The impact of carbon risk factor on equity dynamics

Deriving one-year shocks for brown versus green assets

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Multiple studies emerge on assessing impacts of climate change on insurance activity. Modelling assets composing insurers' portfolios from an environmental point of view is a challenging topic. The calculation of the Solvency Capital Requirement (SCR) may be adapted within internal models to take into account this increasing risk. In this paper we present a methodology to integrate the so-called carbon risk factor within equity modelling, and we illustrate how it may impact the equity risk module for SCR calculation.

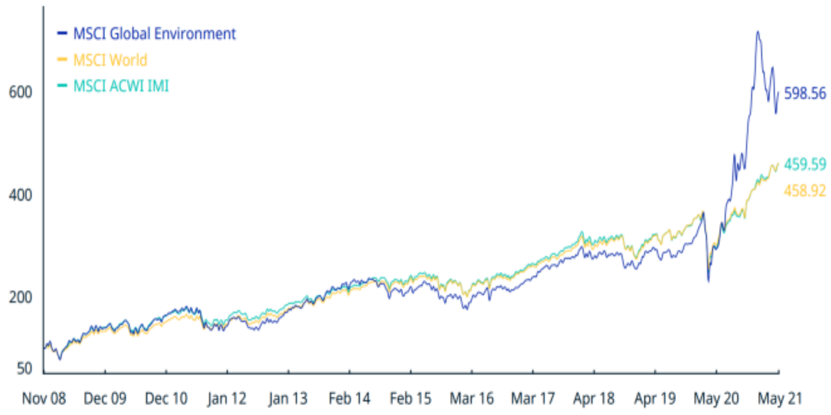
Context

Climate change is having increasing impacts on our societies. To restrain its effects, emission of greenhouse gases including carbon dioxide (CO2) caused by human activities should be considerably lowered in the years to come. According to the Intergovernmental Panel on Climate Change (IPCC) report[1] (August 2021) the concentration of CO2 in the atmosphere measured in 2019 was at its highest level in the last 2,000 years. In view of the inertia of the climate system, this will cause troubles for decades, while any shift towards a low-carbon society is expected to have consequences on the economy, as materialised by the so-called transition risk.

The opinion published by European Insurance and Occupational Pensions Authority (EIOPA), *EIOPA 2019*, provides a study of the impact of climate change on equity risk based on already available market information. To do so, it distinguishes traditional funds from "green" funds. EIOPA compared the values they obtain for equity shock (in Solvency II standards) on four different indices: three conventional and one green.

The shock obtained with the green asset is greater than for the others, which would tend to indicate that the risk embedded in portfolios designed to be virtuous from a climate point of view is greater than in historical portfolios. However, the study only covered the period 2009 to 2019 and therefore did not include the 2008 global financial crisis nor the COVID-19 crisis that started in 2020.

FIGURE 1: CUMULATIVE INDEX PERFORMANCE – GROSS RETURN (USD) FROM NOV. 2008 TO MAY 2021 (SOURCE: MSCI 2020)



[1] IPCC. Climate Change 2021: The Physical Science Basis. Retrieved 6 October 2022 from https://www.ipcc.ch/report/ar6/wg1/.

When reproducing EIOPA's study, based on MSCI's indices, over a larger period of 2008 to 2021, some new lessons can be learned. The cumulative performances of the MSCI World, the MSCI ACWI IMI and the MSCI Global Environment are in line with EIOPA's conclusions over the 2008-2019 period (Figure 1): the three indices appear to be highly correlated over this period with the green index (MSCI Global Environment) underperforming the conventional indices.

However, these conclusions can be questioned in subsequent years. Indeed, from the COVID-19 crisis, there is a clear divergence between the conventional and the green indices. In 2020, the annual performance of the green index was +96% as opposed to the +17% return for the MSCI World.

