industry

Firms operating in the financial services sector are not typically perceived as brown as they do not, for example, generally emit carbon in their daily operations. Therefore, the current practice of assigning carbon emissions does not apply to equity financing or lending financial institutions. Thus, they 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 taking into consideration the carbon beta of their home countries. We compute the average carbon beta of all non-financial firms in each country, and are therefore able to distinguish between high, middle, and low carbon beta countries (CBC). In Table 7 Panel A the results are shown.

[Insert Table 7 here.]

A bank in a low CBC has on average a carbon beta of −0.337. In comparison with a high CBC, it has a significantly lower carbon beta of −0.587. There is also a significant difference between high and middle, and middle and low CBC betas.[25] These results remain robust if we use financial services firms in general including banks (see Panel B). Hence, even though banks and other financial firms are not directly subject to high carbon risk, they are indirectly exposed to the carbon risk of the firms they finance. In other words, even the financial industry is strongly affected by carbon risk through their financing decisions.

6 A risk decomposition of BMG and carbon beta portfolios

In this section, we analyze the economic mechanisms driving BMG and the market beta of carbon beta sorted portfolios. We follow the decomposition approaches of Campbell (1991) and Campbell and Vuolteenaho (2004). The analysis is geared towards understanding whether changes in expectations about firm cash flows or changes in discount rates are driving BMG, carbon beta, and the correlation of firm's 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-

[25] We also use quartiles to highlight the fact that the results are not conditional on data sub-setting.

evaluations towards a new equilibrium. In contrast, discount rate changes have temporary wealth effects on the aggregate stock market driven by investor sentiment.

We use the VAR methodology introduced by Campbell (1991) to decompose BMG and assume that the data are generated by a first-order vector autoregression (VAR) model.[26] 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 8, 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 BMG is mainly determined by expectations about future cash flows and not about changes in the discount rate that investors apply to these cash flows. This is consistent with the transition process of the economy that is highly sensitive to changes in technologies (investments) and customers preferences for goods and services (revenues).[27]

[Insert Table 8 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.[28] 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 5 here.]

As shown in Figure 5, 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

[26] For further details on the model specification see Appendix A.1.
[27] 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).
[28] 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 BMG as first state variable can be found in Figure A.1.

show a U-shaped pattern. This suggests that the extreme portfolios, i.e. high absolute carbon beta firms, have higher cash-flow betas and are thus more exposed to fundamental re-evaluations of firm values.[29]

[Insert Table 9 here.]

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 ("bad beta") than for transitory discount-rate shocks ("good beta"). In Table 9, 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. We show results of an unrestricted factor model and a two-factor ICAPM that restricts the price of the discount-rate beta to the variance of the market return. Like Campbell and Vuolteenaho (2004), we estimate both models with and without a constant to account for different assumptions about the risk-free rate. 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). In the two-beta ICAPM the results remain economically the same. Since carbon beta 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.

7 Conclusion

The global economy is engaged in a transition process from a high-carbon to a low-carbon economy. Some firms are well positioned to deal with the carbon risk associated with an unexpected change in the transition process towards a green economy, whereas others are not. The carbon risk in this transition process is relevant at the firm, industry, and country level.

To capture and quantify this new carbon risk, we develop a novel capital market-based measure, "carbon beta", which is easy to calculate and requires only one firm specific input: stock returns. Carbon beta is designed to capture firms' sensitivities to an unexpected change in the transition process towards a green economy. It is estimated using a carbon risk mimicking portfolio (BMG) that we construct from a subset of firms with detailed and reliable carbon and transition-related information. Extensive tests of BMG support our notion of its relative

[29] In Figure IA.3, we show that extreme portfolios display higher systematic risk per se, which is primarily driven by cash-flow risk as shown in Figure 5.

importance for explaining variation in global equity returns during our sample period. BMG captures the effects of fundamental re-evaluations of firm values due to the ongoing transition between an old, brown equilibrium and a new, green equilibrium.

The information contained in the carbon beta can be used by, e.g., investors, analysts, and regulators. 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 or industry and factor allocations. 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. Analysts can use carbon betas to integrate readily available information and sharpen their forecasts. We also demonstrate that banks and other financial services firms are strongly related to the carbon risk of domestic firms they are likely to finance. 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 market betas into cash-flow and discount-rate components reveals that high and low carbon beta 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 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 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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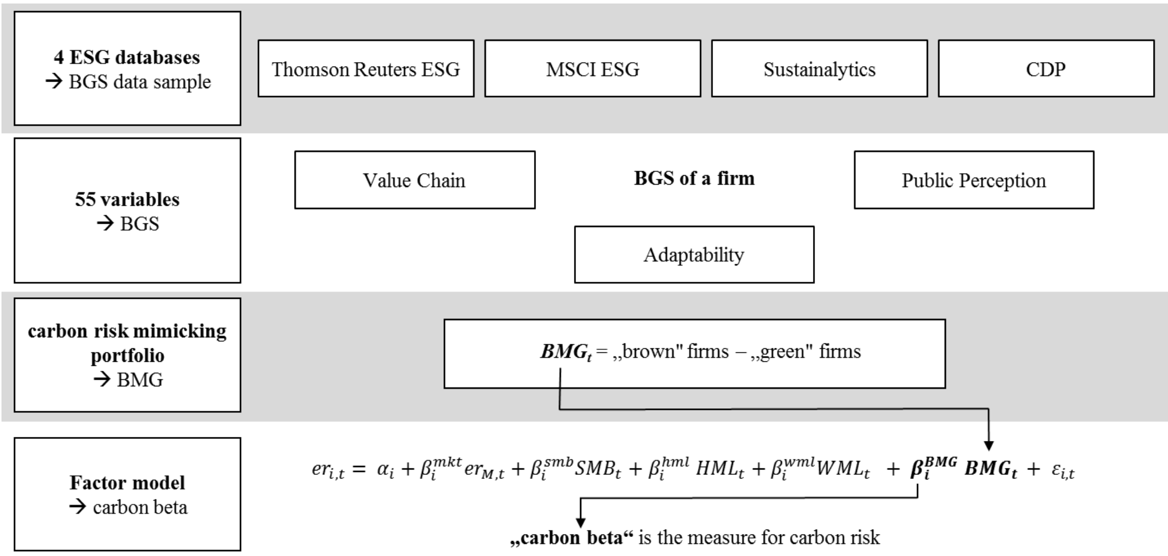
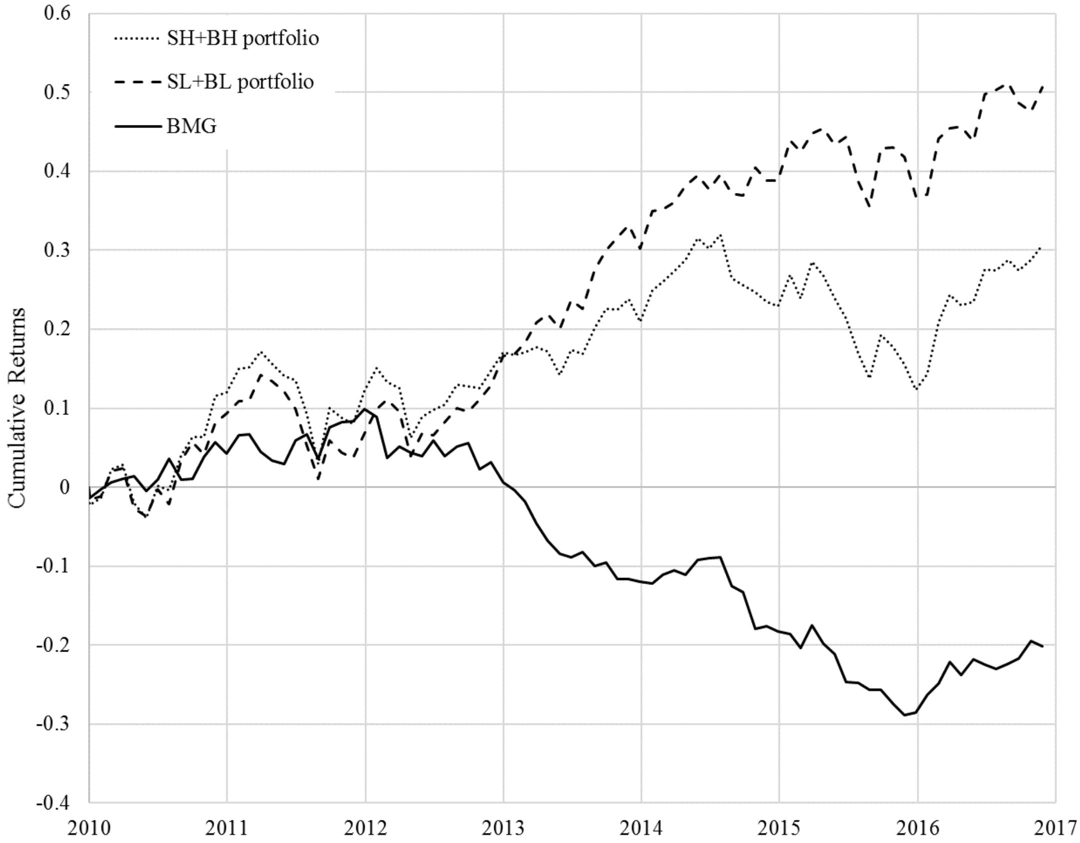
Figures and Tables

