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Time-Varying Co-Movements Between Green Bonds, CO_2 Emissions, the Investor Sentiment, and Financial Stress

S. Boutouria
Probability and Statistics Laboratory, Sfax, Tunisia
University of Sfax, Sfax, Tunisia

ABSTRACT

Green bonds are attracting growing interest as sustainable financial instruments that support the transition to a low-carbon economy by financing environmentally responsible projects. Understanding how these instruments interact with CO_2 emissions and investor sentiment is essential to assess their stability and long-term potential. **The aim** of this study is to explore the dynamic relationships between green bonds and a selection of financial and environmental variables, including US conventional bonds, the WilderHill Clean Energy equity index, and CO_2 emission allowances. Additionally, the study evaluates the impact of investor sentiment and financial stress on green bond performance. **The methods** used include a quantile regression model, which assesses whether the Standard and Poor's (S&P) Green Bond Index can be explained by the aforementioned variables — namely CO_2 emissions, clean energy stocks, investor sentiment (proxied by Google Trends), and financial stress [measured by the Office of Financial Research (OFR) Index]. The analysis covers the period from July 6, 2011, to September 15, 2023. To account for time-varying relationships, a Bayesian time-varying vector autoregressive (BTC–VAR) model is also applied. **The results** show a negative unidirectional effect from CO_2 emissions to the green bond index and a positive unidirectional effect from the clean energy index. However, green bonds appear weakly correlated with the other considered assets. Investor sentiment does not show a significant influence, while financial stress plays a more important role, indicating that green bonds may be perceived as safer assets during periods of uncertainty. **The key conclusion** is that green bonds exhibit selective sensitivity to specific financial and environmental factors. Their relative stability during episodes of financial stress reinforces their position as both sustainable and resilient investment tools. These findings provide useful insights for investors, policymakers, and researchers interested in the evolving dynamics of green finance.

Keywords: green bonds; CO_2 emissions; clean energy; investor sentiment; financial stress; ecology; time-varying VAR; quantile regression

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Изменения во времени соотношения между «зелеными» облигациями, выбросами CO_2, настроениями инвесторов и финансовым стрессом

С. Бутурия
Лаборатория теории вероятностей и статистики, Сфакс, Тунис;
Университет Сфакса, Сфакс, Тунис

АННОТАЦИЯ

«Зеленые» облигации привлекают все больший интерес как устойчивые финансовые инструменты, которые поддерживают переход к экономике с низким уровнем выбросов углерода путем финансирования экологически ответственных проектов. Понимание того, как эти инструменты взаимодействуют с выбросами CO_2 и настроениями инвесторов, имеет важное значение для оценки их стабильности и долгосрочного потенциала. **Целью** данного исследования является изучение динамических взаимосвязей между «зелеными» облигациями и рядом финансовых и экологических переменных, включая обычные облигации США, индекс акций WilderHill Clean Energy и квоты на выбросы CO_2. Кроме того, в исследовании оценивается влияние настроений инвесторов и финансового стресса на эффективность «зеленых» облигаций. **Используемые методы** включают модель квантильной регрессии, которая оценивает, можно ли объяснить индекс «зеленых» облигаций Standard and Poor's (S&P) вышеупомянутыми переменными, а именно выбросами CO_2, акциями чистой энергии, настроениями инвесторов (по данным Google Trends) и финансовым стрессом [(измеренным индексом Управления финансовых исследований (OFR)]. Анализ охватывает период 06.07.2011–15.09.2023 гг. Для учета изменяющихся во времени взаимосвязей также применяется байесовская векторная авторегрессия с изменяющимися во времени параметрами (BTC–VAR). **Результаты** показывают отрицательное однонаправленное влияние выбросов CO_2 на индекс «зеленых» облигаций и положительное однонаправленное влияние индекса чистой энергии. Однако «зеленые» облигации, по-видимому, слабо коррелируют с другими рассматриваемыми активами. Настроения инвесторов не оказывают существенного влияния, в то время как финансовый стресс играет более важную роль, что указывает на то, что «зеленые» облигации могут восприниматься как более безопасные активы в периоды неопределенности. **Основной вывод** заключается в том, что «зеленые» облигации демонстрируют избирательную чувствительность к определенным финансовым и экологическим факторам. Их относительная стабильность во время эпизодов финансового стресса укрепляет их позицию как устойчивых и надежных инвестиционных инструментов. Эти результаты дают полезную информацию инвесторам, политикам и исследователям, интересующимся развивающейся динамикой «зеленых» финансов.

Ключевые слова: «зеленые» облигации; выбросы CO_2; чистая энергия; настроения инвесторов; финансовый стресс; экология; векторная авторегрессия с изменяющимися во времени параметрами; квантильная регрессия

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1. Introduction

Climate risk can notably serve as a transmission channel for policy action by influencing public and political opinion, according to R. Willis et al. [1]. As the impact of climate change becomes more severe and apparent, it often yields an increased public awareness and concern about the issue. This growing awareness, coupled with the tangible effects of climate change, can create pressure on policymakers to act and implement appropriate policies to address the challenges posed by climate change.

When the consequences of climate change, such as extreme weather events, rising sea levels, or disruptions in ecosystems, become more pronounced, people are more likely to claim that their governments take steps to mitigate and adapt to these risks. They expect policymakers to develop and implement policies that reduce uncertainty and effectively address climate risks, as claimed by C. Wamsler and J. Bristow [2].

To effectively handle climate change, policies need to be designed to reduce uncertainty by providing clear goals, guidelines, and regulations. This can include setting emissions reduction targets, implementing renewable energy incentives, promoting sustainable practices, and encouraging adaptation measures [the United Nations Framework Convention on Climate Change (UNFCCC) and Kyoto Protocol]. Through implementing these policies, governments can help mitigate climate risk and provide a framework for businesses, organizations, and individuals to make informed decisions and push towards a more sustainable future.

Additionally, policies aimed at reducing climate risk often involve promoting research and development of clean technologies, investing in infrastructure that can withstand climate impacts, and facilitating international cooperation to tackle global climate challenges. These measures can help mitigate the risks associated with climate change and enhance societal resilience.

In recent years, both governmental bodies and non-governmental organizations have increasingly acknowledged the danger posed by the release of excessive quantities of greenhouse gases. This has prompted them to initiate significant actions aimed at reducing the impact of these emissions on the environment and the well-being of humanity. Eventually, a new approach urging investors to claim environmental difficulties and work to diminish them — known as "the Green finance" — emerged in the financial sector.

It focuses basically on allocating capital towards projects, businesses, and technologies aiming to foster a more sustainable and resilient global financial system.

While there has been some research at the intersection of finance and ecology, the body of literature remains relatively small compared to other interdisciplinary fields. Y. Wang and Q. Zhi [3] asserted that fostering financial support for solar energy is a key avenue for achieving environmental sustainability. Similarly, W. Li and Z. Jia [4] emphasized that environmental finance, or sustainable finance, represents an impactful strategy in mitigating environmental degradation. The consensus is on the fact that sustainable finance, also referred to as green finance, stimulates investments in novel technologies, particularly those related to renewable energy, as highlighted by A. Jones [5]. Notably, previous research has overlooked the correlation between green bonds and other asset classes and considered a proxy for green finance as well as carbon dioxide (CO_2) emissions.

Under these circumstances, green bonds were issued by the European Investment Bank in 2007 and were defined as "a hybrid financial instrument that combines environmental benefits and conventional fixed income instruments to channel funds to environmentally friendly projects," according to S. Hyun et al. [6]. Basically, "Green Bonds are any type of bond instrument where the proceeds or equivalent amount will be exclusively applied to finance or refinance, in part or in full, new and/or existing eligible Green Projects that are aligned with the four core components of the Green Bond Principles" (ICMA, 2021).[1] Green bonds have evolved into a desirable financial investment product that can help maintain the transition to a low-carbon economy.

