*Article*

# Credit risk volatility: evidences from the green bond market

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**Abstract:** The paper is an investigation on the impact of financial markets on the volatility of green bonds credit risk component, measured by the option-adjusted spread/swap curve (OAS) of the Global Bloomberg Barclays MSCI Green Bond Index, for both the non and pandemic periods. For these purpose, after observing the dynamic joint correlations between all the variables through a DCC-GARCH, we adopt GARCH(1,1) and EGARCH(1,1) models, putting the OAS as dependent variable. Our main results show that the conditional variance parameters are significant and persistent in both times, testifying the overall impact of the other markets on the OAS. In more detail, we highlight that the gamma in the two EGARCH models is positive: so the "green" credit risk volatility is more sensitive to positive shocks than negative ones. With reference to the conditional mean, we note that if during the non pandemic time only the stock market is significant, during the pandemic also conventional bonds and gold are impacting. To the best of our knowledge this is the first study that analyzes the specific credit risk component of green bond yields: we deem our findings useful to observe the change of green bonds creditworthiness in a complex market context.

**Keywords:** green bonds; credit risk; volatility

## 1. Introduction

Starting by the concept that green bonds are deemed as instruments that can be adopted in order to implement the intertemporal burden sharing of climate mitigation (Sachs 2014), the attention for these bonds is testified by the exponential growth that the market has recorded, even during the pandemic period. More specifically, even though the sustainable bond market has been characterized by a further split in its themes, on behalf to social, sustainable and pandemic bonds, the green segment has shown an increasing demand and better performances compared to plain vanilla debt instruments. Furthermore, the market has had a discontinuous trend over the 2020 in fact, if in the first quarter its volume has dropped lower than a half of 2019 (Climate Bonds Initiative 2020), in the third quarter of 2020 green bonds have reached the highest volume of issuance for a third quarter, i.e. 69.4 bn USD (Climate Bonds Initiative 2020). Looking to 2021, at the end of the third quarter, the total issuance has reached USD 354.2bn and it has shown a growth by 15.8% compared with Q3 2020 (Climate Bonds Initiative 2021).

In general, the attention of investors for sustainability is reflected by the impact on risk premia and their linkage with the creditworthiness of issuers (Höck et al. 2020). In this context, firms with lower carbon emissions, seem to limit their default risk (Kabir et al. 2021).

In more detail, over the post-covid inflationary environment, investors have put caution on the possibility that their returns could be eroded; notwithstanding, in the first semester of 2021 rates have remained low, thanks to the ongoing support of central banks and of other pandemic measures, contributing to bond price rising. Specifically, analyzing green bonds yields, researchers have observed a premium, called the "greenium", that investors are willing to pay in order to make a sustainable investment (e.g. Hyun et al.

2020; Zerbib 2019), so the cost of debt should be lower than the conventional one. In particular, this phenomenon is typical of the primary market: the price of new issuance is higher than the outstanding debt. However, the market has shown larger spread compression than the plain vanilla's one: in the first half of 2021 it has tightened 24.4 bps (29.9 bps) for the EUR (USD) segment, compared to the 19.6 (24.8) bps of the plain vanilla bonds (Climate Bonds Initiative 2021). This issue is explainable by the oversubscriptions of green bonds compared with the ongoing lack of supply.

With reference to the overall fixed income market, credit risk has raised up during the pandemic period and has shown up and down correlations with the epidemic trend; however, the levels reached are definitely lower than those recorded during the Financial Crisis (Byström 2021).

Our focus is on the credit risk component of green bonds' yield, namely the spread designed to compensate investors for expected loss from default: to this purpose, we observe the option-adjusted spread/swap curve of the Global Bloomberg Barclays MSCI Green Bond Index. The option-adjusted spread takes into account how the embedded option in a bond can influence the future cash flows and the overall value of the bond. In particular, enclosed options can let the issuer to call back the debt early or the investor to convert the bond into underlying company shares or demand early redemption. The option-adjusted spread will discount the bond's value due to any options included in the issue. Its calculation allows an investor to determine if the listed price of a fixed-income security is worthwhile due to the risks associated with the added options. All in all, this variable adjusts the Z-spread to include the embedded option's value.

