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Green bond market and Sentiment: Is there a switching Behaviour?

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ABSTRACT

We examine the impact of Twitter sentiment on the returns of four selected bond indices via the selection of relevant threshold variables, such as the S&P 500 Index, the VIX, and the MSCI World Index. If overreaction or underreaction to significant changes in the market occur regularly (De Bondt and Thaler, 1985, 1987; Jegadeesh and Titman, 1993), it is assumed that Twitter users respond with different intensities in the case of rising, falling or rather indeterminable markets. We fail to find evidence that the S&P 500 Index and VIX are relevant in supporting the switching behaviour. However, the MSCI World Index, to a certain extent, causes this relationship to diverge from the linear one. These claims become stronger when lagged and cubic sentiment variables have been included in the panel smooth transition regression (PSTR).

1. Introduction

The consensus around the risks derived from climate change and environmental protection has increased attention on green finance. The appearance of green bonds as a vehicle to finance green projects makes perfect sense in this context. Green bonds can be defined as an innovative fixed-income product that offers investors the opportunity to help mitigate climate change and support countries' environmental strategies. Green bonds are not significantly different from conventional bonds except that the proceeds from bond sales must be invested in projects susceptible to generating environmental benefits. In the due-diligence process, the issuer is expected to identify and monitor the projects (Reichelt, 2010). Although the volume of green bond issues has practically doubled each year after 2016, and the portion of corporate green bonds is constantly growing, the green bond market remains smaller than the conventional bond market.

The existence of a yield differential between a green bond and a conventional bond (the green bond premium or 'greenium') has been widely studied in previous literature without conclusive results, although most of the authors have confirmed the greenium hypothesis (Bachelet et al., 2019; Gianfrate and Peri 2019; Fatica et al. 2019; Karpf and Mandel, 2018; Nanayakkara and Colombage, 2019; Rila, 2017). The potential greenium and lower liquidity risk (Febi et al., 2018; Wulandari et al., 2018) have compensated one of the main obstacles constraining the development of the green bond market, which is the lack of commonly acknowledged standards (Cowan, 2017) that is essential for investors to assess whether green bonds are truly 'green'.

Reality has shown that the issuance of stocks is less efficient than the issuance of green bonds to finance green projects. Most of the time, investors cannot gather sufficient rights to participate in the company's decision-making processes. Previous research has analysed the potential determinants of the correlation between these two main asset classes (Aslanidis and Christiansen, 2012; Chiang et al., 2015; Ilmanen, 2003; Li, 2002). Specifically, stock market volatility (Connolly et al., 2005, 2007) or the VIX volatility index (Bansal et al., 2010) have been considered economic forces driving stock–bond correlations. At this point, a new strand of research on the impact of financial markets on green bond markets has emerged, especially those that aim to analyse the dependence structure of the green bond market on other related financial markets (Reboredo, 2018; Reboredo and Ugolini, 2020). In this same line of research, Broadstock and Cheng (2019) provided evidence that the connection between green and conventional bonds is sensitive to, among others, market volatility and news-based sentiment towards green bonds. Based on this study and considering the increasing impact of social media on financial markets (Gan et al., 2020), the need to analyse the influence of social network sentiment on the green bond market has strongly emerged. As green bonds are a relatively new asset class, investor sentiment related to green bonds has not yet been closely

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studied.

Investor sentiment is defined as how investors form their beliefs (Barberis et al. 1998), specifically how social network sentiment influences equity markets (Brown and Cliff, 2005; Liu, 2015), the S&P 500 Index (Piñeiro-Chousa et al., 2018; Zhang et al., 2011), and sustainable indices such as the S&P 500 Environmental & Socially Responsible Index (López-Cabarcos et al., 2019). However, there is scarce evidence regarding the influence of investor sentiment on the bond market (Fang et al., 2018; Nayak, 2010) and even fewer where the green bond market is considered (Piñeiro-Chousa et al., 2021). It is possible to assume that the coefficients related to the sentiment are not homogeneous in the sample since they may be impacted by other variables, such as the performance of market proxies during prolonged periods of overreaction or underreaction, initially analysed by De Bondt and Thaler (1985, 1987) and Jegadeesh and Titman (1993). Following Hansen (1999), we could claim a specific number of homogeneous sets in the panel, and the coefficients will vary in line with the change in those regimes. Accordingly, much more research is needed in this field, especially to analyse the linear/nonlinear relationship between social media sentiment and green bond returns.

