Carbon Risk*

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

JEL classification: G12; G15; Q51; Q54

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1. Introduction

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

In this paper, we study the relationship between carbon risk and equity prices. In the first part of the paper, we determine the greenness or brownness of a firm – the Brown-Green-Score (BGS) – as a fundamental measure for carbon risk. In the second part, we study carbon risk in equity prices through the lens of a factor-based asset pricing model by constructing the Brown-

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

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

Minus-Green (BMG) portfolio. In the last part, we conduct a formalized test for a priced carbon risk premium.

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

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

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

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

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

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

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

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

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

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

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

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

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

The remainder of this paper is structured as follows. Section 2 presents the data sources. Section 3 contains our methodology for carbon risk measurement and panel regressions to infer the relationship between carbon risk and equity prices. Section 4 contains test to determine the relevance of the carbon risk factor in an asset pricing context. Section 5 analyzes the missing carbon risk premium followed by some robustness tests in section 5. Section 7 concludes.

2. Data

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

Measuring carbon risk in the financial market requires the knowledge of fundamental carbon and transition-related information. For this reason, we merge this information from four major ESG databases to our global stock data: (i) the Carbon Disclosure Project (CDP) Climate Change questionnaire dataset, (ii) the MSCI ESG Stats and the IVA ratings, (iii) the Sustainalytics ESG Ratings data and carbon emissions datasets, and (iv) the Thomson Reuters ESG dataset. We minimize a potential self-reporting bias by using four ESG databases with different approaches in collecting data including estimations by analysts.

We select variables from a total of 785 ESG variables to measure carbon risk in stocks. Leaving out social and governance aspects, 363 variables thereof are potentially useful for describing environmental issues. 131 of the broader environmental variables are directly related to carbon and climate transition issues as opposed to, e.g., waste or water pollution. Thereof, we select ten variables that potentially have the most impact on the financial market via return adjustments and explain the triad of value chain, public perception, and adaptability in our concept (see section 3.1). For example, we take into account carbon emissions, since they are the main target of policy measures to mitigate climate change. They are therefore one of the key measures for a firm's brownness. Second, we focus on environmental pillar scores of each of the four databases, as they are most prominent in public and thus can function as readily available decision criteria for investors. Third, we use scores that mirror the environmental friendliness of internal firm processes and therefore future profitability when taking climate change into account. Choosing ten distinct variables does not only eliminate empirically redundant data points, but also ensures to create a straightforward and easily traceable concept for measuring the impact of climate change on the financial market.

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

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

[Insert Table 1 here.]

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

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

3. Carbon risk in equity prices

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

3.1. Carbon risk measurement methodology

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

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

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

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

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

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

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

The final selection of variables, the mapping of the proxy variables to the risk indicators, and the aggregation of the subscores is the result of two workshops hosted for this purpose with acknowledged sustainability and finance experts from international institutions, consultancies,

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

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

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

universities, asset managers, and NGOs. The variable selection was also subject to data availability and statistical analyses. The weighting scheme has been tested for robustness and our results remain economically similar.

3.2. Panel regressions

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

$$r_{i,t} = \alpha_i + \beta_{i,1} BGS_t + \beta_{i,2} (BGS_t - BGS_{t-1}) + \delta_i Controls_t \qquad (2)$$

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

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

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

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

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

[Insert Table 2 here.]

To better understand differences in brown and green firms, we calculate average annual changes in all variables used to construct the BGS, the respective subscores, and the BGS itself. Table 3 demonstrates that both brown and green firms have become greener over our sample period from 2010 to 2017. However, green firms have become significantly greener than brown firms. For instance, green firms reduced their carbon intensity on average by 15.95%, whereas brown firms reduced their carbon intensity by solely 1.90% per year. This remarkable difference is mirrored in the value chain subscore with a difference of 14.06% between the changes of brown and green firms. All variables except the Environmental Innovation Score show the same pattern. Overall, green firms have reduced their BGS by 4.00% more than brown firms.

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

[Insert Table 3 here.]

4. Relevance of the carbon risk factor BMG

To strengthen the understanding of the relationship between equity prices and carbon risk, we make use of asset pricing theory. Many factor and factor mimicking portfolio papers in the asset pricing literature are seen critically regarding their future impact and relevance. Even though we propose a new factor, we do not want to end up being perceived as another animal of the factor zoo (Cochrane, 2011).[8] Our aim is to develop a framework for measuring and understanding carbon risk in equity prices. Thus, we show the construction and relevance of the BMG factor by following common composition methods and latest asset pricing tests.

4.1. The BMG factor – A mimicking factor portfolio for carbon risk

The BMG portfolio is constructed to mimic a factor related to carbon risk similar in intuition to the Fama and French (1993) size and book-to-market factors. For the construction of the BMG portfolio, we determine the annual BGS for each firm. Subsequently, each year we unconditionally allocate all firms into six portfolios based on their market equity (size) and the BGS using the median and terciles as breakpoints, respectively. We use the value-weighted average monthly returns of the four portfolios "small/high BGS" (SH), "big/high BGS" (BH),

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

"small/low BGS" (SL), and "big/low BGS" (BL) to calculate the BMG factor following Equation (3). Thus, BMG_t is the return in month t of a zero-cost portfolio that is long in brown firms and short in green firms.

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

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

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

[Insert Figure 1 here.]

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

[Insert Table 4 here.]

4.2. BGS quintile portfolio analysis

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

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

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

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

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

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

[Insert Table 5 here.]

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

4.3. Comparison of common factor models

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

[Insert Table 6 here.]

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

4.4. Asset pricing tests

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

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

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

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

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

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

[Insert Table 7 here.]