The analysis of the credit risk component of green bonds, cannot disregard the comovement of the latter and other financial markets (Reboredo 2018) and how it changes over time (Arif et al. 2021). In more detail, research has shown the interconnections between green and conventional bonds (e.g. Broadstock and Cheng 2019; Zerbib 2019; Hachenberg and Schiereck 2018); the spillovers with the stock and commodity market (e.g. Dutta et al. 2021; Naeem et al. 2021; Reboredo and Ugolini 2019). Finally, literature has observed the interrelations with cryptocurrencies (e.g. Naeem and Karim 2021; Huynh et al. 2020). In our study, however, the focus on the OAS aims to find peculiarities for the credit risk of these instruments rather than on their overall performance.

The paper is an investigation on the volatility of the green bonds credit risk component, measured by the option-adjusted spread (hereinafter, OAS). In particular, according to the spillovers between these instruments and financial markets, we study the impact of conventional bonds, stocks, oil, gold and cryptocurriencies on the "green" credit risk volatility, both in the non and pandemic periods. For this purpose, after observing the joint dynamic conditional correlations between all the variables through the DCC-GARCH model, we adopt GARCH(1,1) and EGARCH(1,1) models, putting the OAS as dependent variable. Our main results show a joint DCC between variables both in the short and in the long time. In more detail, during the non pandemic period, only the stock market affects the conditional mean of the "green" adjusted spread; on the other hand, the significance of the conditional volatility parameters, testifies a persistent impact of the one-day lagged performance of the other financial markets, on the current variance of the credit risk component of green bonds. Analogous findings concern the significance of these parameters during the pandemic period. In particular we highlight that, in both cases, the gamma in the EGARCH is positive: so the "green" credit risk volatility is more sensitive to positive shocks than negative ones. On the contrary, during the pandemic, we note the significant impact of the conventional bonds and gold, added to the role of stocks, on the conditional mean estimation.

To the best of our knowledge this is the first study that analyzes specifically the credit risk component of green bond yields. We deem our findings useful to observe the

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change of green bonds creditworthiness in a complex market context. In particular, the analysis could be proceeded studying bi-directional spillovers of volatility between each market and the "green" credit risk component. Moreover, starting from our global observations, the study could be applied specifically to the European, American and Asian markets.

## 2. Materials and Methods

The analysis consists in the study of the conditional volatility of the credit risk component of green bonds. Specifically, the variable is analyzed conditioned on the performance of the principal markets connected to the green bond's one, namely: brown bonds, stocks, gold, oil and cryptocurrencies. The study has been split into two periods:

– pre-pandemic (21$^{th}$ October 2016-7$^{th}$ February 2020)
– pandemic (10$^{th}$ February 2020-29$^{th}$ October 2021).

The dependent variable is represented by the option-adjusted spread/swap curve ( OAS) of the Global Bloomberg Barclays MSCI Green Bond Index.

The independent variables are listed below:

– BROWN: quotation of the S&P 500 Bond Index
– FTSE: quotation of the FTSE All-World Index
– GOLD: quotation of the Gold futures
– WTI: quotation of the Crude Oil WTI Futures
– Crypto: quotation of the S&P Cryptocurrency MegaCap Index (USD)

Data are daily and their sources are Bloomberg, Datastream and S&P.

The methodology adopted is the univariate conditioned GARCH. More specifically, we implement for each period a GARCH(1,1) and a EGARCH (1,1) model.

- Conditional GARCH (1,1)

Starting from the Conditional GARCH model, *Generalized Autoregressive Conditional Heteroskedasticity* (Bollerslev 1986), we calculate the conditional mean and the conditional variance equations, conditioned on the X, i.e. the matrix of the independent variables:

$$E(OAS_t/X_{t-1})=a+bX_{t-1}+\varepsilon_t \tag{1}$$

$$E(\sigma^2_t/X_{t-1}) = \omega + \alpha\, E((\varepsilon^2_{t-1}/X_{t-1})) + \beta\, E((\sigma^2_{t-1}/X_{t-1})) \tag{2}$$