While standard assets have fallen following the first wave of lockdowns, with then a reasonable recovery, green assets have risen unprecedentedly—studies suggest that equities associated with companies having high environmental, social and corporate governance (ESG) scores have been considered as more robust by investors just after the structural market crash of end-February 2020. The faster rising of green indices has created a market opportunity de facto that has amplified the rise of green indices. Standard indices rose again with a certain delay that could be explained by two main causes:

- A forced halt in demand has led to a halt in supply and has thus drastically reduced need for transport and travel, thus impacting carbon-emitting sectors
- The general decline in consumption has impacted many companies' manufacturing products

To some extent, the COVID-19 crisis can be seen as an occurrence of some form of transition risk, even if ephemeral. If its precise origin is still a subject of debate, the consequences were that a substantial part of carbon-issuing sectors were stopped. Therefore, this crisis has partly materialised experience of how the future international economy could function with regular stresses on energy supply (planned or endured).

These observations led us to consider an approach to better differentiate equity shocks by sector, as it is expected that assets for those sectors that are more exposed to the carbon economy would be riskier than the others from the perspective of climate transition risk, capturing a shift towards a low-carbon economy. To do so, we apply a methodology that allows us to identify a specific carbon risk factor in historical asset returns. Henceforth, one is able to calculate differentiated one-year shock values by sector of activity subject to carbon risk factor, and to analyse the sensitivity of each sector to a stress on the volatility parameter of the carbon risk factor.

Using this method, an insurance or reinsurance company would be able to:

1. Use the carbon risk exposure coefficients to understand the sensitivity of the portfolio exposure by sector under climate transition risk scenarios
2. Leverage the model to reflect incentives (or disincentives) on investments within green (or brown) sectors in the framework of strategic asset allocation
3. Use the sector-specific shock values and model a capital charge in coherence with the inclusion of climate transition risk as an additional source of risk within the risk cartography, such as within an internal model or for the own risk and solvency assessment (ORSA) scenario.

Methodology

The approach considered in this paper for the calculation of shocks is based on the identification of a carbon risk factor as proposed in Roncalli et al., 2020.

ESG INDICATOR

The first step is the derivation of an environmental score that is assigned to each considered company, a score between 0 and 1 according to its environmental impact, to distinguish "green" and "brown" companies: green companies have scores close to 0 and are deemed to be virtuous from an environmental point of view; brown companies have scores close to 1 and are considered as not having implemented policies to favour the ecological transition.

Several ESG indicators were considered for the specification of the carbon risk exposure. The CARIMA factor as defined in the literature (Görgen et al., 2019) and studied in Roncalli et al., 2020, will not be used as it is. Indeed, it is calibrated on data from all over the world, whereas we focus in our study on the S&P 500. An approximate factor imitating the CARIMA factor will be used instead.

To build it, we consider yearly data coming from the Thomson Reuters database[2] dating from 2010 to 2020. Namely, the following data were extracted:

1. Emissions score: This is a score constructed on a part of the environmental pillar including variables related to company emissions, such as CO2 emissions, emissions policies and internal carbon price.
2. Carbon intensity: It is a measure defined as the sum of all CO2 emissions (of the three emissions scopes) of a company divided by its revenue (in USD). This factor, used in the present study, is the Brown Green Score (BGS) factor in the following sections.

BROWN MINUS GREEN FACTOR

The second step is to construct a Brown Minus Green (BMG) factor. For this purpose, the six-portfolio decomposition method is used (see Fama and French, 1992). First, an average BGS is calculated for each company over the 2010-2016 period (as in the CARIMA approach). This average score is then used to perform the breakdown of the considered undertakings. The derivation of the BMG factor consists in pooling the considered companies into six different groups (see Figure 2) according to median market capitalisation and the 30% and 70% quantiles of the average BGS score. The reason motivating this decomposition is that, first, the distinction in market values comes from the original work of Fama and French, who observed that small capitalisations generate highest returns (this is the so-called "small firm effect"). Second, the decomposition of the BGS score allows us to identify the surplus of return associated with brown activities. Six portfolios are then defined: "Small Green," "Small Neutral," "Small Brown," "Big Green," "Big Neutral" and "Big Brown," where: "Small" (or "Big") is the group of companies whose market capitalisation is smaller (or bigger) than the median, and "Green" (or "Neutral" or "Brown") is the group whose BGS is below the 30% quantile (or between 30% and 70% or above 70%). Returns of each of the formed groups can be computed by weighting the individual returns with the market capitalisations.