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

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

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

5. The missing carbon risk premium

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

5.1. Cross-sectional regressions

This section tests whether the BMG factor is a priced risk factor. We run a cross-sectional regression using the methodology of Fama and MacBeth (1973) on single stock level. For this purpose, we estimate 36-month-rolling-window coefficients in the first step, and then regress individual stock returns on the estimated coefficient values. Since the Fama and MacBeth

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

(1973) procedure is prone to the errors-in-variables (EIV) problem, we follow the EIV correction of Pukthuanthong et al. (2019). We thus use the returns of double-sorted portfolios as dependent variable.[15] First, each year in June, we sort all stocks based on their market capitalization into deciles. Second, within each size decile, we sort the respective stocks further into deciles based on their estimated OLS beta of each factor resulting in 100 size/beta portfolios for each factor. Then, for example, the average market beta of each size/beta portfolio is assigned to all stocks in the respective portfolio. This procedure is repeated for all of the other factor betas. Cross-sectional regressions are run with individual stock returns on the left hand side and the assigned beta values on the right hand side.

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

[Insert Table 8 here.]

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

5.2. A risk decomposition of the BMG factor and beta portfolios

To further evaluate the non-existence of a risk premium, we analyze the economic mechanisms driving the BMG factor and the market beta of BMG beta sorted portfolios. We follow the decomposition approaches of Campbell (1991) and Campbell and Vuolteenaho (2004).[16] The analysis is geared towards understanding whether changes in expectations about firm cash flows or changes in discount rates are driving the BMG factor and BMG beta sorted portfolios.

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

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

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

process of the economy that is highly sensitive to changes in technologies (investments) and customers' preferences for goods and services (revenues).

[Insert Table 9 here.]

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

[Insert Figure 2 here.]

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

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

We evaluate the prices of cash-flow and discount-rate beta risk following Campbell and Vuolteenaho (2004). Rational investors should demand higher compensation for fundamental and therefore permanent cash-flow shocks ("bad beta") than for transitory discount-rate shocks ("good beta"). In Table 10, we apply the asset pricing models described in Campbell and Vuolteenaho (2004) to our 40 BMG beta/size sorted test asset portfolios to analyze this hypothesis. We show results of an unrestricted factor model and a two-factor ICAPM that restricts the price of the discount-rate beta to the variance of the market return. Like Campbell and Vuolteenaho (2004), we estimate both models with and without a constant to account for different assumptions about the risk-free rate. For our sample period, the price for cash-flow beta risk amounts to –26.61% per year for the unrestricted factor model. The price for discount-rate beta risk is 76.53% per year. Hence, for our sample period, the "good beta" demands a risk premium compared to the "bad beta".[17] This result remains stable for the restricted factor model and the unrestricted two-beta ICAPM. The restricted two-beta ICAPM shows a bad fit for our sample period (R^2 of –0.694) and thus should not be given great importance.

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

[Insert Table 10 here.]

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

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

6. Robustness tests

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

[Insert Table 11 here.]

Table 11 provides a BMG beta landscape and descriptive statistics of the BMG beta distribution globally. First, we calculate the average BMG beta for each country with at least 30 firms within our sample. Second, we assign all countries according to their BMG beta into terciles (brown, neutral, and green) to create the figure in Panel A. Brown countries are mainly fossil and resource dominated economies like, e.g., Canada, Brazil, South Africa, Russia, Australia, or China. In contrast, European countries are mainly green having on average low BMG betas whereas the United States, Poland, Turkey, or Argentina are neutral countries with

BMG betas around zero. Panel B provides further information on the average BMG beta for major countries. It is particularly interesting that all countries have green and brown firms according to the BMG beta, the distribution differs, however. This leads to the question whether we can find a carbon risk premium in different regions.

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

[Insert Table 12 here.]

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

7. Conclusion

The scientific consensus is clear on the link between greenhouse gas emissions and climate change. Investors, firms, regulators, and the general public have been slow to recognize the financial risks associated with climate change despite the seemingly obvious relationship

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

[19] We provide results upon request.

between human activities and a warming planet. Our paper takes a step towards quantifying carbon risk for a broad cross-section of firms across the globe and time.

Our BMG factor explains systematic variation in returns as well as other common risk factors. Surprisingly, we find no evidence of a risk premium associated with carbon risk. This is the case for a number of reasons. First, carbon risk may not be priced because investors are unable to adequately predict or quantify carbon risk. We show that brown firms are associated with higher returns and that when firms become relatively browner their returns are lower. Second, we show that green firms are becoming greener faster that brown firms, leading green firms to outperform brown firms. We also show that green and brown firm carbon risk is better explained by unpriced fundamental re-evaluations of firm cash flows than by priced discount-rate changes. These results are in line with the theoretical model of Pástor et al. (2020) and adds to the understanding of the functioning of carbon risk.

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

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

References

Acemoglu, D., Aghion, P., Bursztyn, L., Hemous, D., 2012. The Environment and directed technical change. American Economic Review, 102 (1), 131-166. DOI: 10.1257/aer.102.1.131.

Alok, S., Kumar, N., Wermers, R., 2020. Do Fund Managers Misestimate Climatic Disaster Risk? Review of Financial Studies, 33 (3), 1146-1183. https://doi.org/10.1093/rfs/hhz143.

Baker, M., Bergstresser, D., Serafeim, G., Wurgler, J., 2018. Financing the Response to Climate Change: The Pricing and Ownership of U.S. Green Bonds. NBER Working Paper Series, No. 25194, October 2018. DOI: 10.3386/w25194.

Bakkensen, L., Barrage, L., 2018. Flood risk belief heterogeneity and coastal home price dynamics: Going under water? NBER Working Paper Series, No. 23854, October 2018. DOI: 10.3386/w23854.

Baldauf, M., Garlappi, L., Yannelis, C., 2020. Does climate change affect real estate prices? Only if you believe in it. Review of Financial Studies, 33 (3), 1256-1295. https://doi.org/10.1093/rfs/hhz073.