Data from four green bond indices downloaded from the Bloomberg database were considered in this research, along with the daily sentiments about green bonds extracted from Twitter messages. The relationships between the Standard & Poor's 500 Index (S&P 500 Index), the Chicago Board Options Exchange Volatility Index (VIX), and the world equity market represented by MSCI (Morgan Stanley Capital International) were also examined in the study. Therefore, using these data and a panel smooth transition regression model (PSTR), the aim of this research is to analyse the potential linear/nonlinear relationship between social media sentiment in financial markets and green bond indices' returns. This paper contributes to the extant body of knowledge in two ways; first, by going deeper into analysing the influence of social network sentiment on green bond returns and second, by carefully examining what kind of relationship is established between both variables based on time variation criteria. There is some confirmation related to our claim that changes in the MSCI index, which is used as a threshold variable and a market proxy, impact investor sentiment and its relationship with returns on green bond indices.

The rest of the paper is organised as follows. Section 2 provides the conceptual framework of the study. Section 3 details the methodology and the data used in the analysis. Section 4 presents the results, while Section 5 offers further clarifications and implications. Finally, Section 6 provides concluding remarks in the form of policy recommendations, study limitations, and suggestions for future research.

2. Literature review

Climate change and population growth raise the demand for natural resources and energy, exerting heavy pressure on all economic sectors and increasing the environmental footprint. In this context, all social, political, and economic agents must urgently design concrete strategies to drastically reduce environmental risks.

According to the United Nations Sustainable Development Goals (SDGs), the consensus for environmental protection and the development of actions on climate change by 2030 (Amidjaya and Widagdo, 2019; Dörry and Schulz, 2018) has increased attention on green finance. Currently, stock markets emphasise developing green finance, including green bonds and innovation around green index products. Green bonds, which are similar to conventional bonds except that green bonds have a 'use of proceeds' clause that states that financing will be used only for green investments, are among the most important financial innovations in sustainable finance. Although there are no significant differences between green and conventional bonds (Ekeland and Lefournier, 2019), it is necessary to highlight that green bonds are designed to facilitate sustainable investing that can help increase sustainable infrastructure investments by improving the liquidity of infrastructure assets (Merk et al., 2012; Della Croce and Yermo, 2013; Šević and Bajalski, 2019; Bhattacharya et al., 2015).

The emergence of green bonds has served to finance green projects and convince those who have traditionally viewed financial engineering products as the main culprits for increased waste and short-term trade. Whether this 'going green' is a fad or an inexcusable need is still an unsolved debate. However, the serious consequences of climate change on the planet are increasing concern about green bonds. Several authors have relativised the use of green bonds to finance ecological transition since investors are not necessarily motivated by environmental issues and green bond principles are not yet legally mandatory (Ekeland and Lefournier, 2019). Either way, from a conceptual point of view, green bonds can be considered a good example of an innovative fixed-income investment product capable of activating a significant amount of capital to finance the fight against climate change. One reason that can justify their increasing importance is that the issuance of stocks instead of bonds to finance socially responsible projects is less efficient because buyers habitually do not own enough stocks to ensure that their preferences are respected by the inability to influence the decisions of the company. Bonds and stocks are the two main asset classes. It is crucial to understand the nature of the stock–bond correlation since it influences asset allocation and risk management (Aslanidis and Christiansen, 2012). Mainly based on low-frequency data, previous research has analysed the economic forces driving the stock–bond correlation. Thus, unexpected inflation (Ilmanen, 2003; Li, 2002), the business cycle of the macroeconomy (Ilmanen, 2003), stock market volatility (Connolly et al., 2005, 2007), and the VIX volatility index (Bansal et al., 2010) are some important determinants of the stock bond correlation. In this sense and a later study, Chiang et al. (2015) documented that both implied volatility of stock and conditional volatility of bond returns significantly negatively affect variations in stock–bond returns. At this point, it is necessary to analyse the stock–bond correlation based on its substantial time variation. Some authors have used economic policy uncertainty (EPU) to justify the time-varying correlations between stock and bond returns (Antonakakis et al., 2013; Jones and Olson, 2013; Li et al., 2015). For example, Antonakakis et al. (2013) found a consistent and negative correlation between EPU and S&P 500 returns over time with the exception of the period of the 2008 global financial crisis, and Li et al. (2015) reported that a rise in EPU has a negative and asymmetrical impact on subsequent stock–bond correlations.