Figure 1
Carbon risk measurement methodology



This figure shows our carbon risk measurement methodology. First, we generate a unique global dataset from four major ESG databases. Second, we extract 55 variables for 1,637 global firms and assign them to our three indicators, value chain, public perception, and adaptability. Thereby, we are able to determine the Brown-Green-Score (BGS) for each firm. Third, we use the BGS to construct a Brown-Minus-Green factor (BMG). Lastly, we integrate BMG into the Carhart model to estimate the carbon beta as our measure for carbon risk.

Figure 2
Cumulative returns of BMG and the long and short portfolios



This figure shows cumulative returns of BMG and the weighted underlying long "small/high BGS" (SH) and "big/high BGS" (BH), and short portfolios "small/low BGS" (SL) and "big/low BGS" (BL) for the sample period from January 2010 to December 2016.

Table 1

Descriptive statistics of variables

Variable	N	Mean	SD	Median
Panel A. Thomson Reuters Financials				
Returns (%)	76,700	0.74	9.01	0.69
Market equity (US$ mio.)	76,700	20,959	38,749	8,557
Net sales (US$ mio.)	76,405	18,528	35,278	7,643
R&D (US$ mio.)	51,153	82	512	5
PPE (US$ mio.)	120,554	1,068	5,782	95
Leverage ratio	120,274	0.22	0.23	0.18
Book-to-market ratio	121,508	0.80	3.56	0.59
Cash (US$ mio.)	104,558	288	2,481	29
Return on Assets	121,481	0.04	7.07	0.03
Net sales full sample (US$ mio.)	121,532	2,351	10,998	294
Panel B. Thomson Reuters ESG				
Energy Use Total (std.)	51,480	119,343	6,682,551	630.74
CO_2 Equivalents Emission Total (std.)	63,959	7,672	465,116	59.69
Clean Technology	72,991	0.76	0.43	1.00
Emission Reduction Prod. Process	72,806	0.49	0.50	0.00
Sustainable Supply Chain	72,806	0.23	0.42	0.00
Renewable Energy Use	72,806	0.32	0.47	0.00
Climate Change Risks/Opportunities	72,806	0.23	0.42	0.00
Energy Efficiency Policy	72,806	0.11	0.31	0.00
Emission Reduction Target/Objective	52,780	0.03	0.16	0.00
Energy Efficiency Target/Objective	36,525	0.05	0.22	0.00
Environmental Investments Initiatives	75,350	0.33	0.47	0.00
Environmental Exp. Investments	75,350	0.51	0.50	1.00
Environmental Expenditures (std.)	29,999	0.01	0.04	0.00
Environmental Partnerships	75,350	0.76	0.43	1.00
Environmental Provisions (std.)	17,677	0.04	0.16	0.01
Policy Emissions	75,350	0.89	0.32	1.00
Environmental R&D Exp. (std.)	8,881	0.09	0.01	0.09
Emission Reduction Score	72,806	16.18	19.76	7.64
Resource Reduction Score	72,806	16.11	19.59	7.93
Environmental Score	72,806	16.14	19.66	7.41
Innovation Score	75,330	38.21	26.05	33.86
Emissions Score	75,330	26.26	20.74	21.52
Panel C. Carbon Disclosure Project				
Greenhouse Gas Emissions (std.)	61,760	47,611	1,541,905	61.29
Regulatory Opportunities Sources	70,670	2.64	2.37	2.00
Climate related Opport. Sources	70,670	1.18	1.04	1.00
Regulatory Risks Sources	70,670	1.85	1.87	1.00
Climate related Risks Sources	70,670	1.22	1.25	1.00
Regulatory Opportunities	62,675	0.08	0.27	0.00
Climate related Opportunities	62,648	0.14	0.34	0.00
Regulatory Risks	62,792	0.94	0.24	1.00
Climate related Risks	62,720	0.81	0.39	1.00
Emission Reduction Target	6,871	0.72	1.18	0.00
Disclosure Score	55,676	22.31	18.80	19.00
Performance Band	58,595	4.30	2.12	3.00