Recent studies have explored the interaction between green bond issuance, investor response, and environmental policy frameworks. Flammer [7] investigates corporate green bonds' role in signaling environmental commitment, while Tang and Zhang [8] show that green bond announcements can lead to positive abnormal stock returns. Wang et al. [9] further demonstrate how climate policies influence green bond development and carbon emissions reduction. Mezghani et al. [10] examine the impact of green bonds on extreme spillover effects and hedging across stocks and commodities, highlighting the role of green bonds in mitigating risk and enhancing portfolio diversification during extreme market conditions. These findings reinforce the relevance of studying green bond dynamics under varying environmental and financial conditions.

Behavioral finance theories assume that investors, in their decision-making processes, can be swayed by information and psychological biases, as evidenced by investor sentiment (T. Yao et al. [11]). The impact of investor sentiment extends to influencing the interconnections within green finance markets through two theoretical channels.

The first channel involves limited information. Due to incomplete information, investors are prone to either underreact or overreact in green finance markets (Z. Chen et al. [12]). This tendency contributes to the biased pricing of green assets and the emergence of systemic risk within green finance markets, amplifying the potential for market inefficiencies.

The second channel is linked to the real economy. Concerns surrounding climate change have the potential to influence consumer spending and alter business investment strategies in the real economy. These shifts can, in turn, have a cascading effect on the valuation of green assets, thereby facilitating the transmission of information among green finance markets. Notably, the interplay between investor sentiment and the broader economic landscape creates a dynamic relationship that shapes the functioning and interconnectedness of green finance markets.

In this respect, several empirical studies have attempted to investigate the relationship between green bonds and a few environmental and financial assets, as well as the impact that investors' behavior has on the green bond market. X. [13] and V. Baulkaran [14] reported the interest that investors have in green bonds and discovered that Chinese stock market investors react favorably to news of green bond issuance. [15], who highlighted the strong correlation between investor responses and green bond market performance, equally reinforced this topic. Several researchers have pointed out that people's motivations for making investments fre-

[1] ICMA stands for International Capital Market Association. See: International Capital Market Association. Green Bond Principles — Voluntary Process Guidelines for Issuing Green Bonds. June 2021. URL: https://www.icmagroup.org/assets/documents/Sustainable-finance/2021-updates/Green-Bond-Principles-June-2021–140621.pdf

quently extend beyond monetary gains and include other aspects such as the impact on society and the environment. X. Zhou and Y. Cui [16] demonstrated that corporate performance and social responsibility to environmental issues have a favorable influence on the growth of the green bond market. Likewise, the analysis performed by O. Zerbib [17] revealed a considerable impact of investors' pro-environmental inclinations on the growth of this market, which was considered as one of the markets with the highest efficiency for reducing future emissions (J. Jin et al. [18]). Furthermore, through inciting investors to participate more effectively, M. Voica et al. [19] clarified how a suitable legal and institutional framework may help countries build up their green bond markets. This reinforces the link between green finance and behavioral finance and highlights the significance of considering not only financial factors but also the behavioral factors that influence individual decision-making when promoting sustainable and environmentally friendly economic activities.

According to [15], there is a correlation between investors' attention, measured using the Google Search Volume Index, and the performance of the green bond market, measured by five green bond market indexes, over the period from 2014 to 2019. The researchers discovered that investors' attention has a significant impact on the return and volatility of the green bond market. Additionally, they found that this relationship varies over time, with stronger effects observed in the short-run compared to the long-run.

A. Elsayed et al. [20] examined the relationship and dynamic interconnectedness between green bonds and financial markets. They accordingly incorporated multiple uncertainty indices. These indices cover financial uncertainty, financial stress, and economic uncertainty. They demonstrated the correlation between the green bonds and the financial stress.

The central objective of this study is not only to examine the causal relationships between green bonds and other related assets — including US conventional bonds, the WilderHill clean energy (WCE) equity index and CO_2 emission allowances price — but also to analyze the effects of investor sentiment and financial stress, as measured through the Google Trends Index and the OFR Financial Stress Index, respectively. The Quantile regression model and Bayesian time-varying vector autoregressive (BTVAR) model have been used to address the connections between multiple time series variables.

Exploring the relationship between green bonds and other eco-friendly market indices holds paramount importance for both portfolio managers and policymakers. Gaining a deeper and better insight into this relationship has the potential to encourage increased investments in cleaner production and foster the development of innovative green financial instruments. In recent years, a substantial body of literature has delved into the interconnections between green bonds and diverse markets, shedding light on the intricate dynamics at play in the realm of sustainable finance.

This research primarily contributes to clarifying how connections between green bonds and several financial instruments evolve throughout quantiles in order to enable investors and policymakers to make more effective choices. Hence, the basic target of this research is to explore the robustness of green bonds in relation to CO_2 emissions, investor sentiment, and financial stress. Furthermore, it implements the Bayesian TVC–VAR to investigate potential shifts and fluctuations in the causal connections across the parameters in discussion. It also highlights the effect of investor sentiment and financial stress on the green bond market.

This study makes three contributions to existing literature. Firstly, compared to prior studies, which mostly emphasize the role of financial development instead of highlighting the effect of green finance on environmental variables, this study presents a pioneering examination of green finance, CO_2 emissions, investor sentiment and financial stress.

Secondly, this study uses the quantile approach that captures the heterogeneous and asymmetric relationship between green finance and CO_2 emissions, investor sentiment and financial stress.

Thirdly, this work corresponds to one of the first studies that use the Bayesian time-varying vector autoregressive (BTC–VAR) model in order to examine the relationship between green finance bonds, CO_2 emissions, investor sentiment and financial stress.

2. Data and methodology

2.1. Data

This research used data covering daily S&P green bond Index, CO_2 Emission index, US Bonds and WCE index prices over a period extending from June the 6th, 2011 to September the 15th, 2023. Data were extracted from the Thomson Reuters DataStream.

Data related to the study of the impact of the investor sentiment and financial stress on the green bonds were collected from Google Trends (Google Trends) and the Office Financial Research (OFR Financial Stress Index | Office of Financial Research) from June 6th, 2011, to September the 15th, 2023.

2.1.1. Google trends index and financial stress index

The Google Trends Index, also known as Google Trends, refers to a free online tool provided by Google that allows users to explore the popularity and search interest for specific keywords or topics over time. It provides insights into the relative search volume of specific terms and helps users understand trends in search behavior.

The Google Trends Index aggregates and normalizes search data from Google Search, providing a numerical representation of search interest over a selected time period.

The OFR Financial Stress Index (FSI) stands for an indicator developed by the Office of Financial Research (OFR), which is part of the U.S. Department of Treasury. It is designed to measure the level of stress in the financial system through incorporating various market-based indicators and economic data. It takes into consideration factors such as asset price movements, market volatility, credit spreads, and funding conditions so as to assess the overall financial stress experienced in the economy. By monitoring these indicators, the FSI aims to provide early warnings of potential financial instability.

The OFR Financial Stress Index serves as a tool for market participants to monitor the overall health and stability of the financial system. It can help identify periods of growing financial stress and inform policy decisions, aiming at the mitigation of potential risks or imbalances in the financial markets.

Figure 1 illustrates each of the factors' time-trials. We notice that the trends of the green and traditional Treasury bond indices are similar during all the time periods, except for the first trimester of 2018. The WilderHill clean energy index and the CO_2 emission allowance price have a relatively similar motion, distinguished by a substantially stable trend until 2018, when they climbed a rising trend. Moreover, all the mentioned variables crashed during the first quarter of 2020. This sudden bearish peak arose from the COVID-19 crisis and its precarious financial effects on the market, which are reflected by a significant unexpected peak of the OFR Financial stress index during the same period of time.