One key issue that can justify the attractiveness of this new financial product relates to green bond returns. However, this aspect has not been well solved by previous literature. While several authors did not find evidence of a premium for investing in green bonds (Hyun et al., 2019; Larcker and Watts, 2020; Östlund, 2015; Petrova, 2016), other authors have concluded a 20-basis point advantage for green bonds versus traditional bonds (Kim, 2015) or even a 63-basis point advantage (Nanayakkara and Colombage, 2019). Although many authors have confirmed a greenium of corporate green bonds relative to conventional bonds (Bachelet et al., 2019; Gianfrate and Peri 2019; Fatica et al. 2019; Nanayakkara and Colombage, 2019), other authors have found that green bonds, in addition to having lower availability and association with more concentrated ownership, show lower yields (Baker et al., 2018; Zerbib, 2019). In this same sense, Karpf and Mandel (2018) stated that returns on conventional bonds are on average higher than those of green bonds, thus explaining the differences by the fundamental properties of the bonds. Kapraun and Scheins (2019) found evidence of a significant negative premium for green bonds of approximately 20–30 basis points differing across currencies and issuers. Although the presence of any pricing difference is still widely debated in empirical studies, several authors have concluded that the magnitude of the premium is more pronounced if issuers show better performance in CSR, since this one is associated with better financial performance and lower risk reinforcing (Chava, 2014; El Ghoul, 2011; Fernando et al., 2017).

The impact of green bond issuances has been empirically investigated from the investor, the issuer, and the combination of investor and issuer perspectives. It is precisely from the combination of both perspectives that a new line of research arises regarding analysing the impact of financial markets on green bond markets. From the Copenhagen Accord in 2009, financial markets have played a central role in the fight against climate change. Since 2014, the International Capital Market Association's introduced the green bonds principles (ICMA, 2018). The market of green bonds has experienced a continuous increase, achieving USD 257.7 billion in 2019 (Climate Bonds Initiative, 2019). With the prediction of closing 2020 with a figure close to USD 400 billion (Climate Bonds Initiative, 2020), the market for green bonds is still small when compared with the global bond market (USD 6.59 trillion in 2018). Previous research has analysed the dependence structure of the green bond market on other related financial markets. Gormus et al. (2018) concluded that energy markets impact the entire high-yield bond market, including greenness, from price and volatility perspectives. Reboredo (2018) clarified aspects of the diversification benefits of green bonds in investor portfolios and how price oscillations in the financial markets can impact green bond prices. The green bond market correlates more with corporate and treasury bond markets and less with stock and energy commodity markets. The same author found that green bonds are strongly connected to treasury bonds and corporate bonds in the short- and long-term run and are weakly connected to high-yield corporate bonds, stocks, and energy assets. Reboredo and Ugolini (2020) found a consistent correlation between the green bond market, the treasury bond market, and the USD currency market and a lack of or a weak correlation with the high-yield corporate debt market the stock market, and the energy market. In their study, Broadstock and Cheng (2019) provided evidence that the connection between green and conventional bonds is time-varying and sensitive to changes in economic policy uncertainty, daily economic activity, oil prices, financial market volatility, and measures of positive and negative news-based sentiment towards green bonds. Based on this previous study and wishing to go further, in our previous study, we analysed the influence of social network sentiment on the green bond market (Piñeiro-Chousa et al., 2021). In this research, we aim to analyse this relationship assuming a time variation criterion.

Baker and Wurgler (2006) defined investor sentiment as the optimism or pessimism an investor has about the future stock market. Although several ways to measure investor sentiment based on market variables exist (Baker and Wurgler, 2006; Bandopadhyaya and Jones, 2006; Qiu and Welch, 2006), there are also linguistic analysis tools that are used to extract the sentiment directly from the text posted in social networks (Zhang et al., 2016; López-Cabarcos et al., 2019), from websites (Kim and Kim, 2014), or the news (Broadstock and Cheng, 2019).