Table 1 continued

Variable	N	Mean	SD	Median
Panel D. Sustainalytics				
Carbon Intensity	59,492	45.07	39.03	50.00
Renewable Energy Use	59,492	85.08	34.78	100.00
Supplier Environmental Programmes	29,321	64.37	34.59	70.00
Sustainable Products & Services	33,978	73.55	30.90	75.00
Scope of GHG Reporting	58,948	28.85	37.87	0.00
Environmental Policy	72,552	39.84	33.38	50.00
Green Procurement Policy	72,552	55.99	33.16	60.00
Renewable Energy Programmes	59,428	78.94	27.49	75.00
Environmental Management System	72,552	25.52	30.78	20.00
Air Emissions Programmes	26,915	67.59	33.23	75.00
Overall ESG Score	72,552	34.22	8.66	34.38
Panel E. MSCI ESG				
Opportunities in Clean Tech	21,758	0.66	0.47	1.00
Energy Efficiency	7,039	0.57	0.50	1.00
Opportunities Renewable Energy	2,280	0.57	0.49	1.00
Carbon Emissions	51,357	0.48	0.50	0.00
Regulatory Compliance	13,137	0.10	0.30	0.00
Climate Change Controversies	58,358	0.03	0.18	0.00
Industry-adjusted Overall Score	75,171	4.25	2.30	4.20
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 financial and carbon or transition-related variables in the BGS data sample grouped by their origin ESG databases (Panels A–E) for the period from January 2010 to December 2016. Moreover, the table reports returns for the full sample in Panel F. Variables indicated as (std.) are standardized by net sales. All variables are scaled in such a way that higher values denote browner firms. A country and sector breakdown can be found in Table A.2 of the appendix. A list of all variable codes can be found in internet Appendix IA.1.

Table 2
Factor descriptive statistics and correlations

Factor	Mean 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 global market (er_M), size (SMB), value (HML) and momentum (WML) factors as well as BMG 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
BGS-decile portfolio performance

Decile	Median BGS	Coefficient							Δ Coefficient					
		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	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	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 Brown-Green-Scores (BGS), alpha performance, and beta coefficients of the Carhart + BMG model for annually rebalanced, equal-weighted decile portfolios based on the BGS of the stocks in the BGS data sample for the period from January 2010 to December 2016. On the right panel, the table displays Δ alphas and coefficients between the Carhart + BMG model and the Carhart model. *, **, *** denote significance on the 10%, 5%, and 1% level, respectively. For alphas and beta coefficients, significance statistics are based on two-sided t-tests. [c], [b], and [a] denote significance on the 10%, 5%, and 1% level, respectively, for Δ values. Tests on the differences of coefficients are based on two-sided t-tests of bootstrapped Δ values. Significance symbols in the last column are based on the one-sided F-test for nested models (H_0: $\beta_i^{BMG} = 0$).

Table 4

Comparison of common factor models

Panel A. Significance tests for explanatory power of various models

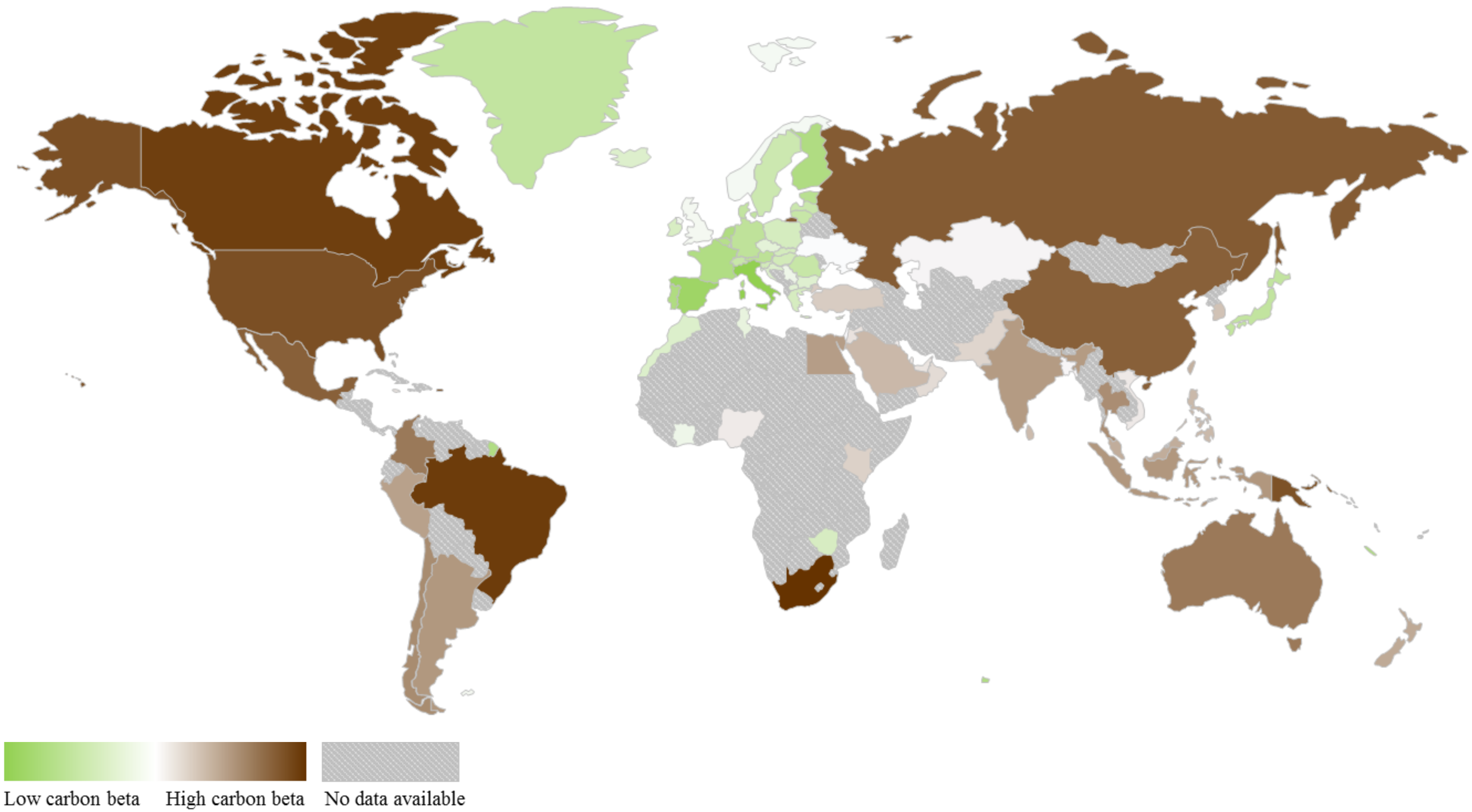
	Avg. Δ adj. R^2 (%)	Significant at 5% F-test (%)
(1) CAPM – Fama/French	1.02	11.49
(2) CAPM – CAPM + BMG	0.84	12.05
(3) Fama/French – Carhart	0.10	5.98
(4) Fama/French – Fama/French + BMG	0.71	11.55
(5) Carhart – Carhart + BMG	0.69	11.55

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

	Avg. coefficient	T-test of significance of coefficients: 10% level #	10% level %	5% level #	5% level %	1% level #	1% level %
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