The Google Trends Index reveals severe bullish peaks during all the presented periods of time. It seems to be excessively random and chaotic to accurately reflect the market sentiment and to evaluate it effectively. The "OFR Financial Stress Index", however, seems more reliable and informative, as its trend accurately captures market sentiment without becoming chaotic, therefore enabling a clear interpretation of the outcomes.

Table 1 depicts some prevalent statistics for all the variables and the descriptive analysis of the data. All daily averages of variables, with the exception of the FSI, are positive, as determined by statistics. The measurement of US Treasury bonds reveals the greatest average. Considering that they have the largest standard deviations among the different stocks, the US Treasury bond index is the second-most risky, closely followed by the WilderHill clean energy index. With regard to the positive and significant values of the skewness, all of the examined time series are skewed to the right.

The graphs demonstrate that the frequency distributions of CO_2 Emissions Index Price are higher than those of other variables, such as the S&P Green Bond Index, the US Treasury Bond Index, and the WCE Index. A distribution is referred to as leptokurtic if it features thick tails, which are indicated by an excess of kurtosis. When the skewness is positive and different from zero for the various variables, the distribution is said to be skewed to the right. For these reasons, in view of the low positive skewness, each graph displays a small divergence to the right.

2.2. Methodology

We adopted the VAR model to examine the causal relationship between the green bonds and the three other parameters as well as the effects of investor sentiment and financial stress on the green bond market. Moreover, the quantile regression method is invested to analyze the predictive ability of the various parameters. In addition, in order to explore the dynamic correlations among the variables, we apply the Bayesian time-varying VAR that allows the coefficients to change over time.

2.2.1. Quantile regression

In a traditional quantile regression, the influence of the independent variable is investigated to examine the impacts of the dependent variables' conditional distribution on the dependent variable itself.

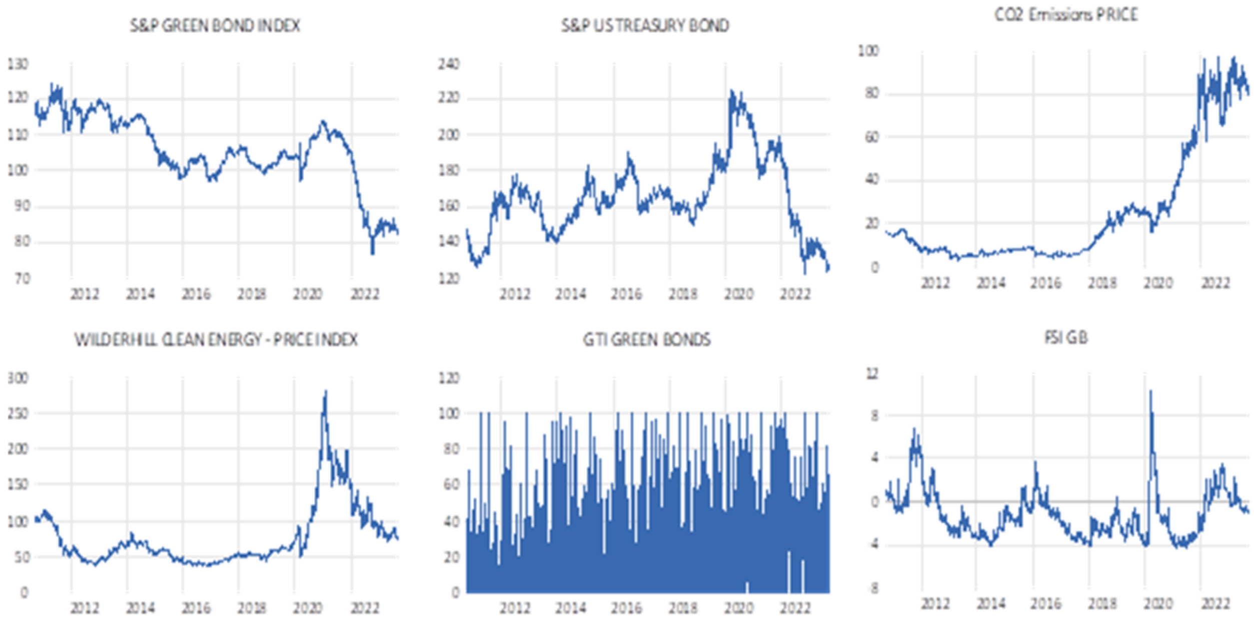

Fig. 1. **Time-paths of the considered variables**

Source: The Thomson Reuters DataStream.

Table 1

Descriptive statistics

Measures	SP_GB	USBOND	WCEI	CO2	GTI	OFR_FSI
Mean	105.3629	164.5726	76.54208	24.23333	19.04885	−1.195171
Maximum	124.3048	224.4338	281.4400	97.58000	100.0000	10.26600
Minimum	76.26968	122.1600	36.53000	2.680000	0.000000	−4.364000
Std. Dev.	9.815400	20.76409	42.91041	26.70824	23.06387	2.226883
Skewness	−0.742488	0.527290	1.968251	1.465266	1.148842	1.285019
Kurtosis	3.298509	3.249986	6.983676	3.714539	3.857872	5.142189

Source: Authors' calculation.

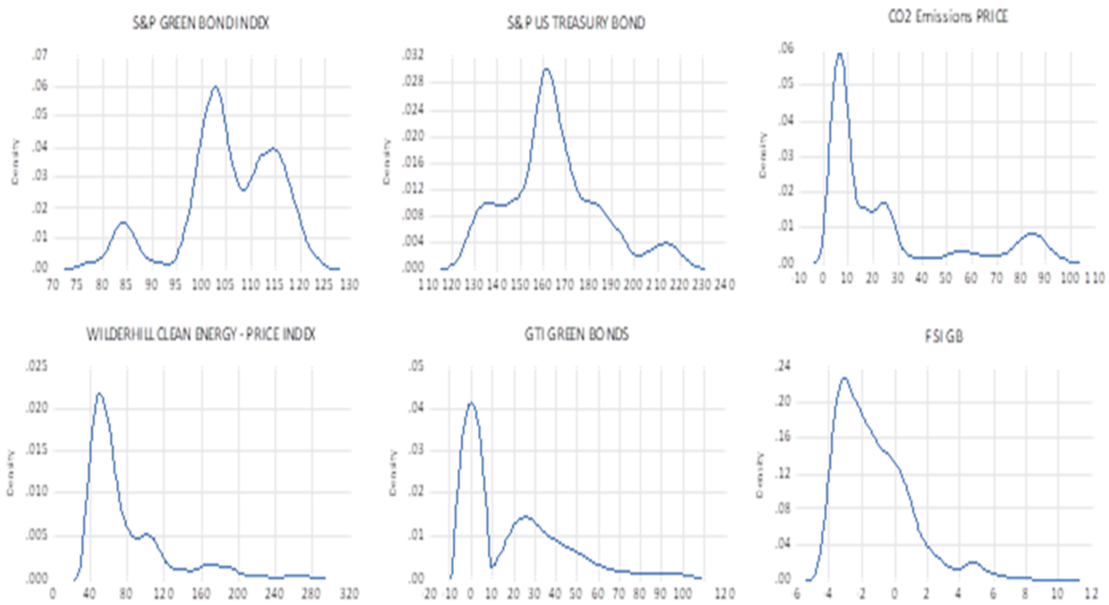

Fig. 2. **The distributive properties of the variables**

Source: Created by the authors.

2.2.2. The Bayesian time-varying VAR (BTVC–VAR)

Bayesian time-varying vector autoregressive (BTC–VAR) models correspond to a statistical framework that is used to analyze multivariate time series data. They extend the traditional Vector Autoregressive (VAR) models by allowing the parameters to vary over time in a Bayesian setting.