FIGURE 2: SIX GROUPS SPLITTING

	Median market value	
70% quantile	Small Brown	Big Brown
BGS score	Small Neutral	Big Neutral
30% quantile	Small Green	Big Green

We can then define a carbon risk factor R_{bmg} (see Equation (1) below) from the returns of the retained groups. This factor can be interpreted as the difference between the returns served by activities deemed to be harmful from a climate point of view and those served by activities deemed to be more beneficial.

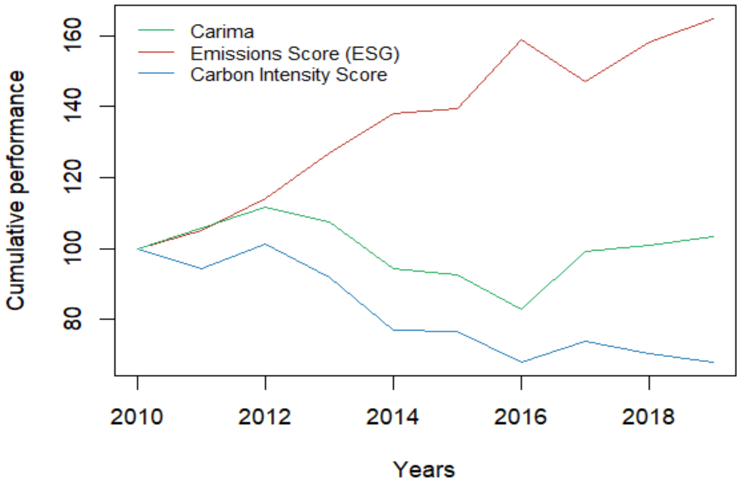
$$\boldsymbol{R_{bmg}(t) = \frac{1}{2}\left(R_{SB}(t) + R_{BB}(t)\right) - \frac{1}{2}\left(R_{SG}(t) + R_{BG}(t)\right) \quad (1)}$$

The study of correlations confirms that the carbon risk factor R_{bmg} we define is positively correlated to the CARIMA (Figure 3). On present data, the correlations are of 63% between CARIMA and the R_{bmg} obtained, considering companies composing the S&P 500.

The second factor built on the emissions score has lower correlations (-48% for the S&P 500). As such, the following study will be based on the BMG carbon intensity score (in blue on Figure 3 for the S&P 500).

[2] See the Refinitiv website at https://www.refinitiv.com/en.

FIGURE 3: CUMULATIVE PERFORMANCES AMONG THE DIFFERENT SCORES CONSIDERED (FOR THE S&P 500, FROM 2010 TO 2019)



Finally, the return $R_i(t)$ of a given company i can be decomposed into three terms: a constant, one relating to the market factor and one relating to the carbon risk factor (see Equation (2)).

$$\boldsymbol{R_i(t) = \alpha_i(t) + \beta_{mkt,i}(t)R_{mkt}(t) + \beta_{bmg,i}(t)R_{bmg}(t) + \epsilon_i(t)\ (2)}$$

The factor $R_{mkt}(t)$ is the return of the overall economic activity (the “market”) while $R_{bmg}(t)$ represents the surplus between returns of companies with carbon-intensive emissions and those whose activities issue little CO2 gas. Thus, $\beta_{mkt,i}(t)$ and $\beta_{bmg,i}(t)$ can be interpreted, respectively, as exposures to market risk and carbon risk. The parameters $\alpha_i(t)$ and $\epsilon_i(t)$ correspond to the excess return of an investment over the risk-free return and the idiosyncratic risk of the firm i respectively.

Model calibration

The parameters $\alpha_i, \beta_{mkt,i}, \beta_{bmg,i}$ and ϵ_i are estimated by applying a Kalman filter (Fabozzi and Francis, 1978). The market factor $R_{mkt}(t)$ is extracted from the time series available on the website[3] of Kenneth R. French. The method is applied to financial data between January 2010 and December 2020, by normalising the variance of the BMG factor to equal that of the market factor.