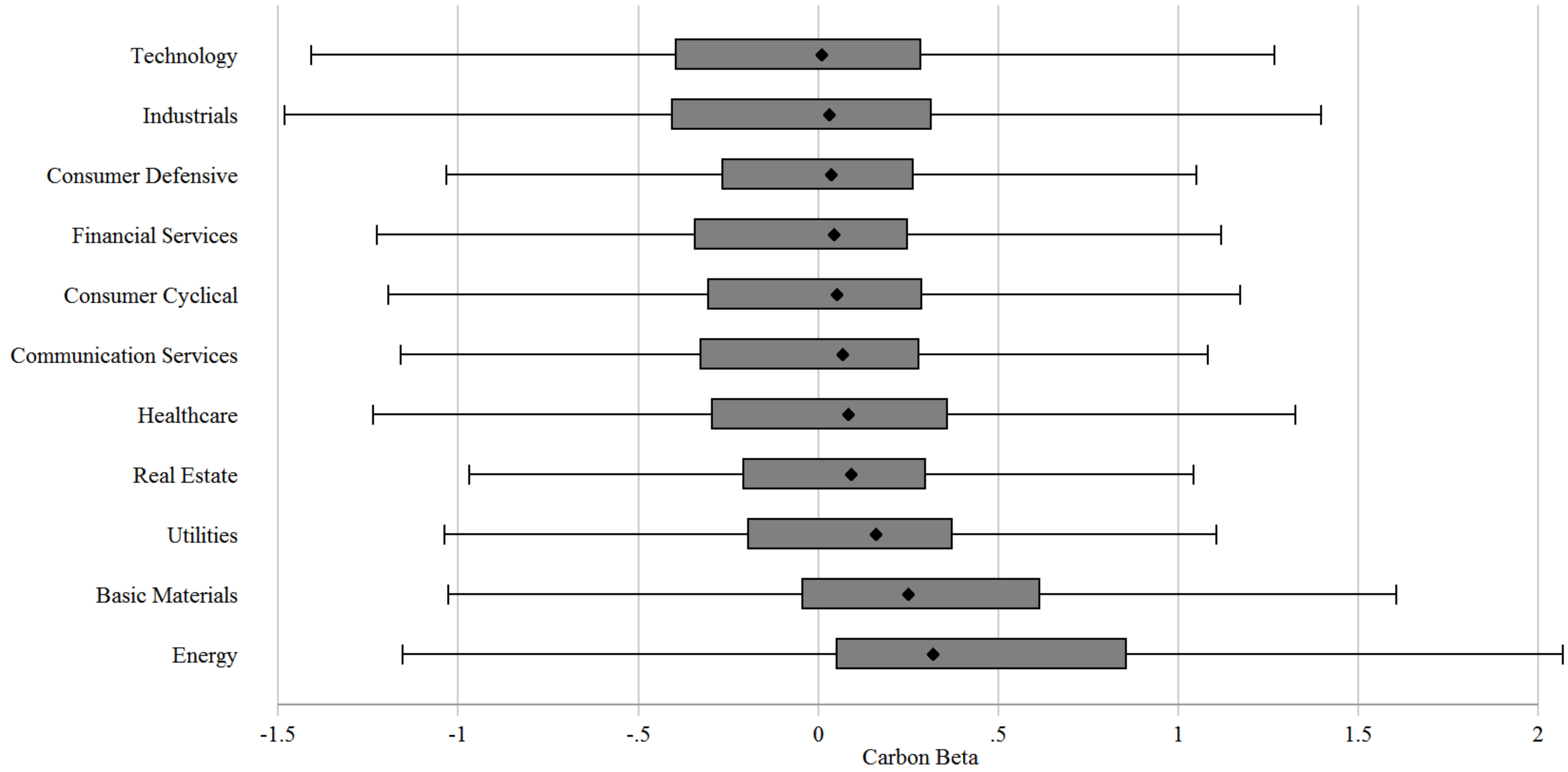
This table provides comparisons of common factor models including and excluding BMG. Panel A reports the average Δ adj. R^2 between different factor models run on single stocks from the full sample in the sample period from January 2010 to December 2016. Significance statistics are based on one-sided F-tests for nested models (H_0: $\beta_i^{BMG} = 0$). Panel B shows average beta coefficients as well as the absolute (#) and relative (%) number of statistically significant beta coefficients from Carhart + BMG model regressions run on single stocks from the full sample. Statistical significance is based on two-sided t-tests.

Figure 3
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 brown color states that, on average, the country's firms have high carbon betas.

Figure 4
Carbon beta industry breakdown



This figure shows box plots of the carbon beta distributions within different industries based on the full sample in the period from January 2010 to December 2016. The industries are identified by the super sectors of the Morningstar Global Equity Classification Structure (MGECS). The diamonds indicate the median carbon beta per industry. The left and right box edges indicate the lower and upper quartiles, respectively. The whiskers indicate the minimum and maximum carbon betas within 1.5 times the interquartile ranges. The sectors are sorted in ascending order by their carbon beta.

Table 5
Carbon beta in portfolios

	SR	Excess return	SD	β^{BMG}	β^{mkt}	β^{smb}	β^{hml}
Panel A. 11 Industry portfolios							
All firms	0.41	0.17	0.41	0.01			
Best-in-class	0.43	0.17	0.39	−0.50			
Worst-in-class	0.40	0.17	0.43	0.52			
Best – Worst	0.04	0.00	−0.04***	−1.03***			
Panel B. 125 factor portfolios							
All firms	0.44	0.18	0.41	−0.02	0.65	0.88	0.21
Best-in-class	0.48	0.19	0.39	−0.44	0.65	0.89	0.22
Worst-in-class	0.40	0.18	0.44	0.47	0.65	0.87	0.20
Best – Worst	0.08***	0.01	−0.04***	−0.91***	0.00	0.02	0.03

This table shows the average Sharpe ratio (SR), yearly excess returns in %, and yearly volatility (SD) in % as well as the carbon beta of 11 industry portfolios in Panel A, and additionally the market (mkt), SMB, and HML beta for 125 factor portfolios in Panel B. The portfolios are conditionally constructed on the MKT, SMB, and HML beta of all stocks in the full sample, aggregated equal-weighted, and annually rebalanced. In both panels, a firm is categorized as worst-in-class (best-in-class) if its carbon beta is above (below) its respective group's carbon beta median. 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 6
Panel regressions

	Panel A. BGS 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	-0.04^{**}	-0.03^{***}	-0.06^{***}	-0.03^{**}	-0.02^{***}	-0.02^{***}	-0.02^{***}	-0.02^{***}
PPE	0.07^{**}	0.08^{***}	0.06	0.07^{**}	0.04^{***}	0.01^{**}	0.04^{***}	0.04^{***}
Leverage Ratio	0.04^{**}	-0.03^{**}	0.06^{***}	0.04^{**}	0.02^{***}	-0.01^{***}	0.02^{***}	0.02^{***}
Book-to-market Ratio	-0.20^{***}	0.01	-0.22^{***}	-0.19^{***}	-0.16^{***}	−0.00	-0.16^{***}	-0.15^{***}
Cash	0.01	0.01	−0.01	0.01	-0.04^{***}	-0.01^{***}	-0.04^{***}	-0.04^{***}
RoA	0.09^{***}	-0.03^{**}	0.07^{***}	0.10^{***}	−0.00	-0.01^{***}	−0.00	−0.00
Net Sales	−0.01	-0.06^{***}	0.03	−0.00	-0.02^{***}	0.00	-0.02^{***}	-0.02^{***}
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		0.06	0.14	0.16		0.01	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 of carbon beta as the dependent variable on BG subscores and further firm fundamentals as well as country, industry, and time fixed effects. Standard errors are clustered on firm level. All accounting variables are logarithmized. *, **, *** denote significance on the 10%, 5%, and 1% level, respectively. Significance tests are based on two-sided t-tests.