Previous studies have concluded that social network sentiment can predict the stock market activity (Asur and Huberman, 2010; Oh and Sheng, 2011). Previous research has supported the relationship between social network sentiment and the S&P 500 Index (Zhang et al., 2011; Piñeiro-Chousa et al., 2018). In this same sense, Gan et al. (2020) demonstrated that for the S&P 500 Index, social media has been the dominant media source since 2016. With growing environmental awareness, researchers have also begun to analyse the influence of social network sentiment on sustainable indices for example, the S&P 500 Environmental & Socially Responsible Index (López-Cabarcos et al., 2019). However, there is scarce evidence regarding the influence of investor sentiment on the bond market (Fang et al., 2018; Nayak, 2010) and even less on, specifically, the green bond market. Broadstock and Cheng (2019) provided evidence that the connection between this kind of bond and conventional bonds is sensitive to news-based sentiment towards green bonds. Piñeiro-Chousa et al. (2021) investigated the impact of investor sentiment from social media on green bond returns. The rise of the green bond market, investors' growing interest in climate change and financial formulas to fight against its consequences, and the close relationship between social media and financial markets (Gan et al., 2020) demand to go deeper into the analysis of the influence of social network sentiment on green bond returns, mainly if time variation is considered.

The question to analyse is whether the impact of social sentiment on green bond returns can diverge from a linear relationship. If messages posted on Twitter are mainly phatic (Miller, 2008) and overreaction or underreaction to significant changes in the market occur regularly (De Bondt and Thaler, 1985, 1987; Jegadeesh and Titman, 1993), it is assumed that the users of this social networking platform respond with different intensities in the case of rising, falling or rather indeterminable markets. Thus, Twitter followers may closely follow local volatility indices. Still, if a relevant market volatility measurement is not available, the alternative variable could provoke changes in global market indices and trends, leading to divergences from a linear relationship. If market proxies in the sample demonstrate upward or downward momentums, the assumption that the impact of social sentiment on green bond returns can diverge from the linear relationship strongly arises.

Classical panel models examine heterogeneity in intercepts; however, by going further, it is interesting to analyse whether, during the sample period, there were any structural changes. Extraordinary regional and global events can justify structural breaks, although behavioural patterns impacted by specific market trends can also clarify unexpected nonlinear changes. Investors' attitudes towards risk and expected returns may vary over time because the strategic interactions among market participants and the dynamics of economy-wide fluctuations are all inherently nonlinear. According to Campbell et al. (1997), time-varying investors' attitudes due to changing business conditions can generate explanations for risky asset returns. There are two lines of research on how bond returns vary over time. One line uses a linear framework that explains the variation of bond returns by changing factor risk premia (Ang and Piazzesi, 2003; Chan and Wu, 1995; Elton et al., 1996; Fama and French, 1989). The other line of research examines time-varying bond returns in a nonlinear framework. In this case, the existing literature is very limited. Using a Markov chain model, Guidolin and Timmermann (2006) found that government bond returns vary across bull and bear markets. Using a smooth transition regression regime-switching model, Lekkos and Milas (2004) concluded that the behaviour of UK government bonds differs according to economic regimes.

Hansen's (1999) panel transition regression model allows the regression coefficients to vary over time and between crossed units, thereby allowing the heterogeneity of the parameters to be estimated. The assumption that different groups of observations can be clearly distinguished from each other may or may not respond to real situations. There is a steady growth in the number of studies that apply this approach to examining nonlinearity in panel datasets (Chiang et al., 2015; Eggoh and Khan, 2014; Fouquau et al., 2009; Gu et al., 2016; Humpe and McMillan, 2018; Kim et al., 2018; Omay et al., 2018; Seleteng et al., 2013). The transition variable in the PSTR is essential in determining how the dependent variable can change and the confirmation of marginal effects that regressors can have (Wu et al., 2016; Wu et al., 2013). Unlike Wu et al. (2016), who used three investor sentiment proxies to examine the impact on three risk factors, this research juxtaposes the Twitter sentiment variable with dominant market forces in the US and globally in the determination of our transition variables.

It is necessary to deepen the study of the relationship between social network sentiment and green bond returns, mainly if the S&P 500, VIX, and MSCI are considered economic forces that drive the stockbond correlation and time variation phenomena. In 1993, the Chicago Board Options Exchange first applied the VIX as a relevant proxy for market expectations of stock return volatility over the next 30 calendar days. It started as a weighted measure of the implied volatility for selected S&P 100 Index constituents but currently spans the S&P 500 Index, thereby making it a relevant market-wide volatility measurement in our study. Market volatility is a good predictor of market returns, and the VIX is a good measure of market volatility (Whaley, 2000; Fleming et al., 1995; Durand et al., 2011). The VIX mainly refers to the volatilities of markets located in developed economies (Lee et al., 2014); however, it can also

Table 1
The evaluation of the single-threshold model.