The study of the $\beta_{bmg,i}(t)$ parameters allow us to deduce which companies or sectors are more subject to carbon risk. Indeed, the higher the beta factor, the more the company is sensitive to the transition risk (sudden drops in returns sustained by activities that are harmful from a climate point of view).

In Figure 4, the coefficients $\beta_{bmg,i}$ for the year 2020 and for the companies composing the S&P 500 are displayed by sector. On average, it turns out that companies working in the energy sector have higher exposure to carbon risk, which confirms the intuition. In Figure 5, the evolution of the coefficients $\beta_{bmg,i}$ over the decade of 2010 to 2020 is presented. The energy sector is clearly seen as the most exposed one at each year. Overall, the order of sensitivity to carbon risk factor between the other sectors is relatively stable, except for the COVID-19 crisis occurrence in 2020 where some rankings change, especially as we observe a decrease of sensitivity regarding consumer staples, as well as an increase for utilities, materials and healthcare. This shows how the COVID-19 outcome can be informative regarding the analysis of carbon risk and the sensitivity of each sector to this risk.

[3] See Kenneth R. French’s Data Library at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

FIGURE 4: PRESENTATION OF THE β_{bmg} PARAMETERS CLASSIFIED BY SECTORS FOR THE S&P 500 (YEAR 2020)

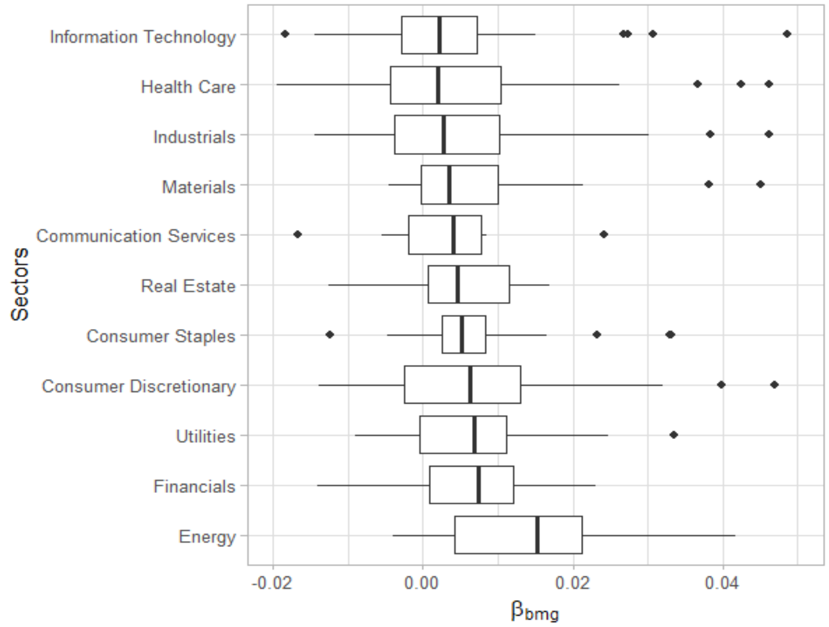
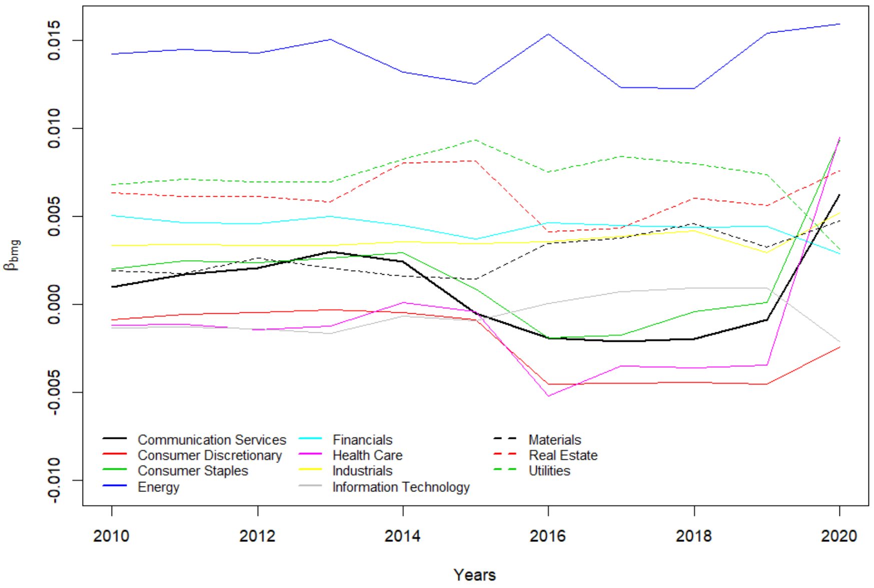