Table 7
Carbon betas in the financial industry

	High CBC	Middle CBC	Low CBC
Panel A. Bank terciles			
Average carbon beta	0.250	0.135	−0.337
Δ middle CBC	−0.116**		
Δ low CBC	−0.587***	−0.472***	
Panel B. Financial services terciles			
Average carbon beta	0.267	0.121	−0.305
Δ middle CBC	−0.147***		
Δ low CBC	−0.572***	−0.425***	

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 based on their average carbon beta (carbon beta country, CBC). 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.

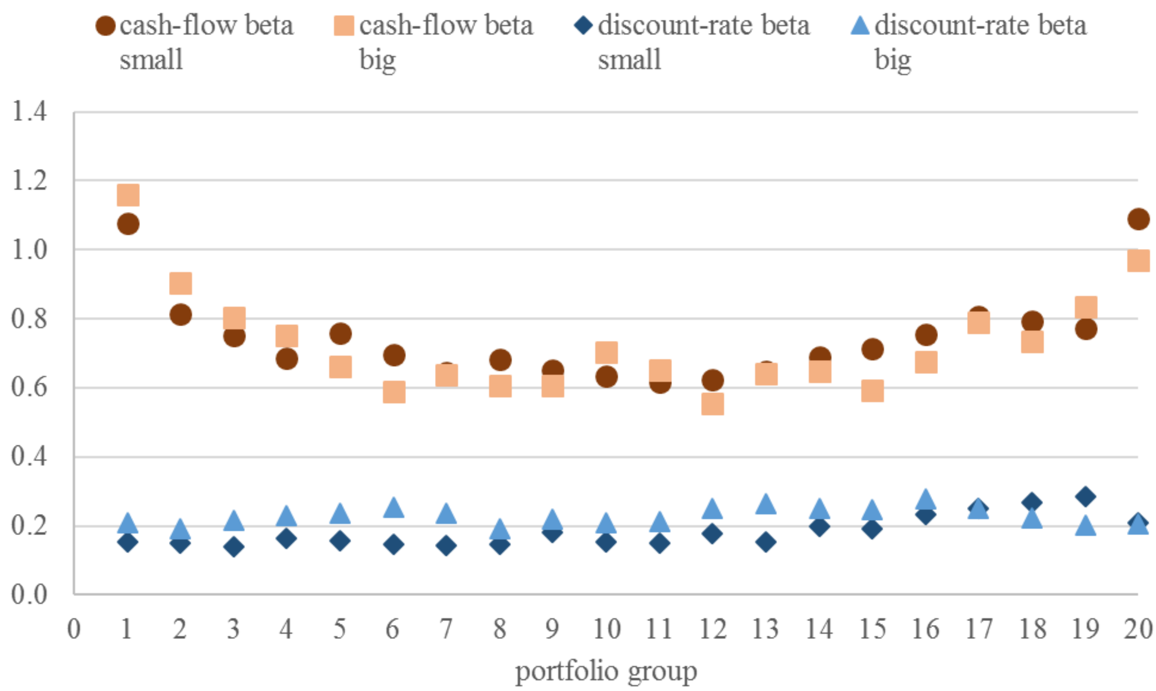
Table 8

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	
	(0.17)	(0.02)	(0.04)	

This table shows the results of the variance decomposition of BMG for the sample period from January 2010 to December 2016 following the methodology of Campbell (1991). We report both the absolute and normalized values of variances and covariance of the cash-flow news and discount-rate news for BMG. The standard errors in parentheses are calculated using a jackknife method.

Figure 5
Beta decomposition of 40 carbon beta sorted portfolios



This figure shows the beta decomposition of 40 test assets built out of the full sample in the period from January 2010 to December 2016 following the methodology of Campbell and Vuolteenaho (2004). The 40 test assets are constructed by sorting all stocks into 20 5%-quantiles based on their carbon beta (portfolio group) and splitting each portfolio by the stocks' median market capitalization.

Table 9

Pricing cash-flow and discount-rate betas

	Factor model		Two-beta ICAPM	
	Unrestricted	α=0	Unrestricted	α=0
R_{zb} less R_{rf} (g_0)	0.003	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 following the methodology of Campbell and Vuolteenaho (2004). The asset pricing models are an unrestricted two-beta model and a two-beta ICAPM with the discount-rate beta price constrained to equal the market variance. The second column per model shows a model with the zero-beta rate equal to the risk-free rate (α=0). Estimates are from a cross-sectional regression using value-weighted portfolio returns of 40 test assets conditionally sorted on carbon beta and size. Standard errors are from the respective cross-sectional regression.

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:

$$z_{t+1} = a + \Gamma z_t + u_{t+1} \tag{4}$$

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

$$N_{DR,t+1} = e1'\lambda u_{t+1} \tag{5}$$

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

where $e1$ is a vector with the first element equal to one and the others equal to zero and $\lambda = \rho\Gamma(I - \rho\Gamma)^{-1}$.[30]

In specifying the aggregate VAR, we follow Campbell and Vuolteenaho (2004) by choosing global proxies for the four state variables. First, we use the log return on BMG. Second, we add the term yield spread (TY) as a weighted average of country specific interest rates by Thomson Reuters Datastream.[31] 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.[32]

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

$$Var(BMG_t - E_{t-1}BMG_t) = Var(N_{CF}) + Var(N_{DR}) - 2Cov(N_{CF}, N_{DR}) \tag{7}$$

[30] We set ρ close to one as defined in Campbell and Vuolteenaho (2004).
[31] We use the weighting scheme of the MSCI World index as of the end of our sample period.
[32] 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.

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

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):

$$\beta_{i,CF} = \frac{Cov(r_{i,t}, N_{CF})}{Var(r_{M,t} - E_{t-1}r_{M,t})} \quad (9)$$

$$\beta_{i,DR} = \frac{Cov(r_{i,t}, -N_{DR})}{Var(r_{M,t} - E_{t-1}r_{M,t})} \quad (10)$$

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 5.