Threshold estimator (level = 95):							
model |			Threshold		Lower		Upper
Th-1 |			0.0079		−0.0018		0.0082
Threshold effect test (bootstrap = 300):							
Threshold |	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single |	0.0149	0.0000	13.85	***0.0633***	9.3386	13.9765	21.3769
Fixed-effects (within) regression					Number of obs	=	2744
Group variable: id					Number of groups	=	4

be a good proxy for returns on international bond indices. For this reason, in this research, the VIX, and the reference index for the stock market, namely, the S&P 500 Index, have been used as threshold variables, thus assuming that investor sentiment varies if the markets show upward or downward trends or lower/higher volatilities. The MSCI has also been used as a proxy of the larger global market since it comprises large and mid-cap firms originating in 23 developed countries, including the US market.

Therefore, the following hypotheses are proposed:

H1. Changes in the S&P 500 and VIX index impact social network sentiment and its relationship with returns on green bond indices.

H2. Changes in the MSCI index impact social network sentiment and its relationship with returns on green bond indices.

3. Methodology

To apply the PSTR, there is a prior requirement to make the panel data stationary. There are several unit root tests for panels; however, based on the study of Maddala and Wu (1999), the Fisher-Phillips-Perron (Fisher-PP) test, as a nonparametric and exact test, seems to be the most appropriate one. Following Choi (2001), our test will combine the p values from the unit root tests, and four methods will be applied in this process. The difference among these processes will be the use of inverse χ^2 , the modification of the inverse χ^2 (if $N\rightarrow\infty$), inverse normal or inverse-logit transformation of p values. The demean function will be used to mitigate the impact of the cross-section dependence, while the number of lags in the ADF regression will be two. In addition, the average values of our variables are nonzero, and it may be necessary to include drift in the analysis.

In Stata, we apply single and multiple fixed-effect panel threshold models suggested by Wang (2015), which are based on the Hansen (1999) study. First, we apply the single threshold model:

$$r_{it} = \mu + X_{it}(m_{it} < \gamma)\beta_1 + X_{it}(m_{it} \geq \gamma)\beta_2 + u_i + e_{it} \tag{1}$$

where m_{it} is the threshold variable and γ is the parameter that splits the sample into two separate regimes. In Eq. (1) $u_i + e_{it}$ are the individual effect and error terms, respectively. To estimate γ, we look for the value that minimises the residual sum of squares, i.e.,

$$\widehat{\gamma} = \arg min S_1(\gamma) \tag{2}$$

Hansen (1999) confirmed that $\widehat{\gamma}$ is a consistent estimator for γ. To test whether $= \gamma_0$, we use the likelihood-ratio statistic (LR):

$$LR_1(\gamma) = \frac{\{LR_1(\gamma) - LR_1(\widehat{\gamma})\}}{\widehat{\sigma}^2} \xrightarrow{Pr} \xi \tag{3}$$

$$Pr(x < \xi) = \left(1 - e^{\frac{-x}{2}}\right)^2 \tag{4}$$

The maximum value of the LR series will equal the lower limit, while the minimum value of the same will be equal to the upper limit for a given significance level α. Respective limits will be determined by the α quintile, which is computed as:

$$c(\alpha) = -2ln\left(1 - \sqrt{(1-\alpha)}\right) \tag{5}$$

If $LR_1(\gamma_0)$ is larger than $c(\alpha)$, we reject the null hypothesis of no difference. If there are more thresholds, we apply the following model:

$$r_{it} = \mu + X_{it}(m_{it} < \gamma_1)\beta_1 + X_{it}(\gamma_1 \leq m_{it} < \gamma_2)\beta_2 + X_{it}(m_{it} \geq \gamma_2)\beta_3 + u_i + e_{it} \tag{6}$$

In which thresholds γ_1 and γ_2 split the equation into three regimes. The threshold effect is evaluated sequentially. If we reject the null hypothesis for a unique threshold, we examine the double threshold model, i.e., whether the null hypothesis of a single threshold model is rejected, and an alternative double-threshold model is accepted:

$$\begin{aligned} RGB_{it} = {} & \beta_0 + \beta_1 RGB_{it-1} + \beta_2 vsent_{it}^2 + \beta_3 VIX_{it} + \beta_4 SP_{it} + \beta_5 vsent_{it} RGB(SP_{it} < \gamma_1) \\ & + \beta_6 vsent_{it} RGB(\gamma_1 \leq SP_{it} < \gamma_2) + \beta_7 vsent_{it} RGB(SP_{it} \geq \gamma_2) + u_i + \varepsilon_{it} \end{aligned} \tag{7}$$