Barillas, F., Shanken, J., 2017. Which alpha? Review of Financial Studies, 30 (4), 1316-1338. https://doi.org/10.1093/rfs/hhw101.

Barnett, M., Brock, W., Hansen, L., 2020. Pricing Uncertainty Induced by Climate Change. Review of Financial Studies, 33 (3), 1024-1066. https://doi.org/10.1093/rfs/hhz144.

Bernstein, A., Gustafson, M., Lewis, R., 2019. Disaster on the Horizon: The Price Effect of Sea Level Rise. Journal of Financial Economics, 134 (2), 253-272. https://doi.org/10.1016/j.jfineco.2019.03.013.

Bolton, P., Kacperczyk, M.T., 2020. Do Investors Care about Carbon Risk? Working Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3398441.

Byun, S. K., Oh, J. M., 2018. Local Corporate Social Responsibility, Media Coverage, and Shareholder Value. Journal of Banking & Finance, 87, 68-86. https://doi.org/10.1016/j.jbankfin.2017.09.010.

Cahan, S. F., Chen, C., Chen, L., Nguyen, N. H., 2015. Corporate Social Responsibility and Media Coverage. Journal of Banking & Finance, 59, 409-422. https://doi.org/10.1016/j.jbankfin.2015.07.004.

Campbell, J. Y., 1991. A Variance Decomposition for Stock Returns. The Economic Journal, 101 (405), 157-179. https://www.jstor.org/stable/2233809.

Campbell, J. Y., Giglio, S., Polk, C., 2013. Hard Times. The Review of Asset Pricing Studies, 3 (1), 95-132. https://doi.org/10.1093/rapstu/ras026.

Campbell, J. Y., Vuolteenaho, T., 2004. Bad Beta, Good Beta. American Economic Review, 94 (5), 1249-1275. https://www.aeaweb.org/articles?id=10.1257/0002828043052240.

Carhart, M. M., 1997. On persistence in mutual fund performance. The Journal of Finance, 52 (1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x.

Chava, S., 2014. Environmental externalities and cost of capital. Management Science, 60 (9), 2223-2247. https://doi.org/10.1287/mnsc.2013.1863.

Chen, L., Zhao, X., 2009. Return decomposition. The Review of Financial Studies, 22 (12), 5213-5249. https://www.jstor.org/stable/40468342.

Choi, D., Gao, Z., Jiang, W., 2020. Attention to global warming. Review of Financial Studies, 33 (3), 1112-1145. https://doi.org/10.1093/rfs/hhz086.

Cochrane, J.H. (2011) Presidential Address: Discount Rates. Journal of Finance, 66 (4), 1047-1108. https://doi.org/10.1111/j.1540-6261.2011.01671.x.

Connor, G., Korajczyk, R.A., 1988. Risk and Return in an Equilibrium APT: Application of a New Test Methodology. Journal of Financial Economics, 21 (2), 255-289. https://doi.org/10.1016/0304-405X(88)90062-1.

Daniel, K., Titman, S., 2012. Testing Factor-Model Explanations of Market Anomalies. Critical Finance Review, 1, 103-139. http://dx.doi.org/10.1561/104.00000003.

Daniel, K., Titman, S., 1997. Evidence on the Characteristics of Cross Sectional Variation in Stock Returns. The Journal of Finance, 52 (1), 1-33. https://doi.org/10.1111/j.1540-6261.1997.tb03806.x.

De Haan, M., Dam, L., Scholtens, B., 2012. The drivers of the relationship between corporate environmental performance and stock market returns. Journal of Sustainable Finance & Investment, 2 (3-4), 338-375. DOI: 10.1080/20430795.2012.738601.

Delis, M. D., de Greiff, K., Ongena, S., 2020. Being Stranded with Fossil Fuel Reserves? Climate Policy Risk and the Pricing of Bank Loans. Swiss Finance Institute Research Paper Series, No. 18-10.

Deng, X., Kang, J. K., Low, B. S., 2013. Corporate Social Responsibility and Stakeholder Value Maximization: Evidence from Mergers. Journal of Financial Economics, 110 (1), 87-109. https://doi.org/10.1016/j.jfineco.2013.04.014.

El Ghoul, S., Guedhami, O., Kwok, C. C., Mishra, D. R., 2011. Does corporate social responsibility affect the cost of capital? Journal of Banking & Finance, 35 (9), 2388-2406. https://doi.org/10.1016/j.jbankfin.2011.02.007.

Engle, R., Giglio, S., Kelly, B., Lee, H., Stroebel, J., 2020. Hedging Climate Change News. Review of Financial Studies, 33 (3), 1184-1216. https://doi.org/10.1093/rfs/hhz072.

Fama, E. F., French, K. R., 2018. Choosing factors. Journal of Financial Economics, 128 (2), 234-252. https://doi.org/10.1016/j.jfineco.2018.02.012.

Fama, E. F., French, K. R., 2016. Dissecting anomalies with a five-factor model. The Review of Financial Studies 29 (1), 69-103. https://doi.org/10.1093/rfs/hhv043.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics, 116 (1), 1-22. https://doi.org/10.1016/j.jfineco.2014.10.010.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics, 33 (1), 3–56. https://doi.org/10.1016/0304-405X(93)90023-5.

Fama, E.F., MacBeth, J.D., 1973. Risk, Return, and Equilibrium: Empirical Tests. Journal of Political Economy, 81 (3), 607-636. https://doi.org/10.1086/260061.

Faruk, A. C., Lamming, R. C., Cousins, P. D., Bowen, F. E., 2001. Analyzing, mapping, and managing environmental impacts along supply chains. Journal of Industrial Ecology, 5 (2), 13-36. https://doi.org/10.1162/10881980152830114.