In a BTVAR model, the relationships between multiple variables are captured by lagged values of the variables themselves. However, unlike traditional VAR models, where the parameters are assumed to be constant over time, BTC–VAR models introduce time-varying coefficients. This allows for the modeling of changing dynamics and relationships among the variables over different time periods.

The Bayesian approach in BTC–VAR models incorporates prior information about the coefficients and uses Bayesian inference techniques to estimate the parameters. This provides a flexible and robust framework for capturing time-varying patterns and uncertainties in data.

The Bayesian time-varying vector autoregressive models offer outstanding applications in various fields, including economics, finance, and econometrics, where understanding the dynamic relationships between variables and capturing their time-varying nature is crucial for an accurate analysis and forecasting.

The parameter estimates of a Bayesian time-varying vector autoregressive (BTC–VAR) model are presumed to fluctuate throughout intervals of time and are regarded as random variables selected from a given distribution. Furthermore, the Bayesian approach to the model allows the quantification and incorporation of uncertainty in the coefficient estimations. The model incorporates the assumption that there is a linear relationship between each of the different variables and that every parameter in the system is dependent on both their historical values and those of the other variables. The main features of the time-varying VAR coefficient refer to the Bayesian approach, dynamic modeling, Markovian structure, and flexibility.

S. Ahmed and M. Mortaza [21] applied B. Hansen's [22] threshold model to explore the threshold effects on the bivariate inflation-growth correlation. On the other hand, A. Chowdury and R. Ham [23] investigated a bivariate threshold autoregressive (BTVAR) model. They derived the BTVAR model through further elaborating B. Hansen's [22] threshold model, substituting the dependent and independent variables with vectors of bivariate endogenous variables.

The Bayesian TVC–VAR model can be expressed as

$$y_t = c_t + \sum_{i=1}^{p} A_{it} y_{t-i} + \sum_{j=1}^{q} B_{jt} x_{t-J} + e_t ,$$

where y_t denotes the vector of endogenous variables;

X_t indicates the vector of exogenous variables;

C_t represents the vector of constant terms;

A_{it} and B_{jt} stand for the matrices of parameters;

P and q correspond to the number of lags.

3. Results and discussion

3.1. ADF unit root test

In order to analyze the variables' integration order, we applied augmented Dickey-Fuller (ADF) unit root test. The ADF evaluates the stationarity under the alternative hypothesis while assuming the null hypothesis and assessing the existence of unit roots. In both intercept and trend instances, the test was run at the level as well as the first difference.

Table 3 displays an overview of the ADF unit root test's conclusions.

Table 3 demonstrates that except for the GTI, which is stationary at level, all variables are stationary in the first difference $I(1)$. As a matter of fact, the optimum lag to work with is $d = 1$.

3.2. Quantile regression model

Table 4 and *Figs. 3, 4 and 5* unveil the quantile regression models' results.

The results corroborate that β_1, β_2 and β_3 coefficients are significant for the three models. Thus, S&P Green Bond index is largely affected by the explanatory variables (CO_2 EI, WCEI and USBI) over time. Likewise, the positive coefficients disclose that a rise in the dependent variables' (S&P GBI) conditional quantile is related to an increase in the independent variable. Moreover, the significant δ_2 reflects the impact of FSI on the dependent variable. However, δ_1 is not significant, which implies that the GTI does not have an impact on the dependent variable. As a result, we can assume that the investor sentiment does not affect the green bond market. Yet, green investors tend to be sensitive to risky and stressful financial environment.

In fact, the negative coefficient δ_2 reflects a reverse relationship between the OFR financial stress index and the S&P green bond index. Particularly,

Table 2
Quantile regression models

QR model	Equation	Notation
Price	$QP_{GB,t} = \beta_0 + \beta_1(\tau) P_{1,t} + \beta_{1.0}(\tau) P_{1,t-1} + \beta_2(\tau)P_{2,t} + \beta_{2.0}(\tau) P_{2,t-1} + \beta_3(\tau)P_{3,t} + \beta_{3.0}(\tau)P_{3,t-1} + \varepsilon_t$	(1.0)
Investor sentiment	$QP_{GB,t} = \beta_0 + \beta_1(\tau)P_{1,t} + \beta_{1.1}(\tau)P_{1,t-1} + \beta_2(\tau)P_{2,t} + \beta_{2.1}(\tau)P_{2,t-1} + \beta_3(\tau)P_{3,t} + \beta_{3.1}(\tau)P_{3,t-1} + \delta_1(\tau)GTI_t + \delta_{1.1}(\tau) GTI_{t-1} + \varepsilon_t$	(1.1)
Financial stress	$QP_{GB,t} = \beta_0 + \beta_1(\tau)P_{1,t} + \beta_{1.2}(\tau)P_{1,t-1} + \beta_2(\tau)P_{2,t} + \beta_{2.2}(\tau) P_{2,t-1} + \beta_3(\tau)P_{3,t} + \beta_{3.2}(\tau)P_{3,t-1} + \delta_2(\tau)FSI_t + \delta_{2.2}(\tau)FSI_{t-1} + \varepsilon_t$	(1.2)

Source: Developed by the authors.

where:

$P_{GB,t}$ is the price of S&P Green Bond Index,
$P_{1,t}$ is the price of CO_2 Emission Index WCE Index,
$P_{2,t}$ is the price of WCE Index,
$P_{3,t}$ is the price of UST Bonds Index and
GTI_t is the google trends index
FSI_t is the OFR financial stress index
τ is the quantile coefficient
ε_t is the white noise at time t, $\varepsilon_t \sim N(0,1)$

Table 3
Unit root test results

Variable	Level		First difference		Conclusion
	Intercept	Intercept and trend	Intercept	Intercept and trend	
SPGB	0.9026	0.7747	0.0001	0.0000	I(1)
CO2EI	0.9483	0.6467	0.0000	0.0000	I(1)
USBTI	0.4746	0.8868	0.0001	0.0000	I(1)
WCEI	0.3984	0.5559	0.0000	0.0000	I(1)
FSI	0.0337	0.1327	0.0001	0.0000	I(0)
GTI	0.0000	0.0000	0.0000	0.0000	I(0)

Source: Authors' calculation.

the decrease in the independent variable is associated with an increase in the conditional quantile of the dependent variable. Additionally, the results indicate a negative relationship between the OFR financial stress index and prices in the quantiles of the price distribution. This would suggest that high levels of financial stress are associated with low prices, and vice versa. In accordance with our results, A. Tsagkanos et al. [24] found sound evidence about the causal connection between green bonds and financial stress.

3.3. Bayesian time-varying vector autoregressive (BTC–VAR)

Figs. 6, 7 and 8 foreground the empirical results of the generalized impulse response functions conditioned on the initial state. The impulse responses are evaluated from June the 6th 2011 to September the 15th 2023.