FIGURE 5: EVOLUTION OF THE AVERAGE β_{bmg} PARAMETERS CLASSIFIED BY SECTORS FOR THE S&P 500 (FROM 2010 TO 2020)



Model simulation

ONE-YEAR SHOCK FORMULA

We can now simulate the model to compute the SCR (in fact, the shock) relative to the equity risk module. For the purpose of this analysis, we consider the following SCR calculation:

$$\boldsymbol{SCR^*} = \mathbf{E}[\boldsymbol{D_1 S_1}] - \boldsymbol{q_{0.5\%}}(\boldsymbol{D_1 S_1}) \quad \mathbf{(3)}$$

where: S_1 is the index value at the end of the one-year period, and D_1 is the discount factor, so that $\mathrm{E}[D_1 S_1]$ represents the expected value of discounted index in one year and $q_{0.5\%}(D_1 S_1)$ represents its 0.5% quantile.

Note that it intentionally differs from a pure one-year variation that would be:

$$SCR = q_{99.5\%}(S_0 - D_1 S_1) = S_0 - q_{0.5\%}(D_1 S_1) \quad (4)$$

The aim of Equation (3) is to cancel the impact of the one-year expected return within the risk calculation.

In order to calculate values of shocks by sector, we aim to simulate Equation (2) above for each of these sectors. The simulation we describe is implemented by differentiating two regimes: a normal one (associated to period P_1, 2010-2019) and a crisis one (associated to period P_2, 2020). The first step is to consider average values of the parameters of the yield decomposition Equation (2) for each period.

The $\alpha_i(t)$, $\beta_{mkt,i}(t)$, $\beta_{bmg,i}(t)$ and $\epsilon_i(t)$ parameters are calculated by averaging within each period P_1 and P_2. The next step is to project the equity indices over a one-year horizon. To do this, a Black & Scholes model is used. See Equation (5) below. This model is employed to project $R_{mkt}(t)$ and $R_{bmg}(t)$ jointly using the correlations between the historical series of $R_{mkt}(t)$ and $R_{bmg}(t)$.

$$S_t = S_0 e^{\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma W_t}, t \in [0; T] \quad (5)$$

The parameters μ and σ are calibrated for each period on the log-return series related to $R_{mkt}(t)$ and $R_{bmg}(t)$ for that corresponding period.

ONE-YEAR SHOCKS TAKING INTO ACCOUNT THE CARBON RISK FACTOR

To assess the impact of the carbon risk factor that has been introduced in the model we proposed, we compare the values of the equity shocks defined in Equation (3) and obtained when simulating model defined by Equation (2)—the blue bars in Figures 6 and 7—to that obtained when simulating dynamics (2), in which the coefficients β_{bmg} have been set to zero (green bars). For these computations we distinguish the periods: $P_1 = 2010 - 2019$ in Figure 6 and $P_2 = 2020$ in Figure 7.