Fatemi, A., Fooladi, I., Tehranian, H., 2015. Valuation effects of corporate social responsibility. Journal of Banking & Finance, 59, 182-192. https://doi.org/10.1016/j.jbankfin.2015.04.028.

Feng, G., Giglio, S., Xiu, D., 2020. Taming the Factor Zoo: A Test of New Factors. Journal of Finance, 75 (3), 1327-1370. https://doi.org/10.1111/jofi.12883.

Fernando, C. S., Sharfman, M. P., Uysal, V. B., 2017. Corporate environmental policy and shareholder value: Following the smart money. Journal of Financial and Quantitative Analysis, 52 (5), 2023-2051. https://doi.org/10.1017/S0022109017000680.

Gibbons, M. R., Ross, S. A., Shanken, J., 1989. A Test of The Efficiency of a Given Portfolio. Econometrica, 57 (5), 1121-1152. https://www.jstor.org/stable/1913625.

Giglio, S., Maggiori, M., Stroebel, J., Weber, A., 2018. Climate Change and Long-Run Discount Rates: Evidence from Real Estate. NBER Working Paper Series, No. 21767. DOI: 10.3386/w21767.

Hartzmark, S. M., Sussman, A. B., 2019. Do investors value sustainability? A natural experiment examining ranking and fund flows. The Journal of Finance, 74 (6), 2789–2837. https://doi.org/10.1111/jofi.12841.

Harvey, C. R., Liu, Y., 2020. Lucky Factors. Working Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2528780.

Hong, H., Li, F., Xu, J., (2019) Climate Risks and Market Efficiency. Journal of Econometrics, 208 (1), 265–281. https://doi.org/10.1016/j.jeconom.2018.09.015

Hou, K., Karolyi, G.A., Kho, B., 2011. What Factors Drive Global Stock Returns? Review of Financial Studies, 24 (8), 2527-2574. https://doi.org/10.1093/rfs/hhr013.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. The Review of Financial Studies 28 (3), 650-705. https://doi.org/10.1093/rfs/hhu068.

Ilhan, E., Sautner, Z., Vilkov, G., 2020. Carbon tail risk. Review of Financial Studies, forthcoming.

Ince, O. S., Porter, R. B., 2006. Individual equity return data from Thomson Datastream: Handle with care! Journal of Financial Research 29 (4), 463–479. https://doi.org/10.1111/j.1475-6803.2006.00189.x.

IPCC, 2014. Climate change 2014: Synthesis report. Contribution of Working Groups I, II, and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. https://www.ipcc.ch/report/ar5/syr/.

İşlegen, Ö., Reichelstein, S., 2011. Carbon capture by fossil fuel power plants: An economic analysis. Management Science, 57 (1), 21-39. https://doi.org/10.1287/mnsc.1100.1268.

Jegadeesh, N., Noh, J., Pukthuanthong, K., Roll, R., Wang, J., 2019. Empirical tests of asset pricing models with individual assets: Resolving the errors-in-variables bias in risk premium estimation. Journal of Financial Economics, 133 (2), 273-298. https://doi.org/10.1016/j.jfineco.2019.02.010.

Klein, R. F., Chow, V. K., 2013. Orthogonalized factors and systematic risk decomposition. The Quarterly Review of Economics and Finance 53 (2), 175-187. https://doi.org/10.1016/j.qref.2013.02.003.

Krüger, P., 2015. Corporate goodness and shareholder wealth. Journal of Financial Economics, 115 (2), 304-329. https://doi.org/10.1016/j.jfineco.2014.09.008.

Krüger, P., Sautner, Z., Starks, L. T., 2020. The importance of climate risks for institutional investors. Review of Financial Studies, 33 (3), 1067-1111. https://doi.org/10.1093/rfs/hhz137.

Kumar, A., Xin, W., Zhang, C., 2019. Climate Sensitivity and Predictable Returns. Working Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3331872.

Kutner, M. H., Nachtsheim, C. J., Neter J., Li, W., 2005. Applied Linear Statistical Models. Fifth Edition, McGraw-Hill Irwin.

Liang, H., Renneboog, L., 2017. On the foundations of corporate social responsibility. The Journal of Finance, 72 (2), 853-910. https://doi.org/10.1111/jofi.12487.

Lins, K. V., Servaes, H., Tamayo, A., 2017. Social capital, trust, and firm performance: The value of corporate social responsibility during the financial crisis. The Journal of Finance, 72 (4), 1785-1824. https://doi.org/10.1111/jofi.12505.

Lo, A.W., MacKinlay, A.C., 1990. Data-Snooping Biases in Tests of Financial Asset Pricing Models. Review of Financial Studies, 3 (3), 431-467. https://www.jstor.org/stable/2962077.

Lyubich, E., Shapiro, J. S., Walker, R., 2018. Regulating Mismeasured Pollution: Implications of Firm Heterogeneity for Environmental Policy. AEA Papers and Proceedings, 108, 136-142. DOI: 10.1257/pandp.20181089.

Maio, P., 2013. Intertemporal CAPM with Conditioning Variables. Management Science, 59 (1), 122-141. https://doi.org/10.1287/mnsc.1120.1557.

Martin, R., Muûls, M., De Preux, L. B., Wagner, U. J., 2014. Industry compensation under relocation risk: A firm-level analysis of the EU emissions trading scheme. American Economic Review, 104 (8), 2482-2508. DOI: 10.1257/aer.104.8.2482.

Matsumura, E. M., Prakash, R., Vera-Muñoz, S.C., 2014. Firm-value effects of carbon emissions and carbon disclosures. The Accounting Review, 89 (2), 695-724. https://doi.org/10.2308/accr-50629.

Monasterolo, I., De Angelis, L., 2020. Blind to Carbon Risk? An Analysis of Stock Market's Reaction to the Paris Agreement. Ecological Economics, 170, 1-9. https://doi.org/10.1016/j.ecolecon.2019.106571.