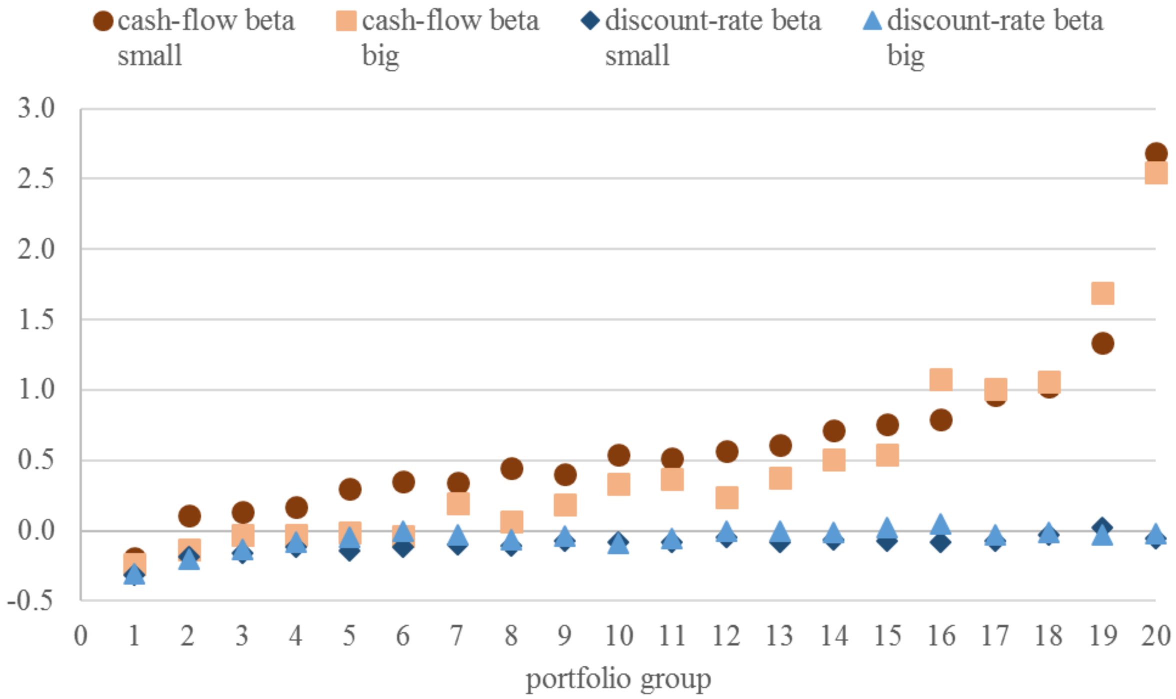
Table A.1

Beta decomposition of carbon beta sorted portfolios

	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 carbon beta sorted portfolios



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

Appendix A.2

Table A.2
Geographic and sectoral breakdown of global firms

Panel A. BGS data sample

a. Geographic			b. Sectoral			
Country	#	%	Sector	TRBC	#	%
United States	418	25.53	Industrials	52	368	22.48
Japan	227	13.87	Cyclical Consumer Goods & Services	53	277	16.92
United Kingdom	193	11.79	Basic Materials	51	239	14.60
Canada	97	5.93	Technology	57	191	11.67
Australia	75	4.58	Non-Cyclical Consumer Goods & Services	54	167	10.20
France	66	4.03	Energy	50	118	7.21
South Africa	59	3.60	Utilities	59	104	6.35
Germany	53	3.24	Healthcare	56	109	6.66
Taiwan	48	2.93	Telecommunications Services	58	64	3.91
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	Total		1,637	100.00

Panel B. Full sample

a. Geographic			b. Sectoral			
Country	#	%	Sector	MGECS	#	%
United States	5,106	12.91	Consumer Cyclical	102	6,343	16.04
China	4,104	10.38	Technology	311	6,276	15.87
Japan	3,800	9.61	Industrials	310	6,234	15.77
India	3,569	9.03	Basic Materials	101	5,637	14.26
Canada	2,998	7.58	Financial Services	103	4,208	10.64
South Korea	1,957	4.95	Healthcare	206	2,854	7.22
Taiwan	1,860	4.70	Consumer Defensive	205	2,624	6.64
Australia	1,775	4.49	Real Estate	104	2,367	5.99
United Kingdom	1,711	4.33	Energy	309	1,560	3.95
Malaysia	951	2.41	Utilities	207	873	2.21
Other Europe	5,830	14.74	Communication Services	308	561	1.42
Other Asia	4,197	10.6				
Other Americas	774	1.96				
Other Africa	691	1.74				
Other Australasia	156	0.39				
Other *(no code available)*	58	0.15				
Total	39,537	100.00	Total		39,537	100.00

This table shows the geographic (a.) and sectoral breakdown (b.) in absolute numbers and percentages for the BGS data sample (Panel A) and the full sample (Panel B) for the sample period from January 2010 to December 2016. The BGS 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 of carbon beta as the dependent variable on BG subscores and country, industry, and time fixed effects. 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 Investment	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-adj. Overall Score	Ind.-adj. 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	Env. 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, Carbon Disclosure Project (CDP), MSCI ESG KLD and Sustainalytics ESG datasets used to construct the stock specific Brown-Green-Score (BGS).

Table IA.2

Comparison of common factor models – BGS data sample

Panel A. Significance tests for explanatory power of various models

	Avg. Δ adj. R^2 (%)	Significant at 5% F-test (%)
(1) CAPM – Fama/French	2.15	17.23
(2) CAPM – CAPM + BMG	2.80	22.13
(3) Fama/French – Carhart	0.21	8.61
(4) Fama/French – Fama/French + BMG	2.55	21.07
(5) Carhart – Carhart + BMG	2.62	21.67

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

	Avg. coefficient	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 comparisons of common factor models including and excluding BMG. Panel A reports the average Δ adj. R^2 between different factor models run on single stocks from the BGS 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: $\beta_i^{BMG} = 0$). Panel B shows average beta coefficients as well as the absolute (#) and relative (%) number of statistically significant beta coefficients from Carhart + BMG model regressions run on single stocks from the BGS data sample. Statistical significance is based on two-sided t-tests.

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 BMG 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 factors and the reverse BMG* 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 continued

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 BMG, 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 factors

Factor	Mean 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 factors of the Carhart model and BMG for the sample period from January 2010 to December 2016. Correlations are reported between the orthogonalized factors and the original factors. The original factors er_M, SMB, HML, and WML are provided by Kenneth French.