FIGURE 6: EQUITY SCHOCKS IMPLIED BY MODEL (2), WITH AND WITHOUT CARBON RISK FACTOR (PERIOD P_1)

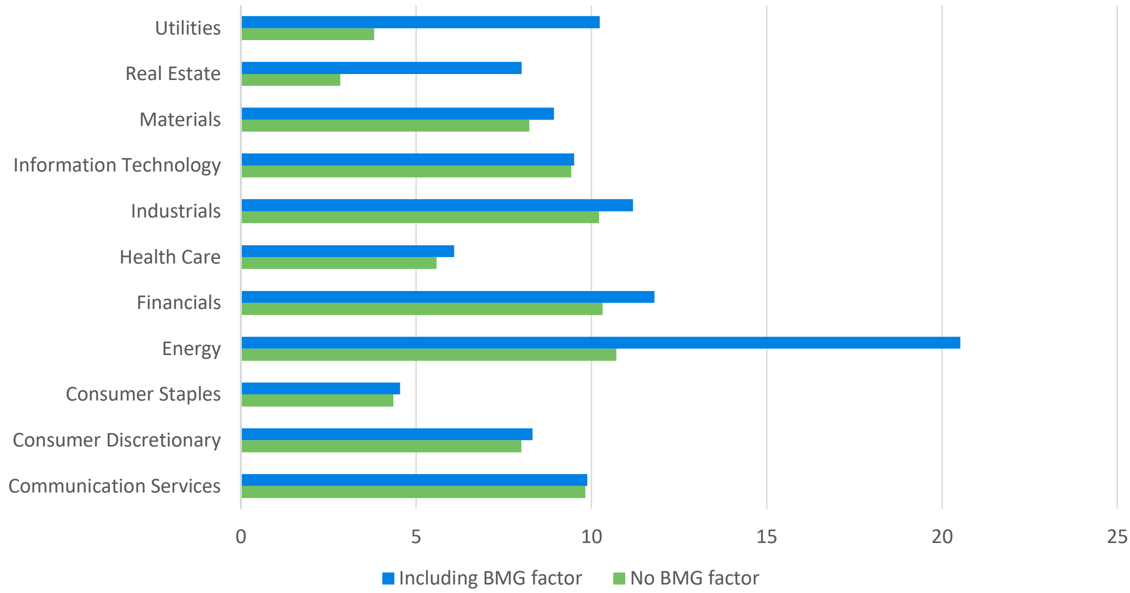
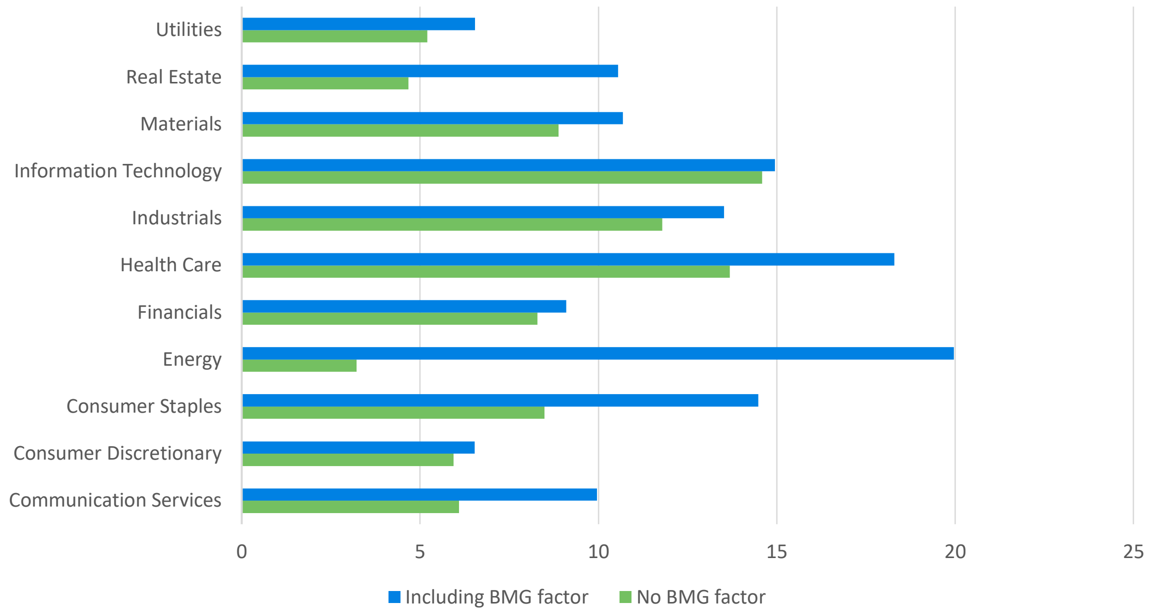