The Bayesian time-varying vector autoregressive (BTC–VAR*)* relying on the VAR model, is basically undertaken to establish the direction and intensity of the relationship between the multiple factors. We can, therefore, detect (price model) a unidirectional relation between the CO_2 emission index, the WCE index, and the S&P green bond index. In particular, the S&P green bond index results from the WCE index and the CO_2 emission index. These analyses are the byproduct of a p-value for the CO_2 emission index, the WCE index being less than 5%, and a p-value for S&P green bond index, being greater than 5%. The results for the investor sentiment model are nearly identical to those obtained for the price model, confirming that there is no correlation or cause-and-effect link between the Google Trends index, reflecting investor sentiment and green bonds. Conversely, financial stress model enacts a one-way causal relationship between investor sentiment and

Table 4
Quantile regression models' results

Quantile estimated			0.1	0.25	0.5	0.75	0.9
Price	β$_1$	Coefficient	−0.265919	−0.316009	−0.382785	−0.393565	−0.248491
		t-Stat	−27.62621	−34.73561	−97.13579	−80.58878	−7.502641
		Prob	0.0000	0.0000	0.0000	0.0000	0.0000
	β$_2$	Coefficient	0.094794	0.122053	0.173293	0.156419	0.068103
		t-Stat	22.71782	20.33995	37.79350	25.94855	4.654177
		Prob	0.0000	0.0000	0.0000	0.0000	0.0000
	β$_3$	Coefficient	0.054486	−0.008794	−0.063881	−0.050856	−0.084877
		t-Stat	6.827608	−0.877826	−17.35557	−9.858895	−4.318385
		Prob	0.0000	0.3801	0.0000	0.0000	0.0000
Investor sentiment	β$_1$	Coefficient	−0.269059	−0.315790	−0.371838	−0.379668	−0.302397
		t-Stat	−28.85390	−31.83710	−91.06599	−64.59437	−4.280244
		Prob	0.0000	0.0000	0.0000	0.0000	0.0000
	β$_2$	Coefficient	0.094498	0.124933	0.173144	0.158026	0.104642
		t-Stat	18.22665	18.17301	37.25314	26.77436	3.235499
		Prob	0.0000	0.0000	0.0000	0.0000	0.0012
	β$_3$	Coefficient	0.056202	−0.007789	−0.051872	−0.036083	−0.054284
		t-Stat	6.418509	−0.700073	−12.68903	−5.655350	−1.979815
		Prob	0.0000	0.4839	0.0000	0.0000	0.0478
	δ$_1$	Coefficient	−0.041291	−0.027000	−0.049865	−0.084267	−0.099267
		t-Stat	−4.715703	−3.417428	−7.695369	−10.55924	−5.138084
		Prob	0.0000	0.0006	0.0000	0.0000	0.0000
Financial stress	β$_1$	Coefficient	−0.180840	−0.254527	−0.397125	−0.415001	−0.334763
		t-Stat	−20.14647	−20.97903	−71.87070	−78.86707	−0.434230
		Prob	0.0000	0.0000	0.0000	0.0000	0.6642
	β$_2$	Coefficient	0.051512	0.089019	0.183621	0.175619	0.101859
		t-Stat	14.74505	12.92019	37.91039	27.40639	0.340841
		Prob	0.0000	0.0000	0.0000	0.0000	0.7332
	β$_3$	Coefficient	0.143594	0.054364	−0.068436	−0.051167	−0.031571
		t-Stat	18.65303	4.102865	−11.98628	−8.224422	−0.121686
		Prob	0.0000	0.0000	0.0000	0.0000	0.9032
	δ$_2$	Coefficient	−0.991332	−0.614027	0.373884	0.684301	0.9032
		t-Stat	−11.68967	−7.237133	3.418207	13.52946	1.297509
		Prob	0.0000	0.0000	0.0006	0.0000	0.1946

Source: Authors' calculation.

green bonds, with the OFR financial stress index contributing to the S&P green bond index. This essentially illustrates the impact of financial stress on the green bond market and how sensitive green investors are to financial news, whether it involves positive or negative published information. Furthermore, this exemplifies pessimistic biases, which are marked by a propensity to overestimate the chance of unfavorable outcomes while underestimating the likelihood of favorable outcomes.

A financial stress index is a measure of the overall level of financial stress in the economy, such as increased uncertainty, increased volatility, and decreased liquidity. Hence, the negative correlation between the financial stress index and the S&P Green Bond Index is suggestive that the dependent variable is overvalued. These results can be attributed to psychological biases within the field of behavioral finance. Notably, the overconfidence bias contributes to inflated assessments of one's abilities.

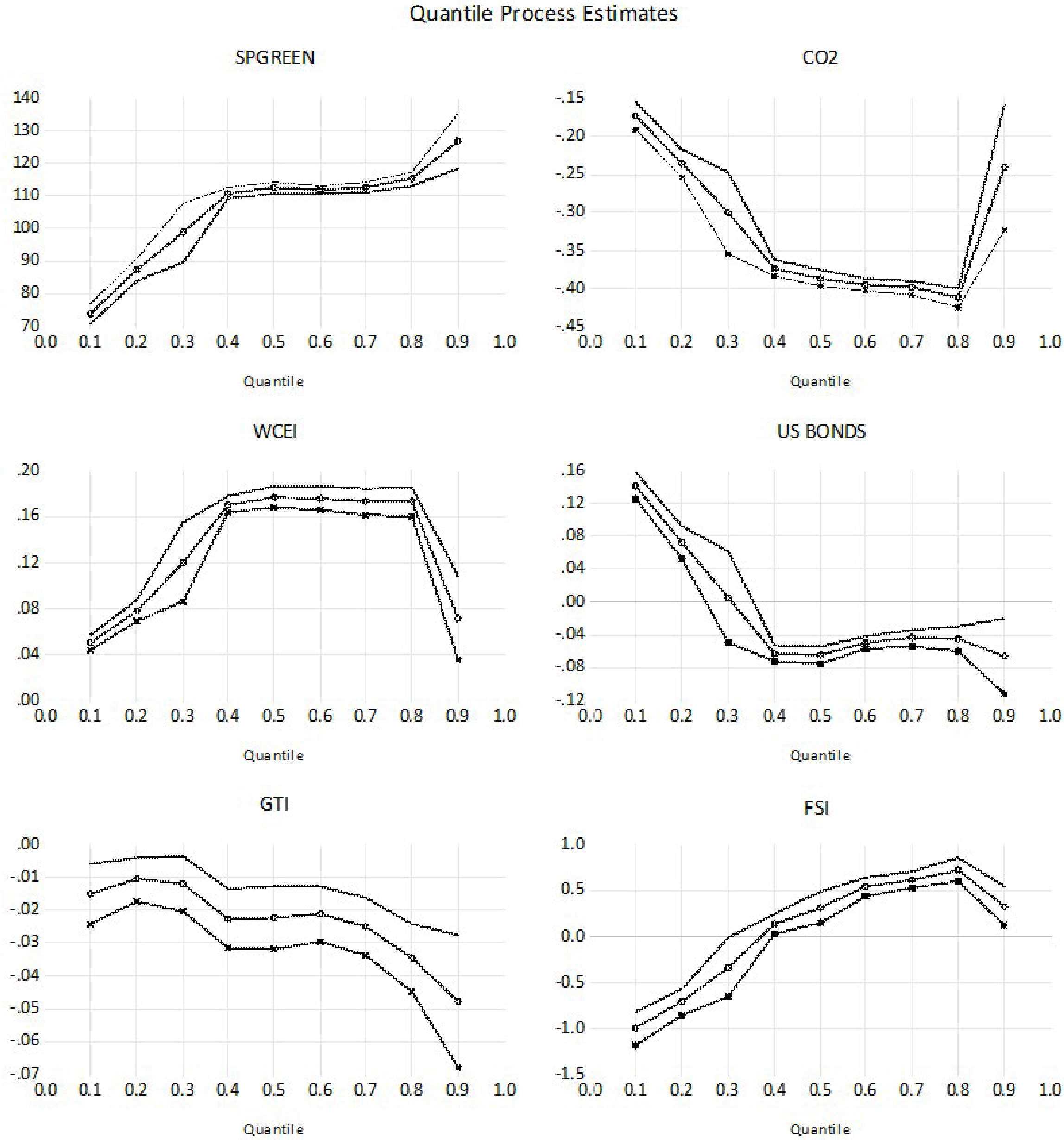

Fig. 3. **Quantile process estimates of the price model**

Source: Created by the authors.