NASA, 2019. Scientific Consensus: Earth's Climate is Warming. https://climate.nasa.gov/scientific-consensus/.

Oestreich, A. M., Tsiakas, I., 2015. Carbon emissions and stock returns: Evidence from the EU emissions trading scheme. Journal of Banking & Finance, 58, 294-308. https://doi.org/10.1016/j.jbankfin.2015.05.005.

Ortega, F., Taspinar, S., 2018. Rising Sea Levels and Sinking Property Values: Hurricane Sandy and New York's Housing Market. Journal of Urban Economics, 106, 81-100. https://doi.org/10.1016/j.jue.2018.06.005

Pástor, L., Stambaugh, R., Taylor, L., 2020. Sustainable Investing in Equilibrium. NBER Working Paper Series, No. 26549.

Pukthuanthong, K., Roll, R., Subrahmanyam, A., 2019. A Protocol for Factor Identification. Review of Financial Studies, 32 (4), 1573-1607. https://doi.org/10.1093/rfs/hhy093.

Rainforest Action Network, BankTrack, the Sierra Club, Oil Change International, 2019. Banking on Climate Change. Fossil Fuel Finance Report Card 2019.

Rehse, D., Riordan, R., Rottke, N., Zietz, J., 2019. The effects of uncertainty on market liquidity: Evidence from Hurricane Sandy. Journal of Financial Economics, 134 (2), 318–332. https://doi.org/10.1016/j.jfineco.2019.04.006.

Schmidt, P.S., von Arx, U., Schrimpf, A., Wagner, A.F., Ziegler, A., 2019. Common Risk Factors in International Stock Markets. Financial Markets and Portfolio Management, 33 (3), 213–241. https://doi.org/10.1007/s11408-019-00334-3.

World Bank Group, 2019. State and Trends of Carbon Pricing 2019. Washington DC, June 2019.

Xu, L., Wang, C., Li, H., 2017. Decision and coordination of low-carbon supply chain considering technological spillover and environmental awareness. Scientific Reports, 7 (3107), 1-14. https://doi.org/10.1038/s41598-017-03270-2.