FIGURE 7: EQUITY SHOCKS INDUCED BY MODEL (2), WITH AND WITHOUT CARBON RISK FACTOR (PERIOD P_2)



First, we observe that including the carbon risk factor in the simulations increases the equity shock, which was expected because it amounts to adding a source of risk in the model. Second, the impact of the carbon risk factor is more pronounced when using the parameters calibrated over the crisis period $P_2 = 2020$; again, this was expected given the values of sensitivity parameters estimated in Figure 5 above, which on average are higher in 2020 than for the previous period. We note that the shock values themselves are far from any reference (such as the 39% type 1 base Solvency II equity shock, or a similar value that would be captured based on calculating the 0.5% percentile of historical returns); this is expected because not all sources of risk are considered in this approach. In particular, the model presented in Equation (2) above operates as a smoothing effect (it aims to ”project” returns on selected risk factors), noting that residuals are not included in the simulations. As such we are providing analyses of the increases of the shocks taking into account the carbon risk factor rather than commenting on the values themselves.

FIGURE 8: CLASSICAL VS. STRESSED BY SECTORS

	P_1 (classical)	P_2 (stressed)
Energy	85.43%	107.41%
Real Estate	100.25%	92.70%
Utilities	98.93%	48.47%
Communication Services	-1.11%	73.69%
Consumer Staples	9.47%	78.59%

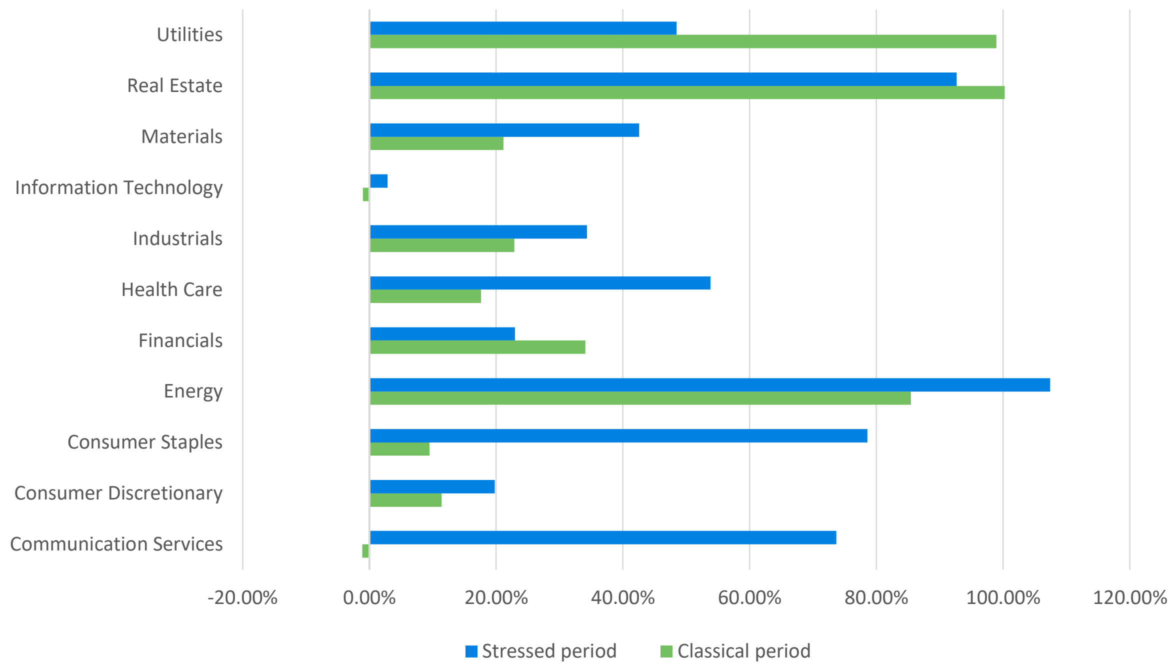
The increase of equity shocks resulting from the integration of the carbon risk factor in the model is heterogeneous as a result of the sensitivity of each sector to the carbon risk factor; the shock increase from including the carbon risk factor is more pronounced for energy, real estate and utilities when the period $P_1 = 2010 - 2019$ is used for model calibration, see Figure 6 above, while the impact of the carbon risk factor remains limited for the other sectors. When the period $P_2 = 2020$ is considered for calibration, the conclusions remain the same for the energy and real estate sectors; however, due to the increase in sensitivity to carbon risk as outlined above, other sectors see their shocks increasing, such as consumer staples and communication services, while for utilities the increase in the shock is not significant. Overall, this analysis tends to show that energy and real estate are typical sectors that would be sensitive to adding the carbon risk factor in the shock calculation methodology.