The comparison between clinical and statistical prediction methods underscores the prevalence of subjective judgment over objective analysis. Additionally, confirmation bias plays a role as individuals selectively process information to align with preexisting beliefs.

Evidence from studies corroborates that psychological biases can result in systemic inefficiencies as well as cognitive biases that may influence investors' decision-making. Our instance is concerned, green investors have a propensity to overestimate their own capabilities and judgements when it comes to the stability of green bonds. This refers to the fact that they frequently assume that one would have forecasted or anticipated the outcome after a positive occurrence has actually happened (overconfidence bias). Consequently, they interpret data in a way that supports existing assumptions or expectations on the connection between green bonds and low financial stress (confirmation bias). Indeed, this leads individuals to base their decisions on widely accessible favorable information on green bonds

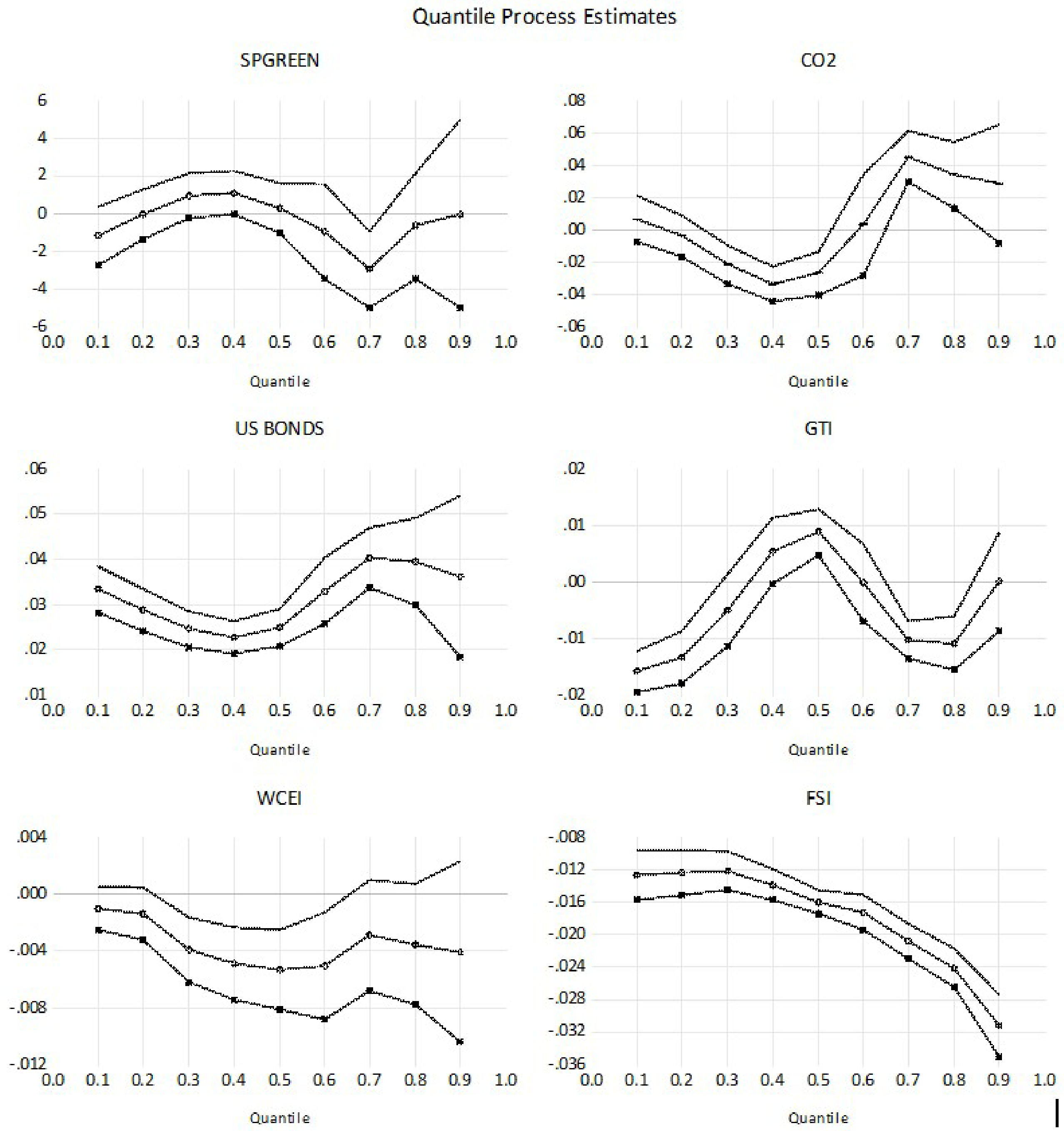

Fig. 4. **Quantile process estimates of the investor sentiment model**

Source: Created by the authors.

rather than considering all pertinent data (heuristic availability). They equally tend to think that future events will be better than comparable ones in the past (optimism bias).

4. Conclusion

The ultimate objective of the present research resides primarily in assessing the causal connections between green bonds and other related assets (including US conventional bonds, the WilderHill clean energy (equity) index, and the price of CO_2 emission allowances), along with analyzing the effects of investor sentiment and financial stress.

Our research goes in good agreement with prior literature results, establishing a unidirectional causal relationship between financial stress and green bonds as well as other financial and environmental assets. We anticipate that the price-shifting mechanisms of green bonds will be heavily influenced by investor behavior regarding green bonds. To build up an empirical framework, we examined time series data from green bonds, treasury, clean energy as