Figures and Tables

Table 1
Descriptive statistics of variables

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

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

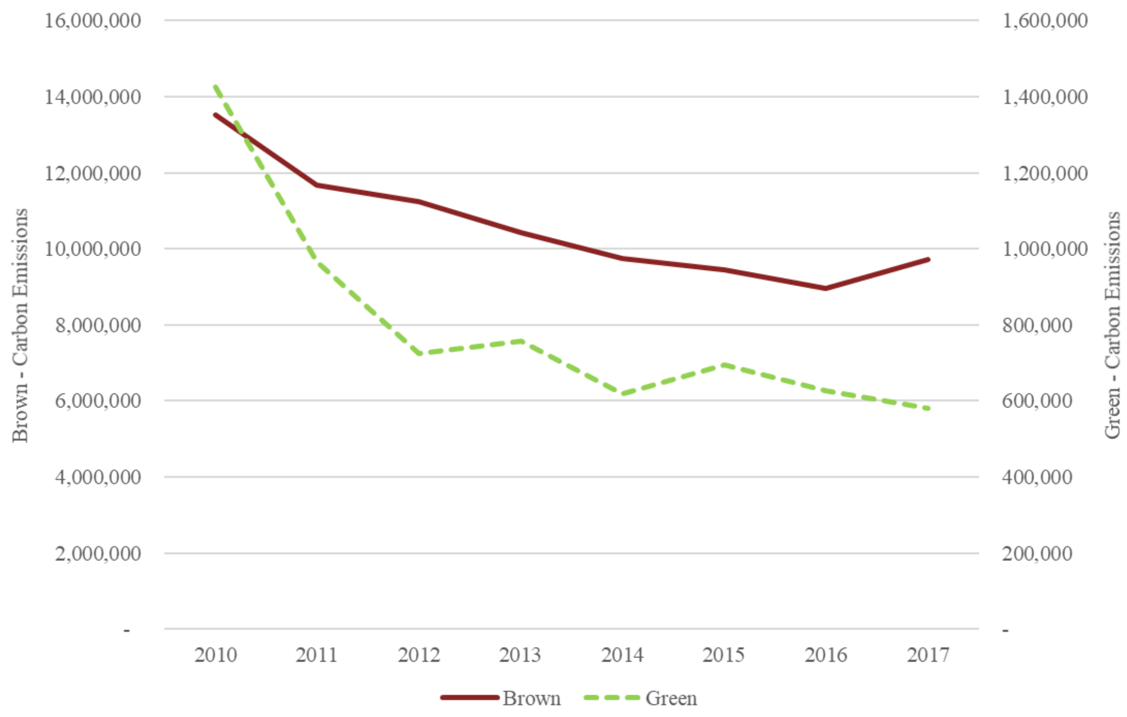
Table 2
Panel regressions

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

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

Table 3
Development of brown and green firms

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

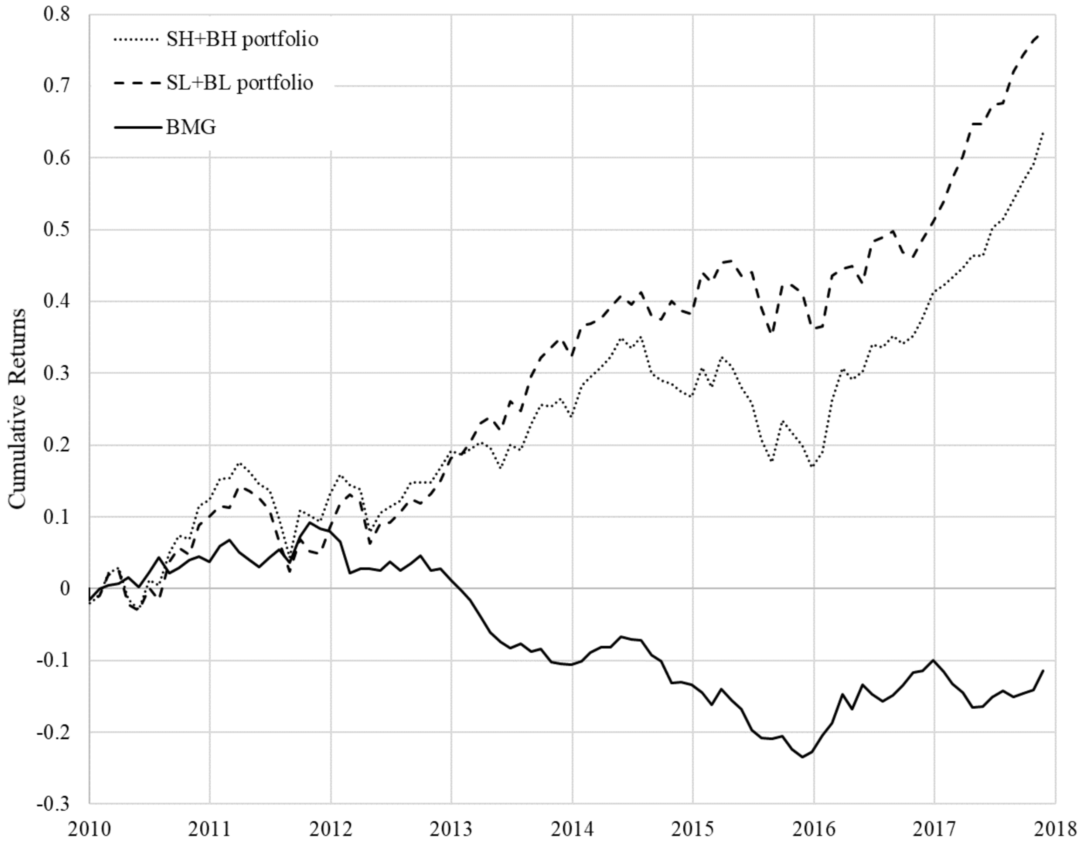


Panel B. Development of carbon and transition-related variables of brown and green firms

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

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

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



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

Table 4
Factor descriptive statistics and correlations

Panel A. Carhart and BMG

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

Panel B. Fama/French 5F and BMG

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

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

Table 5
BGS quintile portfolio performance

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

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

Table 6
Comparison of common factor models

Panel A. Significance tests for explanatory power of various models

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

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

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

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

Table 7
Asset pricing tests

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

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

Table 8
Cross-sectional regressions

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

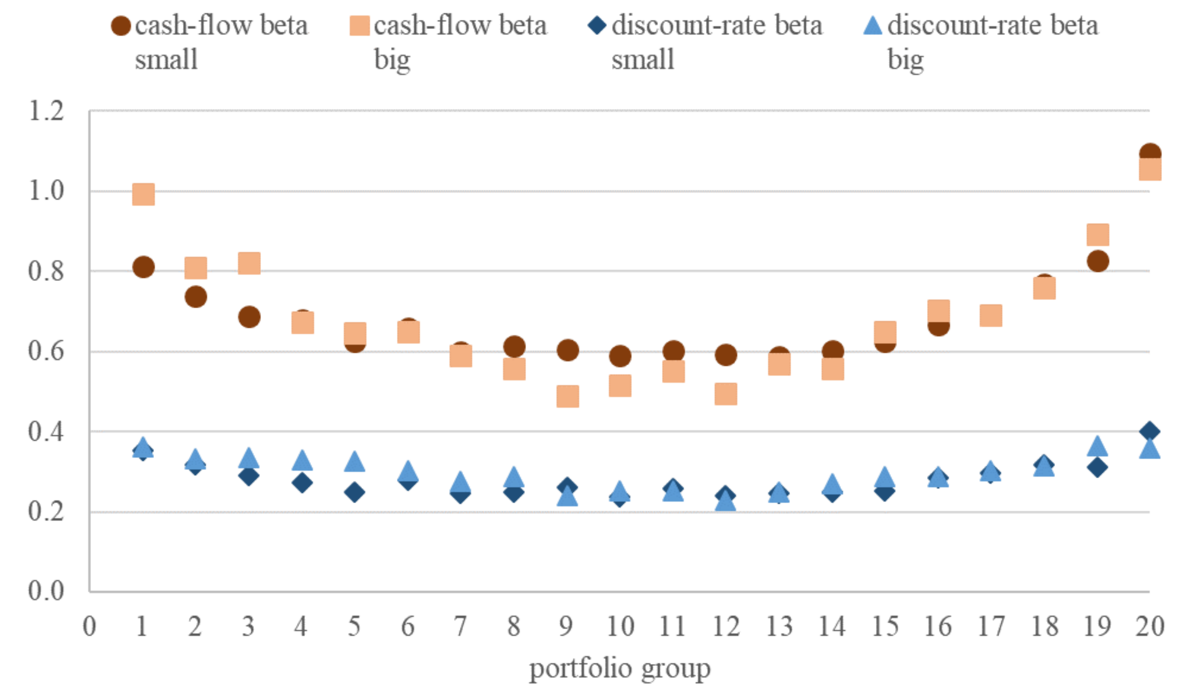
This table shows results of cross-sectional Fama and MacBeth (1973) regressions. We follow the implementation of Pukthuanthong et al. (2019) and use two different methodologies. First, we simply conduct single-stock cross-sectional regressions (no EIV correction). Second, we us double sorted portfolios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