Table IA.8

BGS-decile portfolio performance – orthogonalized factors

Panel A. Carhart + BMG model

Decile	Coefficient						Adj. R^2 (%)	ΔAdj. R^2 (%)
	$Alpha^{\perp}$	$er_M^{\perp}$	$SMB^{\perp}$	$HML^{\perp}$	$WML^{\perp}$	$BMG^{\perp}$		
Low	−0.001	1.138***	0.086	0.072	−0.247***	−0.241***	95.32	1.60***
2	0.001	1.007***	0.053	0.119**	−0.169***	−0.212***	95.61	1.58***
3	0.002**	1.025***	0.137*	0.076	−0.209***	−0.067	94.59	0.32**
4	0.001	1.043***	0.143*	0.106	−0.183***	−0.022	94.06	0.09
5	0.000	1.013***	0.123	0.147**	−0.215***	0.060	93.55	−0.08
6	0.001	0.953***	0.197**	0.206***	−0.223***	0.206***	93.99	0.26**
7	0.001	1.000***	0.247***	0.180**	−0.225***	0.482***	94.06	3.12***
8	0.000	1.104***	0.262***	0.252***	−0.362***	0.539***	94.45	2.93***
9	−0.003**	1.093***	0.155	0.204**	−0.256***	0.740***	93.06	6.88***
High	−0.001	1.122***	0.322**	0.292***	−0.383***	1.091***	91.52	12.47***

Panel B. Decomposition of R^2 on deciles level

Decile	Decomposed-R^2 (%)					Systematic R^2 (%)	Idiosyncratic variance (1-R^2) (%)
	$er_M^{\perp}$	$SMB^{\perp}$	$HML^{\perp}$	$WML^{\perp}$	$BMG^{\perp}$		
Low	92.76	0.06	0.06	1.73	0.99	95.60	4.40
2	93.59	0.03	0.23	1.04	0.98	95.88	4.12
3	93.00	0.20	0.09	1.54	0.10	94.92	5.08
4	92.89	0.21	0.17	1.13	0.01	94.41	5.59
5	91.73	0.16	0.34	1.63	0.08	93.94	6.06
6	90.19	0.46	0.74	1.96	1.00	94.35	5.65
7	86.78	0.64	0.49	1.74	4.76	94.42	5.58
8	85.04	0.58	0.77	3.61	4.79	94.79	5.21
9	82.11	0.20	0.50	1.78	8.89	93.48	6.52
High	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 Brown-Green-Score (BGS) of the stocks in the BGS data sample for the sample period. The 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: $\beta_i^{BMG} = 0$). Panel B shows the decomposed-R^2 of each democratically orthogonalized factor for the global BGS-deciles. The systematic variance is the sum of all decomposed-R^2s, 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 factors

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

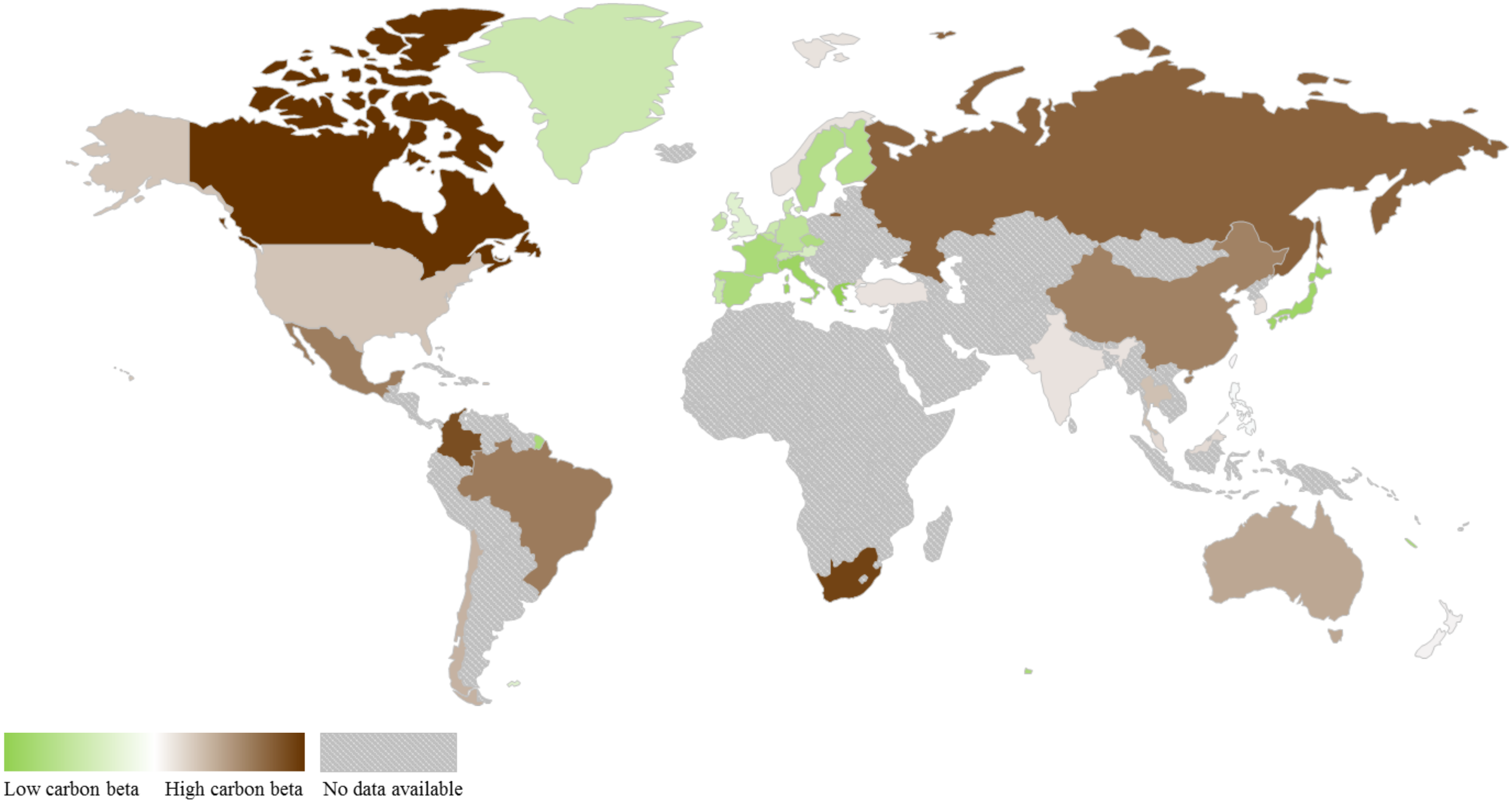
Avg. decomposed-R^2 (%)					Avg. systematic R^2 (%)	Avg. idiosyncratic variance (1-R^2) (%)
$er_M^{\perp}$	$SMB^{\perp}$	$HML^{\perp}$	$WML^{\perp}$	$BMG^{\perp}$		
12.31	2.30	1.73	1.87	2.42	20.63	79.37

Panel B. Significance tests for orthogonalized factor betas for the 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