In more detail, in Eq(1), the OAS is expressed as a function of a constant term, "a" , and the one-day lagged value of the matrix X, while in Eq. (2), $\sigma^2_t$ is the conditional variance dependent on $X_{t-1}$, and it denotes the conditioned one-day ahead forecast variance that relies on past information. It is calculated though three terms, namely, a constant one, $\omega$, an ARCH term, $\varepsilon^2_{t-1}/X_{t-1}$, which captures the news about the past period's volatility conditioned on the independent variables, and the GARCH term, $\sigma^2_{t-1}/X_{t-1}$ , which denotes the conditioned forecast variance of the last period. The coefficients of the ARCH and GARCH terms (i.e., $\alpha$ and $\beta$) are usually summed up to determine the persistence degree of volatility shocks. If the sum is close to one, there is persistence, implying the permanent effect of volatility shocks. If, on the other hand, the sum is significantly less than unity, there is an evidence of a mean-reverting variance process, with shock impacts being just temporary

- Conditional EGARCH (1,1)

The conditional EGARCH model, is calculated through *Exponential Generalized Autoregressive Conditional Heteroskedasticity* (Nelson 1991), conditioned on the X matrix:

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$$E(\ln(\sigma^2_t/X_{t-1}))= \omega + \alpha[E((\varepsilon^2_{t-1}/ \sigma^2_{t-1})/X_{t-1}]^{1/2} + \gamma[E(\varepsilon^2_{t-1}/ \sigma^2_{t-1})/X_{t-1}]^{1/2} +\beta E(\ln(\sigma^2_{t-1}/ X_{t-1})) \quad (3)$$

In particular, $\gamma$ measures the asymmetric effect. There is an asymmetric effect if $\gamma$ is significantly different from zero, with $\gamma < 0$ ($\gamma > 0$) implying that negative (positive) shocks increase (decrease) volatility greater than positive (negative) shocks of equal magnitude.

In accordance to the non-significance of the most of series, we have calculated their first differences, before implementing the models.

Furthermore, we adopt a preliminary analysis of the joint dynamic conditional correlations in the short and long run, among all variables though the DCC GARCH (Engle 2002). The details of the model are reported in Appendix A.

## 3. Results


**Figure 1.** OAS time series
*Source: Authors' calculations*

Figure 1 shows graphically the OAS time series over all the period of analysis (10th October 2016-29th October 2021). We note a peak at the beginning of the pandemic, but there's a steep decline in the following months, almost reaching the lowest level shown between 2017 and 2018.

**Table 1.** Descriptive statistics, Normality and Unit-root test

| Non-pandemic period | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **Min** | **Max** | **St. Dev.** | **Skewness** | **Kurtosis** | **JB test** | **ADF** |
| OAS | 37.28457 | 24.81105 | 58.67745 | 7.579078 | 0.47508 | -0.33263 | 36.1887*** | -1.61755 |
| BROWN | 441.5637 | 410.08 | 502.06 | 23.465 | 1.0881 | -0.071622 | 169.305*** | -0.562887 |
| FTSE | 327.2462 | 266.43 | 382.32 | 24.52129 | -0.42833 | -0.17648 | 27.3171*** | -2.34836 |
| GOLD | 1378.505 | 1134.55 | 1627.3 | 92.18629 | 0.78465 | -0.0095716 | 87.9424*** | -1.67602 |
| WTI | 57.07138 | 42.53 | 76.41 | 7.573489 | 0.37090 | -0.69993 | 37.143*** | -1.91119 |
| CRYPTO | 801.307 | 83.71 | 76.41 | 477.7884 | 0.39164 | -0.089349 | 22.1928*** | -2.32614 |
| Obs. 857 | | | | | | | | |

Source: Authors' calculations.
****, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.*

**Table 2.** Descriptive statistics, Normality and Unit-root test

| Pandemic period | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Variable** | **Mean** | **Min** | **Max** | **St. Dev.** | **Skewness** | **Kurtosis** | **JB test** | **ADF** |
| OAS | 45.18318 | 28.6139 | 109.4884 | 18.92903 | 11.150 | 178.52 | 594714*** | -3.87494*** |
| BROWN | 523.2907 | 445.3 | 543.53 | 16.83547 | -1.8161 | 4.1938 | 566.88*** | -2.57302 |
| FTSE | 409.7724 | 253.51 | 491.71 | 59.78223 | -0.40853 | -0.94898 | 28.8804*** | -5.30737*** |