FURTHER ANALYSIS OF THE SENSITIVITY OF EACH SECTOR TO THE CARBON RISK FACTOR

To further analyse the sensitivity of the results to the volatility of the carbon risk factor, we depict in Figure 9 the relative variation of equity shocks $\left(\frac{shock_2 - shock_1}{shock_1}\right)$ obtained between two scenarios. The first one is built by considering the volatility for the R_{bmg} factor, which has been estimated based on historical data. The second one is built by multiplying this estimated volatility by two. This approach is considered to measure the impact of transition risk modelled as a stress on the volatility of the BMG factor. For example, this would capture the risk of a large range of possible outcomes for the differences in returns between brown and green assets in the case of a sudden reduction of energy supply.

The comparison of computed shocks is made over the previously identified two periods P_1 (green bars) and P_2 (blue bars). We observe that, both periods combined, the sectors most exposed to carbon risk factor volatility increase are energy, real estate and utilities, because they are associated with a substantial increase of shocks between each period. For instance, we observe for the utilities sector that doubling the BMG volatility increases by almost 90% the equity shock when the model has been calibrated over period P_1, while the increase of shock is 48% when parameters calibrated on period P_2 are used.

FIGURE 9: EQUITY SHOCKS EVOLUTION BY SECTOR AND BY PERIODS BETWEEN TWO SCENARIOS ON THE VOLATILITY OF THE CARBON RISK FACTOR



Conclusion

In view of better understanding climate transition risk exposure as well as stress tests proposed by regulators such as EIOPA, models can be leveraged to provide insights. We have presented an approach based on the definition of a so-called carbon risk factor, built to reflect the differentiated dynamics of brown versus green assets. As such, it is interpreted as a carbon risk factor, materialising the risk related to a shift towards a low-carbon economy (in the uncertainty and probabilistic sense). The exposure to carbon risk (coefficients β_{bmg}) allows us to assess the exposure of the portfolio to the climate risk from a sector-level point of view. Establishing scenarios on the carbon risk factor and its exposure can allow linking incentive (or disincentive) policies on investments in green (or brown) activities to a value of shock on the newly composed portfolio. Indeed, as observed during the COVID-19 crisis, typical green assets are showing more differentiated behaviour under specific energy demand and supply circumstances compared to what was observed in the past, hence suggesting that this differentiation would materialise more under climate transition. However, using only the COVID-19 crisis to define a stressed period is not robust from a statistician viewpoint. Using both defined periods P_1 and P_2 to compute values of shocks would be the best practice to date. Our implementation of the approach based on the components of the S&P 500 has shown that the proposed framework allowed us to separate pure market risk from carbon risk within the dynamics of assets by sector, and as such to provide one-year shocks for the calculation of an economic capital that differ from those sectors that are sensitive to carbon risk (such as energy). The deformation of the values of shocks identified in this paper can be used by companies for comparison to the shocks obtained when considering climate risk in internal models.

Let us finally mention that the present work paves the way to some extensions: inclusion of more recent data (related to current lack of supply in energy) would allow us to consolidate the results and realising a similar work at the company level could be valuable for practical implementations in internal models.

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