Table 9
Variance decomposition

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

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

Figure 2
Beta decomposition of 40 BMG beta sorted portfolios



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

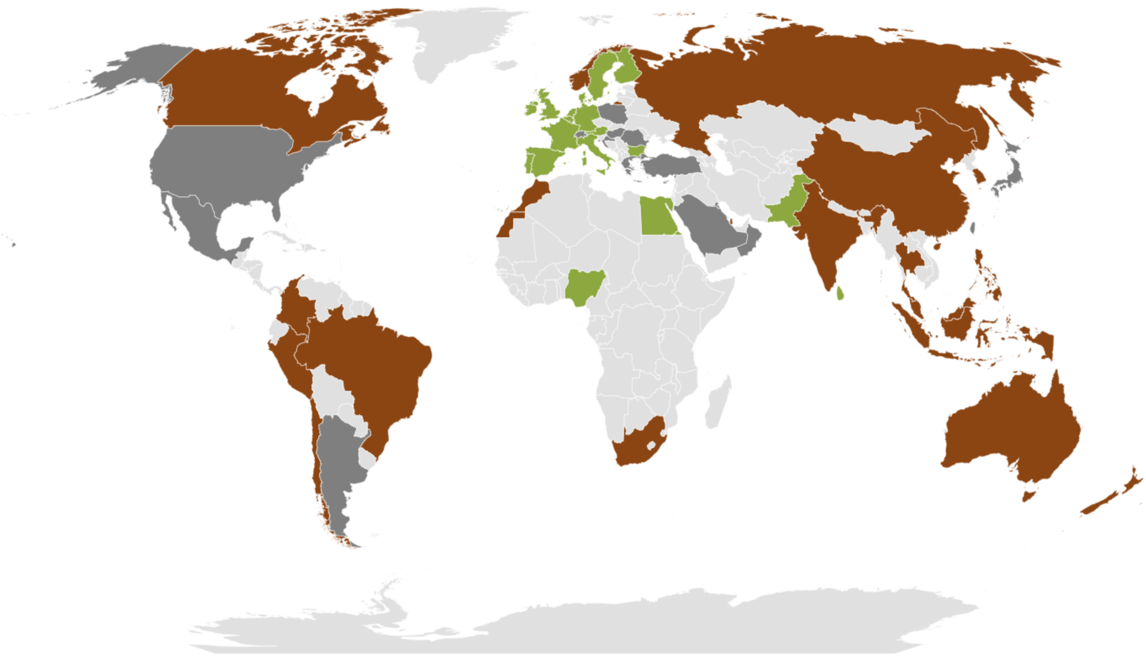
Table 10
Pricing cash-flow and discount-rate betas

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

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

Table 11
Global breakdown of BMG beta

Panel A. BMG beta landscape



Panel B. BMG beta in major countries

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

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

Table 12
Regional cross-sectional regressions

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

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

Internet Appendix

Internet Appendix A: Further descriptive statistics

Table A.1
Geographic and sectoral breakdown of data sample

Panel A. Geographic			**Panel B. Sectoral**			
Country	#	%	Sector	TRBC	#	%
United States	419	25.29	Industrials	52	374	22.57
Japan	231	13.94	Cyclical Consumer Goods & Services	53	281	16.96
United Kingdom	192	11.59	Basic Materials	51	242	14.60
Canada	98	5.91	Technology	57	193	11.65
Australia	74	4.47	Non-Cyclical Cons. Goods & Services	54	169	10.20
France	70	4.22	Energy	50	122	7.36
South Africa	59	3.56	Healthcare	56	108	6.52
Germany	54	3.26	Utilities	59	105	6.34
Taiwan	47	2.84	Telecommunications Services	58	63	3.80
South Korea	35	2.11				
Other Europe	249	15.03				
Other Asia	80	4.83				
Other Americas	37	2.23				
Other Australasia	12	0.72				
Total	1,657	100.00	Total		1,657	100.00

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

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

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

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

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

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

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

Table A.3
Transition probabilities of firms

Panel A. from year t − 1 to year t

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

Panel B. from year t − 5 to year t

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

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

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

Internet Appendix B: Further asset pricing tests

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

[Insert Table B.1 here.]

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

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

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

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

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

LHS	Alpha	er_M	SMB	HML	Mean |Alpha|	Adj. R^2
WML	0.55	-0.0880	-0.0190	-0.516***	0.1375	0.139
	(2.37)	(-1.45)	(-0.11)	(-3.71)		
BMG	-0.000967	-0.00160	0.0898	0.300***	0.0002418	0.059
	(-0.56)	(-0.04)	(0.71)	(2.89)		

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

LHS	Alpha	er_M	SMB	HML	Mean |Alpha|	Adj. R^2
RMW	0.377	-0.116***	-0.305***	-0.316***	0.1885	0.514
	(4.37)	(-5.16)	(-4.77)	(-6.08)		
CMA	0.148	-0.0477**	-0.0458	0.352***	0.074	0.514
	(1.71)	(-2.10)	(-0.71)	(6.72)		
BMG	-0.104	0.0000499	0.0903	0.293***	0.052	0.060
	(-0.60)	(0.00)	(0.70)	(2.80)		

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

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

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

In this section, we stick to the "Protocol for Factor Identification" of Pukthuanthong et al. (2019) and follow their two-step procedure. For the first stage, we show that the BMG factor moves asset prices systematically, i.e. that it is related to the covariance matrix of returns – a necessary condition for a factor to be relevant. We deal with the second stage in section 5.1.