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| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| GOLD | 1812.119 | 1491 | 491.71 | 96.80841 | -0.10282 | 0.38950 | 3.57276*** | -2.17263 |
| WTI | 51.4041 | -37.63 | 84.65 | 17.16826 | -0.38477 | 0.57117 | 16.9142*** | -4.0026*** |
| CRYPTO | 3736.643 | 712.43 | 8855.37 | 2496.129 | 0.36424 | -1.3977 | 45.7516*** | -1.98593 |
| Obs. 442 | | | | | | | | |

*Source: Authors' calculations.*
****, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.*

Tables 1 and 2 illustrate the descriptive statistics, the normality and the unit-root test of the variables, respectively for the non and the pandemic period. We obserbe that for both periods GOLD and CRYPTO have the highest values of the standard deviation. As concerns OAS, we note that the standard deviation is quite low, however the value is more than doubled during the pandemic period. We also observe that the mean value of the green bonds' credit risk component doesn't change too much between the two periods (respectively 37.28457 and 45.18318), while the maximum value is almost doubled with reference to the pandemic.

We also highlight that all the variables show a non-normal distribution, as the Jarque-Bera test is significant for both periods. Looking to ADF test, we note that over the non-pandemic period the test is not significant: so all the variables are not stationary; during the pandemic, instead, the test is significant for OAS, FTSE and WTI variables.

**Table 3**. Correlation matrix for the non-pandemic period

| | OAS | BROWN | FTSE | GOLD | WTI | CRYPTO |
|---|---|---|---|---|---|---|
| **OAS** | 1 | | | | | |
| **BROWN** | -3.87494 | 1 | | | | |
| **FTSE** | -0.4811 | 0.7061 | 1 | | | |
| **GOLD** | -0.2837 | 0.8500 | 0.6667 | 1 | | |
| **WTI** | -0.2087 | 0.0489 | 0.5872 | 0.0621 | 1 | |
| **CRYPTO** | -0.4838 | 0.5386 | 0.7668 | 0.5690 | 0.5074 | 1 |

*Source: Authors' calculations.*

**Table 4.** Correlation matrix for the pandemic period

| | OAS | BROWN | FTSE | GOLD | WTI | CRYPTO |
|---|---|---|---|---|---|---|
| **OAS** | 1 | | | | | |
| **BROWN** | -0.8084 | 1 | | | | |
| **FTSE** | -0.8928 | 0.7522 | 1 | | | |
| **GOLD** | -0.2369 | 0.6025 | 0.1456 | 1 | | |
| **WTI** | -0.8312 | 0.6245 | 0.9338 | 0.2985 | 1 | |
| **CRYPTO** | -0.7064 | 0.4384 | 0.8634 | 0.5266 | 0.8333 | 1 |

*Source: Authors' calculations.*

Table 3 and 4 display the correlation matrices for both periods: during the non-pandemic one OAS shows the highest correlations with stock market and crypto index, while over the pandemic the correlation grows, and is high also with reference to the bond and oil market. The sign of correlation is negative with reference to all the independent variables. Overall, the latter are highly correlated, with a growth during the pandemic period. The only exceptions are given by the correlations between GOLD and the OAS and FTSE variables, that decrease (especially in the last case).

**Table 5.** DCC-GARCH parameters for non and pandemic period

| | Non pandemic | Pandemic |
|---|---|---|
| $\lambda_1$ | 0.002991*** | 0.019764*** |
| $\lambda_2$ | 0.985858*** | 0.881506*** |

*Source: Authors' calculations.*
****, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.*

Table 5 reports the dynamic parameters of the DCC-GARCH (the details of the model and of the results are reported in Appendix A). Specifically, the $\lambda_1$ and the $\lambda_2$ express respectively, the short and long run joint dymanic conditional correlation of all the variables. As shown by the table, the results are positively significant in any case.