$$\begin{aligned} RGB_{it} = {} & \beta_0 + \beta_1 RGB_{it-1} + \beta_2 vsent_{it}^2 + \beta_3 VIX_{it} + \beta_4 SP_{it} + \beta_5 vsent_{it} RGB(VIX_{it} < \gamma_1) \\ & + \beta_6 vsent_{it} RGB(\gamma_1 \leq VIX_{it} < \gamma_2) + \beta_7 vsent_{it} RGB(VIX_{it} \geq \gamma_2) + u_i + \varepsilon_{it} \end{aligned} \tag{8}$$

where RGB_{it} is a return on selected four green bond indices, Bloomberg Barclays MSCI Global Green Index Total Return Index Value Unhedged, the S&P Green Bond Index, the Solactive Green ESG Bond EUR USD IG TR Index, and the FTSE Chinese (Onshore CNY) Green Bond Index, from 6th July 2016 until 29th November 2019, $vsent_{it}^2$ is the squared sentiment term, VIX_{it} is the market volatility measure and SP_{it} is a return on the S&P 500 index in our sample period. The threshold variables SP_{it} and VIX_{it} are trimmed at 1 percent at both ends.

An alternative model would include the MSCI World index to reflect the international constituency of green bond indices:

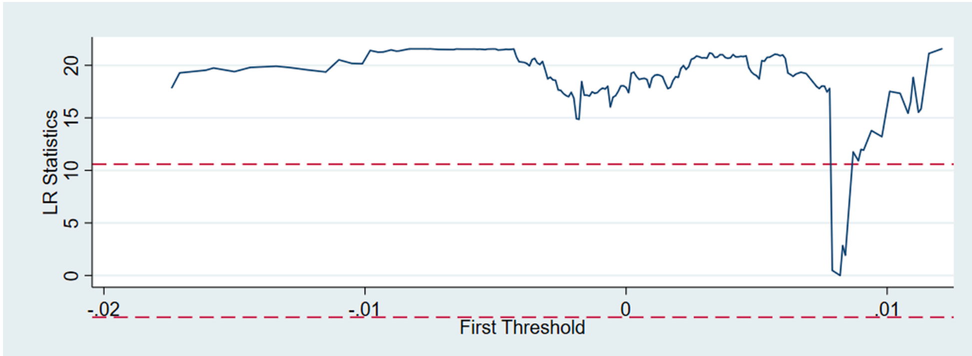
$$\begin{aligned} RGB_{it} = {} & \beta_0 + \beta_1 RGB_{it-1} + \beta_2 vsent_{it}^2 + \beta_3 MSCI_{it} + \beta_4 vsent_{it} RGB(MSCI_{it} < \gamma_1) \\ & + \beta_5 vsent_{it} RGB(\gamma_1 \leq MSCI_{it} < \gamma_2) + \beta_6 vsent_{it} RGB(MSCI_{it} \geq \gamma_2) + u_i + \varepsilon_{it} \end{aligned} \tag{9}$$

where RGB_{it} is a return on four selected green bond indices, $vsent_{it}^2$ is the squared sentiment term, and $MSCI_{it}$ is a return on the MSCI World index in our sample period. The threshold variable $MSCI_{it}$ is trimmed at 1 percent at both ends.

Thus, this model allows for the sequential analysis of various models. If the single-threshold model's null hypothesis has been rejected, we proceed to the double-threshold model. Bootstrapping is used to test the null hypothesis of no threshold. In the model, it is possible to manipulate the number of Monte Carlo simulations. Still, with an increase in the number of observations and T, the confidence interval becomes wider because the inverse LR method demonstrates some inefficiencies.

3.1. Analysis

The Fisher PP test strongly rejects the null hypothesis that all panels



Graph 1. LR Statistics for the single-threshold model.

Table 2
The evaluation of the double- and triple-threshold model.

Threshold estimator (level = 95):

model |	Threshold	Lower	Upper
Th-1 |	0.0079	−0.0018	0.0082
Th-21 |	0.0082	0.0078	0.0083
Th-22 |	0.0121	.	.
Th-3 |	−0.0018	−0.0019	−0.0017

Threshold effect test (bootstrap = 0 300 300):

Threshold |	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single |							
Double |	0.0148	0.0000	7.75	***0.0700***	6.9931	16.0069	16.3705
Triple |	0.0148	0.0000	3.85	0.6433	11.0179	13.4094	14.7425

contain unit roots across all four methods: inverse χ^2, the modification of the inverse χ^2 (if $N\rightarrow\infty$), inverse normal or inverse-logit transformation of p values.