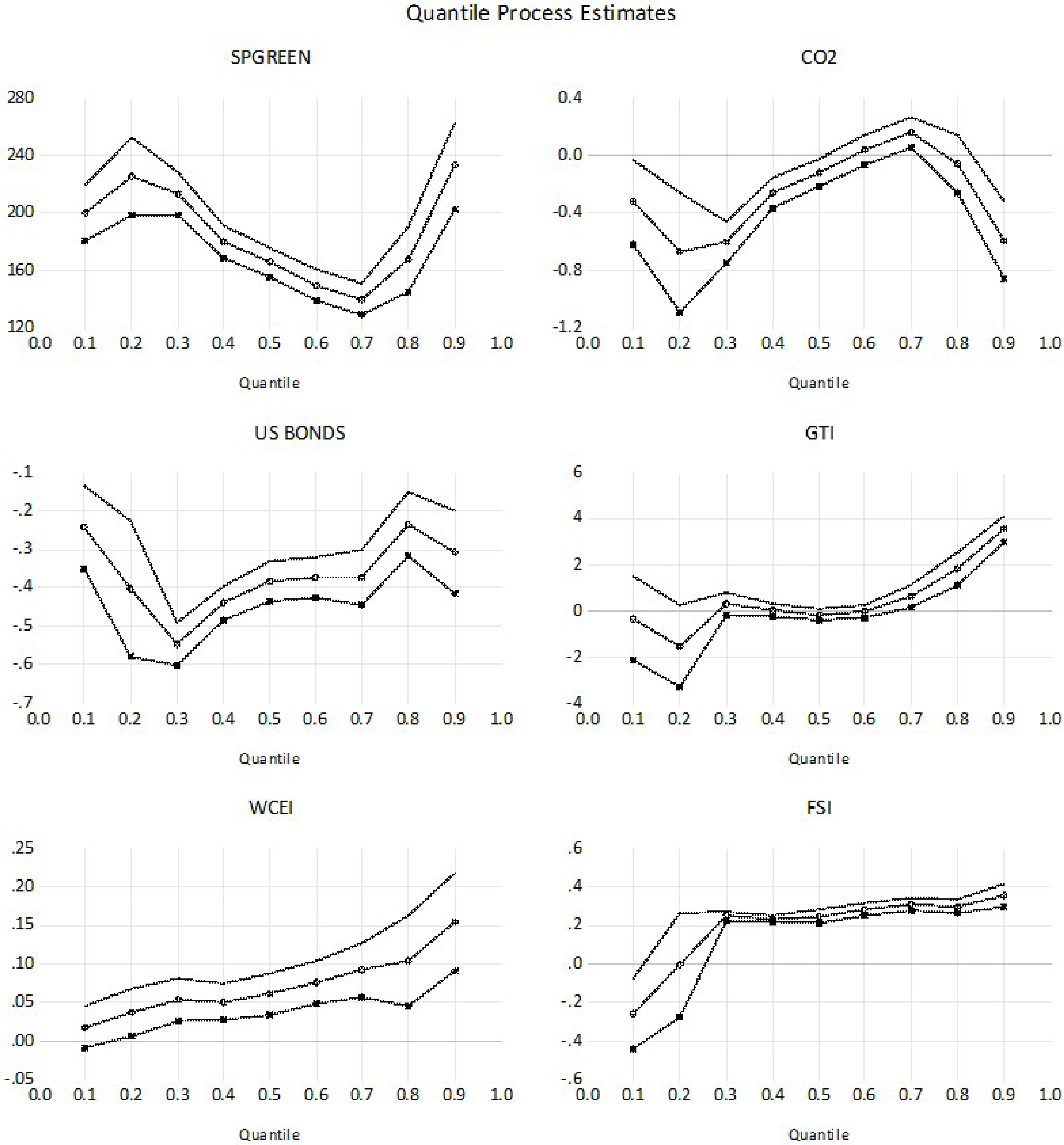

Fig. 5. **Quantile process estimates of the financial stress model**

Source: Created by the authors.

well as CO_2 emission assets and investor sentiment measurements. Furthermore, we applied quantile autoregressive models to examine the prediction of green bonds. Moreover, we deployed The Bayesian Time-Varying Vector Autoregressive (BTC–VAR) to analyze the relation between green bonds and the different variables.

Our findings demonstrated that green bonds' statistical properties are distinct from those of other financial and environmental assets, leading us to use quantile regressions to account for the factors of these fluctuations. Additionally, the negative unidirectional causal relationship between the S&P green bond index and the CO_2 Emission index was interpreted in terms of the divergence of objectives of each asset. However, the positive unidirectional causal relationship between the S&P green bond index and the Wilderhill Clean Energy index was outlined by resemblance and uniformity purposes. Besides, the investor sentiment measured by Google Trend Index was insignificant and didn't reflect accurately the impact of investor sentiment on green bonds

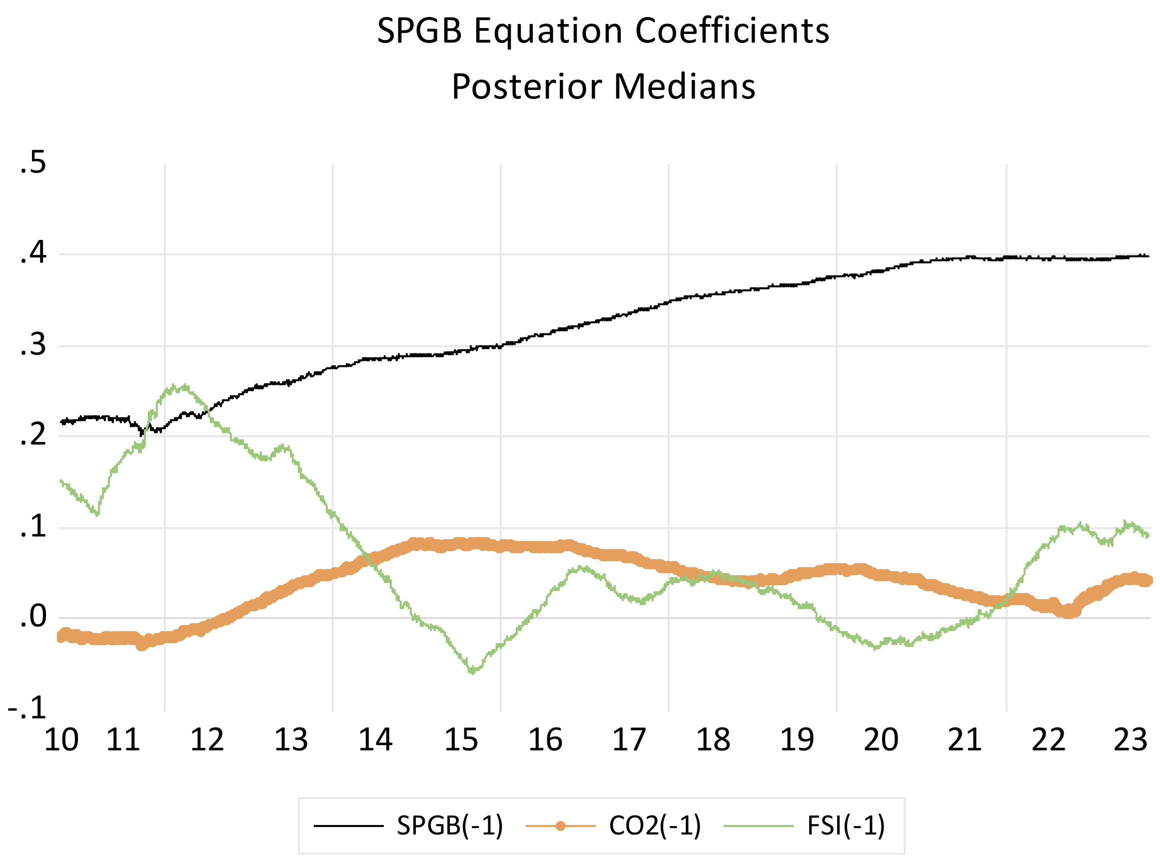

Fig. 6. **TVC VAR estimates of the price model**

Source: Created by the authors.