**Table 6.** GARCH(1,1) e EGARCH(1,1) Non-pandemic period

| | GARCH (1,1) | | EGARCH (1,1) |
|---|---|---|---|
| Conditional mean equation | | | |
| **const.** | -0.0109560<br>(0.0244236) | | -0.00259771<br>(0.0226700) |
| **BROWN** | 0.00136029<br>(0.0297917) | | 0.0135164<br>(0.0223349) |
| **FTSE** | -0.0868853***<br>(0.0166575) | | -0.103072***<br>(0.0101822) |
| **GOLD** | -0.000531682<br>(0.00126244) | | -0.000961943<br>(0.00138471) |
| **WTI** | 0.0137599<br>(0.0287625) | | 0.0226080<br>(0.0189228) |
| **CRYPTO** | 1.96895e-06<br>(0.000505605) | | -0.000120975<br>(0.000399805) |
| Conditional variance equation | | | |
| **ω** | 0.00288388 | **ω** | -0.0246728 |
| **α** | -0.00803509*** | **α** | -0.0269679*** |
| **β** | 1.00165*** | **β** | 0.952638*** |
| | | **γ** | 0.0294900** |
| Llik: | -823.41617 | Llik: | -840.81092 |
| AIC: | 1664.83234 | AIC: | 1701.62184 |
| BIC: | 1707.60277 | BIC: | 1749.14454 |
| HQC: | 1681.21015 | HQC: | 1719.81941 |

*Source: Authors' calculations. Standard error is indicated in parentheses.*
****, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.*

**Table 7.** GARCH(1,1) e EGARCH(1,1) Pandemic period

| | GARCH (1,1) | EGARCH (1,1) |
|---|---|---|
| Conditional mean equation | | |
| **const.** | -0.0788347***<br>(0.0269829) | -0.0358703***<br>(0.00714484) |
| **BROWN** | -0.0755672***<br>(0.0251314) | -0.0703375***<br>(0.00762255) |

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| | | | |
|---|---|---|---|
| FTSE | -0.0757507*** (0.0124336) | | -0.0777886*** (0.0151549) |
| GOLD | 0.00275261 (0.00170304) | | 0.00210806** (0.000976945) |
| WTI | -0.0141384 (0.00885890) | | -0.00810409 (0.0309157) |
| CRYPTO | 8.82047e-05 (9.58609e-05) | | 5.75369e-05 (9.96625e-05) |
| Conditional variance equation | | | |
| ω | 0.0340737*** | ω | -0.431527*** |
| α | 0.439593*** | α | 0.557806*** |
| β | 0.606476*** | β | 0.959009*** |
| | | γ | 0.106633* |
| Llik: | -450.45081 | Llik: | -452.67476 |
| AIC: | 918.90162 | AIC: | 925.34952 |
| BIC: | 955.70302 | BIC: | 966.23997 |
| HQC: | 933.41846 | HQC: | 941.47935 |

*Source: Authors' calculations. Standard error is indicated in parentheses.*
****, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.*

Table 6 and Table 7 exhibit, respectively, the results of the GARCH(1,1) and EGARCH(1,1) for the non-pandemic and the pandemic period. In particular, the first part of the tables, shows the impact of different markets on the conditional mean of the optipn adjusted spread of green bonds. The second part, exhibits the parameters of the conditional variance equation: in particular α and β express, respectively, the ARCH and the GARCH coefficients. With reference to the EGARCH, the γ parameter measures the asymmetric reaction of OAS volatility to the independent variables.

Specifically to non-pandemic period, looking to the information criteria, the values are lower with reference to the GARCH(1,1) model; however, the adoption of the EGARCH, allows us to have an adding information through the γ parameter.

Both GARCH(1,1) and EGARCH(1,1) results for the conditional mean, are characterized by the 1% significance of the only FTSE variable. As concernerns the conditional variance equation, the parameters are all significant, with the exception of the constant ω.

With reference to the pandemic period, the informarion criteria would suggest that the GARCH(1,1) model will be a bit more efficient than the EGARCH(1,1); notwithstanding, the values are quite similar, so there's not a model better than the other one.