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

Next, we compute canonical correlations between the PCs and factors from the Carhart (1997) model and the BMG factor. In total, we have K = 5 factors. Thus, we have two sets for calculating canonical correlations. Let u_K be the canonical scores out of the set of factors and v_L the canonical scores out of the set of PCs (with L = 13). The procedure now allows to determine weights for the linear combinations of the factors and PCs, respectively, that maximize the correlation between both sets. Thus, a canonical variate that maximizes the correlation using the weights can be constructed. One then repeats this procedure to obtain another canonical variate that is orthogonal to the previous one. In total, there are $\min(K, L)$ canonical variates, i.e. in our case five pairs of u_K and v_L. The canonical correlations are displayed in Panel A of Table B.2 sorted from the highest to the lowest correlation. We also

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

test the canonical correlations for significance according to Wilks' lambda. F-statistics for each canonical correlation are displayed in the third column of Panel A. The first canonical correlation is large and close to one with a value of 0.924. Only the fifth correlation falls below 0.5 and is not significantly different from zero at the 5% level with an F-statistic of 0.951.

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

[Insert Table B.2 here.]

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

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

Panel A. Canonical correlations

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

Panel B. Significance levels for factors

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

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

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

[Insert Table B.3 here.]

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

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

Panel A. Canonical correlations

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

Panel B. Significance levels for factors

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

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

Internet Appendix C: Orthogonalization

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

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

[Insert Table C.1 here.]

Applying the orthogonalized factors to our previous analyses leads to the following conclusions. For the BGS quintile portfolio performance there are basically no changes in our reasoning (Table C.2). Note that although the newly estimated beta coefficients for the orthogonalized factors may change in magnitude and direction, the alpha and the adjusted R^2 values remain the same by construction. However, most values are very similar. In addition, the BMG factor continues to be highly significant for the extreme portfolios and increases monotonically from the lowest to the highest quintile.

[Insert Table C.2 here.]

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

[Insert Table C.3 here.]

Additionally, Table C.4 shows the average decomposed-R^2 values of the orthogonalized factors on single stock level. Single stock regressions are run with the orthogonalized factors of the Carhart + BMG model. The average systematic R^2 sums up to 21.14% and the average idiosyncratic variance obtained from the systematic variance is 78.86%. As expected, the market factor er_M explains the most variation in excess returns with an average decomposed-

R^2 of 12.89%, while $BMG^{\perp}$ is, with an average contribution of 2.28%, approximately on the same level as $SMB^{\perp}$ with 2.38%, and well above the level of $HML^{\perp}$ with 1.68% and $WML^{\perp}$ with 1.90%. Therefore, the orthogonalized BMG factor can explain a relevant amount of variance in stock returns.

[Insert Table C.4 here.]

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

[Insert Table C.5 here.]

Table C.1
Descriptive statistics - orthogonalized factors

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

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

Table C.2
Quintiles with orthogonalized factors

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

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

Table C.3
Decomposition of R^2

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

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

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

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

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

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

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

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

Internet Appendix D: Further risk decomposition

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

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

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

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

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

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

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

[21] We set ρ close to one as defined in Campbell and Vuolteenaho (2004).

[22] We use the weighting scheme of the MSCI World index as of the end of our sample period.

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.[23]

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

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

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

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

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

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

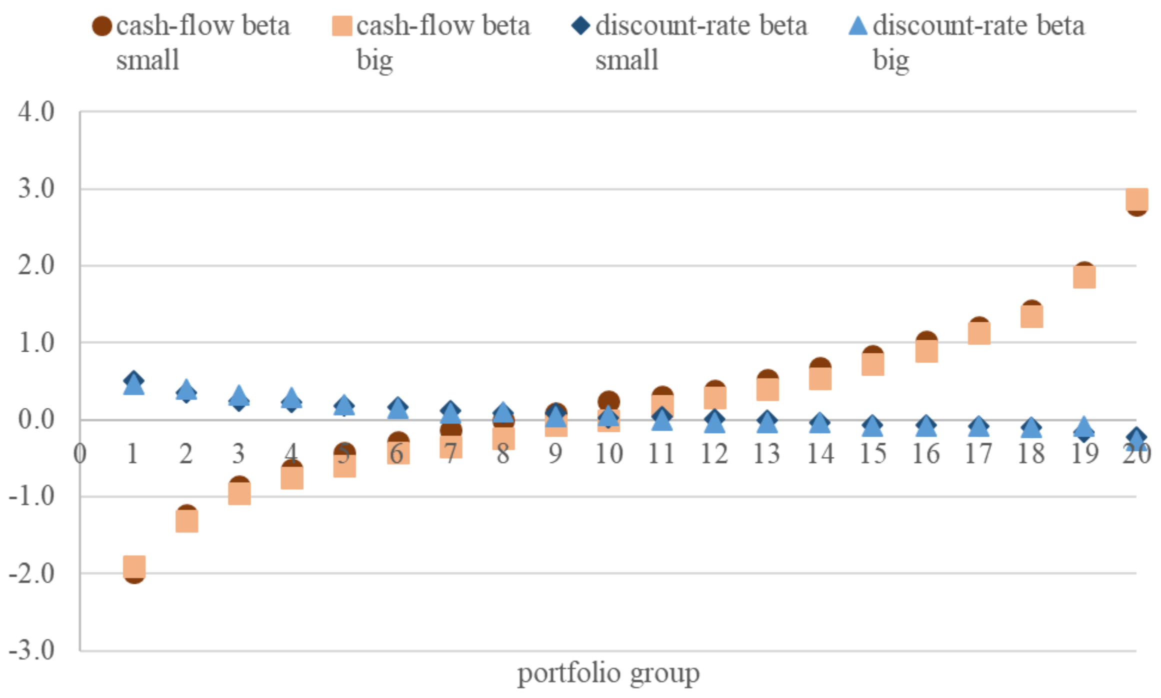
[23] The portfolios are constructed using all firms in the Thomson Reuters Equity Global Index following the approach of Fama and French (1993). As suggested in Chen and Zhao (2009), we used several state variable sets to determine the news components. Our results remain stable.

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

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

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

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



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