When examining Eq. (7), it is evident that the threshold 1 model estimator of 0.0121 has an F-statistic that is not significant at 10% (p value 0.11). Accordingly, we fail to reject the claim about the linear relationship and cannot find evidence that Twitter users' sentiment is impacted by the S&P 500 Index returns. There is a nonlinear relationship with returns on bond indices. In addition, the estimates in Eq. (8) do not provide any supporting evidence for VIX as a relevant threshold.

When applying Eq. (9), our initial test offers weak support for the single threshold model. The value of the threshold 1 model estimator (Th-1 in Table 1) is 0.0079, which lies within the 95% confidence interval. The F-statistic is weakly significant, and we reject the null hypothesis of a linear relationship with a p value smaller than 0.1. Using Eq. (5), for $\alpha = 0.1$, the quintile value is 10.59. Since $LR_1(\gamma_0)$ is larger than this number, we reject the null hypothesis (Graph 1.). We then proceed with the evaluation of double- and triple-threshold models (Table 2).

When estimating the double and triple threshold models, we reduce the computational time by omitting the first bootstrapping for Th-1 and immediately evaluating other thresholds. Th-22 amounts to 0.0121, and the F-stat for the double threshold model is weakly significant (p value 0.07). This implies that we could reject the null hypothesis on the single-threshold model and examine the double-threshold model, thereby rendering further support for multiple regimes in our sample.

3.2. Robustness check

It could be claimed that instead of $vsent_{it}$, the relationship with the threshold variable could exist via $vsent_{it}^2$. Therefore, we examine the following panel regressions:

$$\begin{aligned}RGB_{it} = {} & \beta_0+\beta_1 RGB_{it-1}+\beta_2 vsent_{it}+\beta_3 VIX_{it}+\beta_4 SP_{it}+\beta_5 vsent_{it}^2 RGB(SP_{it}<\gamma_1)\\ & +\beta_6 vsent_{it}^2 RGB(\gamma_1\le SP_{it}<\gamma_2)+\beta_7 vsent_{it}^2 RGB(SP_{it}\ge\gamma_2)+u_i+\varepsilon_{it}\end{aligned} \tag{10}$$

$$\begin{aligned}RGB_{it} = {} & \beta_0+\beta_1 RGB_{it-1}+\beta_2 vsent_{it}+\beta_3 VIX_{it}+\beta_4 SP_{it}+\beta_5 vsent_{it}^2 RGB(VIX_{it}<\gamma_1)\\ & +\beta_6 vsent_{it}^2 RGB(\gamma_1\le VIX_{it}<\gamma_2)+\beta_7 vsent_{it}^2 RGB(VIX_{it}\ge\gamma_2)+u_i+\varepsilon_{it}\end{aligned} \tag{11}$$

$$\begin{aligned}RGB_{it} = {} & \beta_0+\beta_1 RGB_{it-1}+\beta_2 vsent_{it}+\beta_3 MSCI_{it}+\beta_4 vsent_{it}^2 RGB(MSCI_{it}<\gamma_1)\\ & +\beta_5 vsent_{it}^2 RGB(\gamma_1\le MSCI_{it}<\gamma_2)+\beta_6 vsent_{it}^2 RGB(MSCI_{it}\ge\gamma_2)+u_i+\varepsilon_{it}\end{aligned} \tag{12}$$

In addition, we examine whether there is a lagged influence of sentiment variables on bond return indices. To examine this viewpoint, we include variables lagged by one period. We also include the cubic sentiment variable in Eq. (13):

$$\begin{aligned}RGB_{it} = {} & \beta_0+\beta_1 RGB_{it-1}+\beta_2 vsent_{it}^2+\beta_3 vsent_{it-1}^2+\beta_4 vsent_{it}^3+\beta_5 MSCI_{it}\\ & +\beta_6 vsent_{it} RGB(MSCI_{it}<\gamma_1)+\beta_7 vsent_{it} RGB(\gamma_1\le MSCI_{it}<\gamma_2)\\ & +\beta_8 vsent_{it} RGB(MSCI_{it}\ge\gamma_2)+u_i+\varepsilon_{it}\end{aligned} \tag{13}$$

We fail to find statistically significant results when evaluating panel regressions Eqs. (10)–(12). It is impossible to claim the existence of thresholds, and the results reported in Pinero-Chousa et al. (2021) are fully supported in terms of linearity and the nonexistence of structural changes.