Looking to the conditional mean equation, the GARCH(1,1) results are characterized by the negative significance of FTSE and BROWN; the parameters of the conditional variance equation are all significant. With reference to the EGARCH (1,1), we note similar findings, except for the positive significance of GOLD. Among the results of the conditional variance equation we highlight the 10% positive significance of the γ.

## 4. Discussion

The analysis conducted aims to investigate the volatility of the credit risk component of green bonds, namely the dispersion from its expected value, expressed by the OAS/swap curve.

The analysis has considered the co-movements of green bonds with financial markets (Reboredo 2018). In more detail, looking to both the non and the pandemic period, after a preliminary implementation of the DCC-GARCH model, we have calculated a

GARCH(1,1) and a EGARCH(1,1), putting the OAS as dependent variable and the conventional bonds, stocks, gold, oil and cryptocurriencies as independent ones.

First of all, the DCC-GARCH (see Table 5) shows, for each period, 1% significant lambda parameters, testifying both the short and long run dynamic correlations among the overall variables, similarly to Gao et al. (2021).

Our main results (see Table 6 and 7) show that if, in the non pandemic period, the conditional mean of the "green" credit risk component is affected only by the stock market, during the pandemic, also conventional bonds and gold are significant. In more detail, while the negative sign of the BROWN and FTSE variables is quite intuitive (a context of good stock and bond markets, should have a negative relation with credit risk and vice-versa), the positive sign of gold is less immediate. However, in this field, Naeem et al (2021) find mixed signs in the spillovers between the two markets.

As concerns the non significant variables, with reference to WTI, our result is quite similar to Dutta et al. (2021), who find that climate bonds record a correlation with crude oil near to zero; on the other side, the non significance of CRYPTO, is in contrast with Naeem and Karim (2021), who testify multiple tail-dependence regimes between Bitcoin and green bonds.

Looking to the conditional variance, the GARCH and EGARCH show significant parameters in both periods. In particular, the $\alpha$ and $\beta$ express, respectively, the impact of the one-day lagged OAS residuals, conditioned on the one-day lagged independent variables, on the OAS volatility in t, and the impact of the one-day lagged OAS volatility, conditioned on the one-day lagged independent variable, on the OAS volatility in t, itself. In both periods, the sum of these parameters is near or even greater than one (see Table 6 and 7): this means that there is a persistence in the volatility of the "green" credit risk component, conditioned on the other financial markets. Our finding differs from Ferrer et al. (2021), who show that the connectedness between the green bond market and the other ones, mainly occurs at short time horizons, suggesting that shocks are rapidly transmitted across markets with an effect lasting less than a week.

Another interesting result is the positive significance of the $\gamma$ parameter in the EGARCH model of each period (see Table 6 and 7). This is particularly important, because testifies the asymmetry of the "green" OAS, consistently to Park et al. (2020). Specifically, the positive sign, means that the "green" credit risk volatility is more sensitive to positive shocks than negative ones, like the pandemic.

Finally, we observe that if the impact of the independent variables on the conditional mean changes from the non and the pandemic period, it is the same with reference to the conditional variance.

## 5. Conclusions

The current paper has analyzed the volatility, through GARCH models, of the OAS/swap curve of the Global Bloomberg Barclays MSCI Green Bond Index conditioned on the performance of the other financial markets for both the non and the pandemic periods. The study has shown that the conditional mean of the "green" credit component changes its dependence over time. Specifically, if in the non pandemic period only the stock markets seems to have a significant influence, during the pandemic one, also conventional bonds and gold are impacting.

With reference to the conditional variance, we note that all parameters are significant for each period, showing the persistence of the impact of the one day lagged matrix of the independent variables on the expected variance of OAS. We highlight that the most interesting result is the positive significance of the lambda parameter in the EGARCH(1,1) models, which shows that the volatility of the "green" credit risk component is quite asymmetric and is more sensitive to positive information.

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We deem that this result could have useful implications for investors, as in bullish contexts green bonds creditworthiness should be particularly robust and inclined to be less volatile; at the same time, even in a bearish market, they shouldn't be very susceptible.