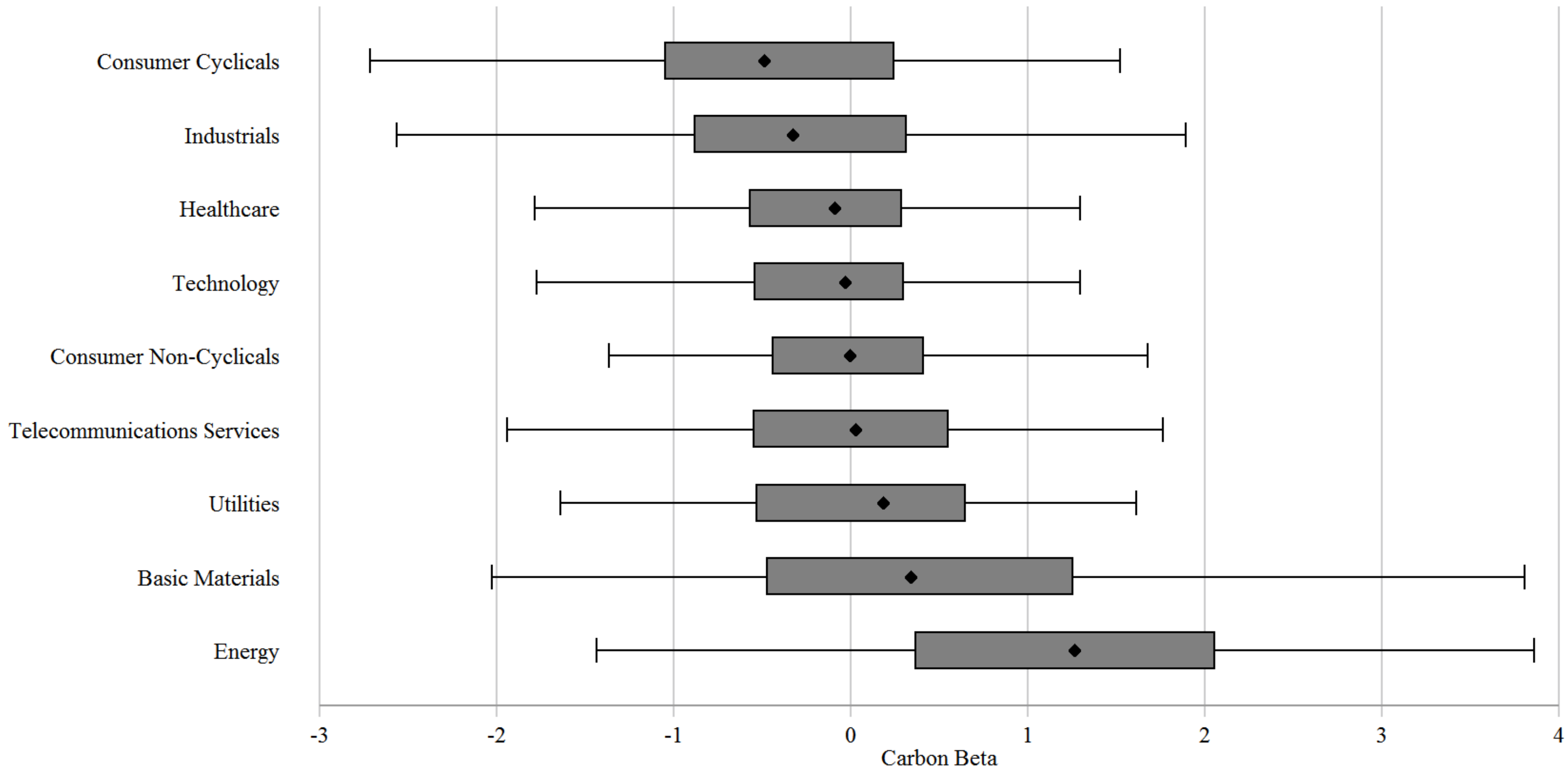
This table provides a comparison of common regression models with orthogonalized factors. Panel A shows the average decomposed-R^2 values of orthogonalized factors. Regressions are run based on the Carhart + BMG model with single stocks from the full sample. Furthermore, the average systematic R^2 and 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 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



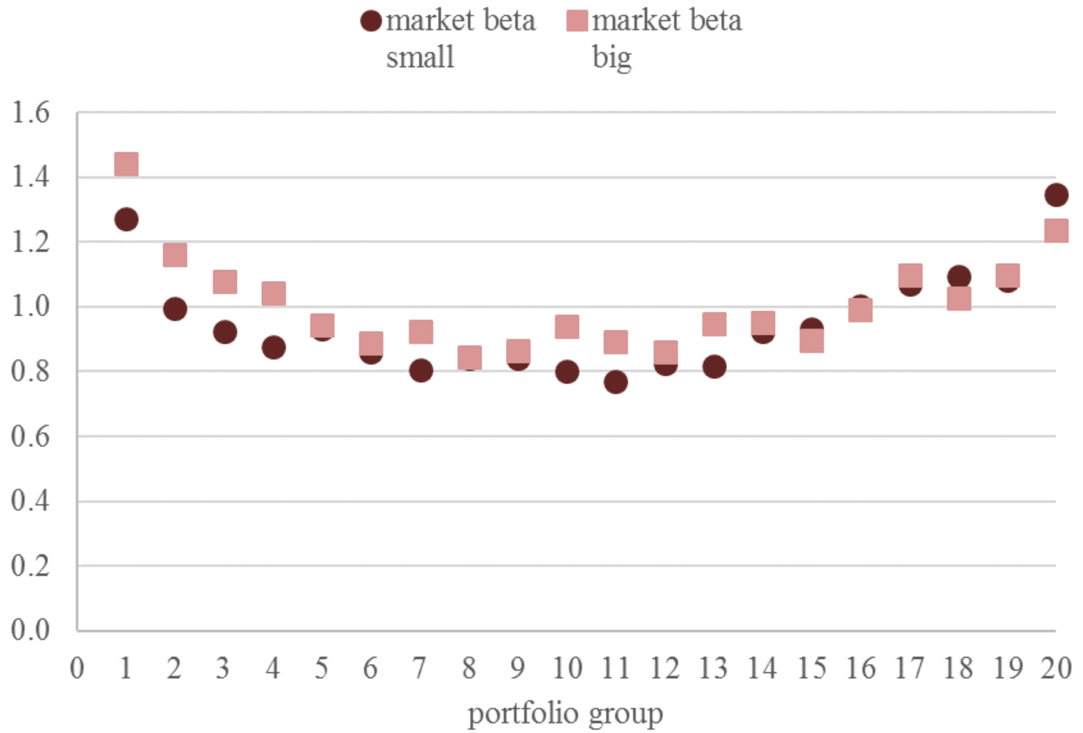
This figure shows the carbon beta of the BGS data sample across the world. We include all countries with at least 30 firms in our BGS data sample to correct for outliers. A greenish color indicates a low average carbon beta of the country, whereas a deep brown color states that, on average, the country's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

Figure IA.2
Carbon beta industry breakdown



This figure shows the carbon beta of the BGS data sample across sectors. The sectoral breakdown is based on the Thomson Reuters Business Classification (TRBC). The diamonds indicate the median carbon beta per industry. The left and right box edges indicate the lower and upper quartiles, respectively. The whiskers indicate the minimum and maximum carbon betas within 1.5 times the interquartile ranges. The sectors are sorted in ascending order by their carbon beta.

Figure IA.3
CAPM betas of 40 carbon beta sorted portfolios



This figure shows the market beta of the 40 test assets built out of the full sample. The 40 test assets are constructed by sorting all stocks into 20 5%-quantiles based on their carbon beta (portfolio group) and splitting each portfolio by the stocks' median market capitalization.