When applying the PSTR, it is essential to have a balanced panel dataset. Initially, $vsent_{it}^2$ and $vsent_{it-1}^2$ were jointly included in the anal-

Table 3
The evaluation of the single-threshold model.

Threshold estimator (level = 95):							
model |			Threshold		Lower		Upper
Th-1 |			0.0079		0.0078		0.0082
Threshold effect test (bootstrap = 300):							
Threshold |	RSS	MSE	Fstat	Prob	Crit10	Crit5	Crit1
Single |	0.0149	0.0000	13.86	***0.0433***	10.4656	10.8173	21.6591
Fixed-effects (within) regression					Number of obs	=	2744
Group variable: id					Number of groups	=	4

ysis, and the coefficient estimate for the single-threshold model was significant at 0.0533. When Eq. (13) is applied in its entirety, the coefficient estimate of Th-1 amounting to 0.0079 has a statistically significant F-statistic at the 5% confidence level (Table 3).

The coefficient estimate for the double threshold model is significant at 10%, and we fail to reject the null hypothesis on the single threshold model.

Finally, following Aslanidis and Christiansen (2012), we decide to include the short-term 3-month treasury bill in the analysis, a spread between a 10-year treasury note and a 3-month treasury bill, which reflects the risk change and US inflation. We have used a logarithmic transformation of their daily changes or monthly variations in the case of the US inflation. Following Aslanidis and Christiansen (2012), if monthly data were available, then the data for every day in the same month were the same. Only changes in the MSCI index and 10-year note yield have a statistically significant impact on bond index returns. In addition, the S&P 500 Index has a weakly (at 10 percent) positive impact on bond index returns. However, we do not find any evidence for regime switches.

4. Discussion

In our study, we applied Wang's (2015) PSTR model, which is based on Hansen's (1999) study, to examine whether the selection of various threshold variables, such as the S&P 500, VIX and MSCI, would have an impact on market sentiment and thus on the return on market indices. Assuming that Twitter communication is mainly phatic (Miller, 2008), if short messages convey information to investors, we believe that strong reversals in the market could potentially impact investors' behaviour and the way they trade. The advantage of the applied methodology is that it allows for more thresholds if the linear violation across the studied period is more severe. We find that the US market and volatility proxies do not lead to a regime switch involving sentiment as long as bond index returns are concerned. These findings are robust regardless of the introduction of dynamic models and additional variables. We do find some limited relevance when the MSCI index is selected. Our finding is not surprising since green bond indices mainly reflect the green bond universe from developed countries. The market co-movements of the most developed countries in the world may have a strong implication for the sentiment among Twitter users who, in turn, may decide to either increase or decrease stakes in the green bond market. The practical implication, despite all limitations imposed by social networks, is that global green bond indices seem to be more related to global market indices, which further supports the broader look beyond the most capitalized market in the world, which is located in the US. From the theoretical perspective to the best of our knowledge, this is the first attempt to link Twitter sentiment to potential regime switching in the green bond market via the evaluation of multiple thresholds in the investment domain.

5. Concluding remarks

We find limited evidence about a nonlinear relationship between sentiments in financial markets and bond indices' returns. Changes in the MSCI World index, which is used as a threshold variable in our study, impact sentiment and its relationship with returns on bonds. If the model applied to the balanced panel dataset does not include the lagged and cubic variables, we find limited evidence regarding the existence of a single threshold. When sentiment variables lagged by one period and cubic variables were introduced, we obtained stronger evidence for a single-threshold model. Unlike Wu et al. (2016), we cannot find any support for the S&P 500 index returns or the VIX as threshold variables. This prompts us to think that Twitter postings are dominated by investors who strongly react to international returns and may not be as strongly influenced by US market returns. Our findings are useful for traders and policy-makers who could pay more attention to how current and future investors behave when referring to international market indices and bond returns.

The sample size limits our study, and the search for new threshold variables pertinent to investors' decision-making process is quite novel, which is also a constraining factor. It is evident that the inclusion of lagged squared and cubic sentiment variables provides stronger support for thresholds, but this claim is only limited to the international index. The inclusion of treasury issues and US inflation data in the analysis does not change our findings. Therefore, future research could continue with the search for other relevant variables even outside of the finance and economics realm since we refer to the complex behavioural patterns of potential investors.

CRediT authorship contribution statement

Juan Piñeiro-Chousa: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **María López:** . **Aleksandar Šević:** Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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