To the best of our knowledge, this is the first study that focuses the analysis on the credit risk component of green bonds.

We deem that the research could be proceeded though a bi-directional analysis between the "green" OAS and each financial market; furthermore, starting from our global results, the study could be applied singularly for the European, American and Asian markets.

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## Appendix A

We briefly illustrate the Dynamic Conditional Correlation GARCH model (DCC-GARCH), (Engle 2002).

The GARCH-DCC calculation is made by two steps.

The first step deals with the conditional heteroskedasticity. It consists in estimating, for each one of the n series of returns $r_{i,t}$, its conditional volatility $\sigma_{i,t}$ using a GARCH model. Let $D_t$ be a diagonal matrix with these conditional volatilities, i.e $Dt^{i,i} = \sigma_{i,t}$ and, if $i \neq j$, $Dt^{i,j} = 0$. Then the standardized residuals are:

$$v_t := D_t^{-1}(r_t - \mu)$$

where:

$r_t$ = nx1 vector of returns

$\mu$= nx1 vector of expected returns

The aforementioned standardised residuals have unit conditional volatility.

Now we define the Constant Conditional Correlation (CCC) (Bollerslev 1990) through the following matrix:

$$R := \frac{1}{T}\sum_{t=1}^{T} v_t v'_t$$

The second step is the Dynamic Conditional Correlation (DCC) itself, i.e. the generalizing CCC model (Bollerslev 1990) that captures the dynamics in the correlation:

$$Q_t = R + \lambda_1 (v_{t-1}v'_{t-1} - R) + \lambda_2(Q_{t-1} - R)$$

So $Q_t^{i,j}$ is the correlation between $r_{i,t}$ and $r_{j,t}$

Table 8 and 9 show the overall results of the DCC-GARCH for both the non and the pandemic periods.

| | Non pandemic | | | | | |
|---|---|---|---|---|---|---|
| | OAS | BROWN | FTSE | GOLD | WTI | CRYPTO |
| ω | 0.017140***<br>(0.007107) | 0.005311<br>(0.003867) | 0.199351***<br>(0.075487) | 0.213978<br>(0.430513) | 0.012115<br>(0.008792) | 10.909610<br>(21.470774) |

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|---|---|---|---|---|---|---|
| α | 0.000000 (0.024768) | 0.025130*** (0.008443) | 0.196584*** (0.058283) | 0.000119 (0.001385) | 0.028060*** (0.008197) | 0.119867*** (0.034793) |
| β | 0.960781*** (0.044283) | 0.968642*** (0.010708) | 0.762447*** (0.059445) | 0.998881*** (0.000040) | 0.961587*** (0.006920) | 0.879133*** (0.053985) |
| $\lambda_1$ | 0.002991*** | | | | | |
| $\lambda_2$ | 0.985858*** | | | | | |
| AIC: 0.9859<br>BIC: 30.270<br>SIC: 30.072<br>HQC:30.150 | | | | | | |

**Table 8.** DCC-GARCH Non pandemic period **Table 9.** DCC-GARCH Pandemic period

| | Non pandemic | | | | | |
|---|---|---|---|---|---|---|
| | OAS | BROWN | FTSE | GOLD | WTI | CRYPTO |
| ω | 0.032725*** (0.014306) | 0.162611 (0.100346) | 1.038840** (0.370653) | 0.000010 (0.001038) | 0.026229 (0.075274) | 69.375370 (63.439659) |
| α | 0.326809*** (0.085849) | 0.260474*** (0.098281) | 0.186463*** (0.057043) | 0.007612*** (0.001109) | 0.055538*** (0.013440) | 0.092037*** (0.024686) |
| β | 0.672191*** (0.052166) | 0.708777*** (0.091966) | 0.751861*** (0.054223) | 0.990283*** (0.001220) | 0.943462*** (0.03023) | 0.906963*** (0.033805) |
| $\lambda_1$ | 0.019764*** | | | | | |
| $\lambda_2$ | 0.881506*** | | | | | |
| AIC: 37.116<br>BIC: 37.441<br>SIC: 37.105<br>HQC:37.244 | | | | | | |

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