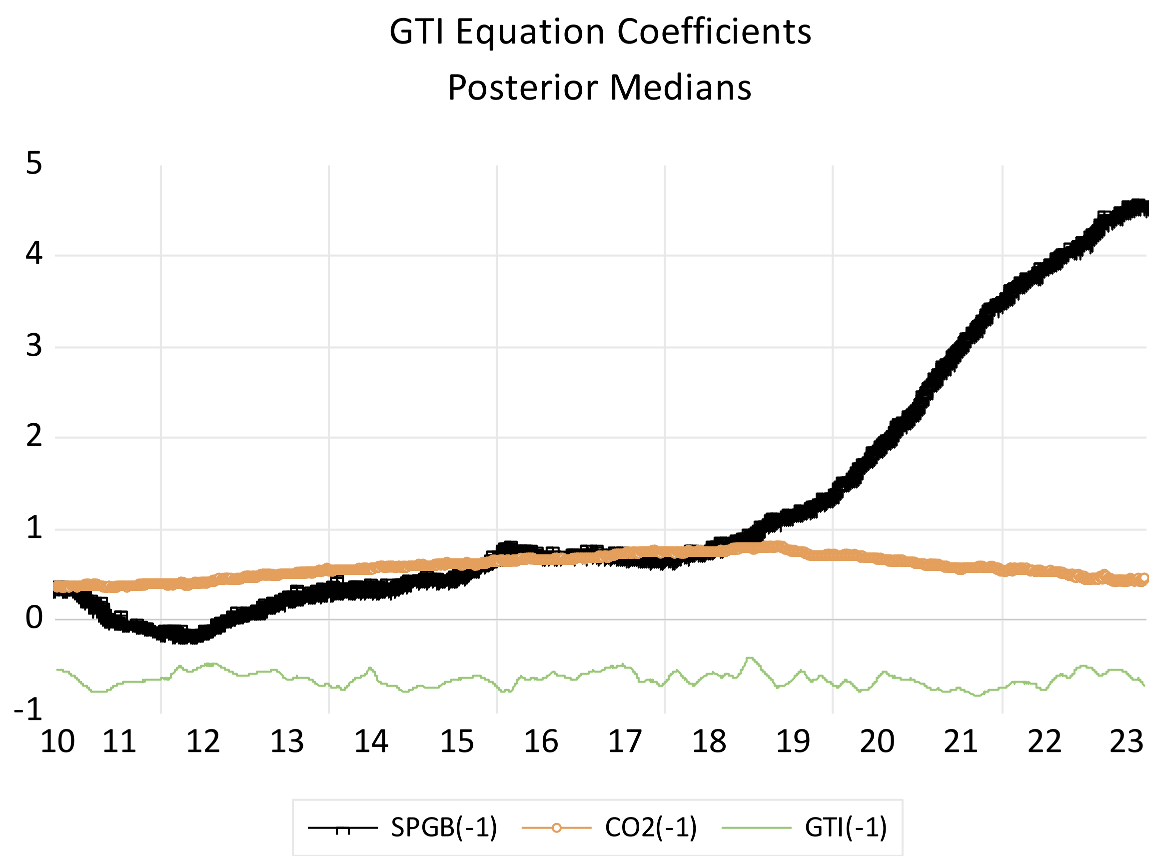

Fig. 7. **TVC VAR estimates of the investor sentiment model**

Source: Created by the authors.

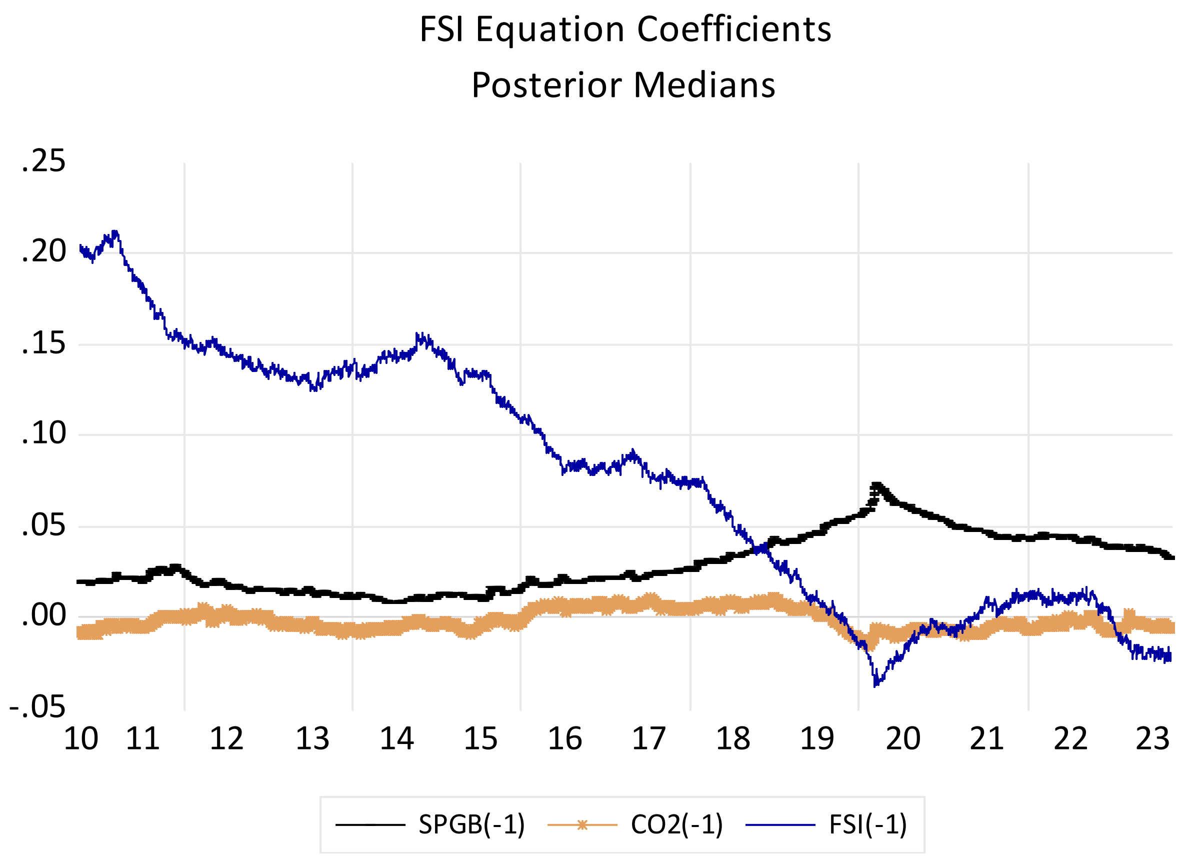

Fig. 8. **TVC VAR estimates of the financial stress model**

Source: Created by the authors.

market. However, the financial stress (measured by the OFR Financial Stress Index) has a significant reversed impact on green bonds, leading us to infer that green investors are sensitive to financial news and that psychological biases might have a noticeable impact on green bond markets.

In fact, based on our findings, we deduce that investor sentiment has no significant influence on the price of green bonds since the investor sentiment index's coefficient was negligible and had no impact on the initial model. Green investors, however, have a propensity to be sensitive to stressful and risky financial environments. This was explicitly corroborated through the financial stress index's negative correlation with the S&P Green Bond Index, indicating an overestimation of the dependent variable's price. Moreover, the over estimation of the S&P Green Bond Index was accounted for in terms of four main psychological biases, namely overconfidence bias, confirmation bias, availability heuristic, and optimism bias.

Despite the fact that green investor sentiment has relatively no impact on the green bond market and that investors tend to overvalue green bonds, investing in such a nascent market without a clear and transparent legal framework is still perceived as a risky investment. Therefore, ethical investors are still highly exposed to greenwashing risk.

The central target of this investigation resides in analyzing the causal relationships between green bonds and various financial and environmental variables (CO_2 emission allowances price). The period of analysis spans from June, 2011, to July 10, 2021.

The basic motivation underlying this research is to surmount the limitations of existing studies that have not thoroughly examined the relationship between the green bond market and other financial and environmental variables. Through conducting this analysis, the study aims to gain a better and deeper insight into the causal dynamics between green bonds and the selected variables, providing enlightening details upon the interactions between the green bond market and the broader financial and environmental landscape.

The results of the study would notably have significant implications for both investors and policymakers. For policymakers, particularly those focusing on achieving goals related to a low-carbon economy, the study highlights the weight of considering not only the green bond market but also the predictive power of traditional bonds as well as the price of CO_2 emission allowances.

Policymakers need to consider the dynamic causality between these variables, which may vary over different periods. This implies that the relationships and causal dynamics between green bonds and CO_2 emission allowances price can alter over time. Policymakers need to be aware of these changing relationships when formulating and implementing policies related to the green bond market.

Furthermore, the study suggests that policymakers should not overlook the predictive power of traditional bonds and the CO_2 emission allowances price when designing policies for the green bond market. These variables can provide valuable information and better insights that can largely help inform policy decisions and promote the effectiveness of measures aimed at fostering a low-carbon economy.

For investors, the findings suggest that understanding the interactions between green bonds, traditional bonds, and the CO_2 emission allowances price is crucial for making informed investment decisions. Recognizing the predictive power and the relationships among these variables can help investors identify potential investment opportunities, manage risks, and align their portfolios with the goals of sustainability and climate change mitigation. Overall, the study emphasizes the need for policymakers and investors to consider the dynamic variability and predictive power of various financial and environmental variables when addressing the green bond market. This comprehensive approach can contribute to more effective policymaking, appropriate investment strategies, and the advancement of a low-carbon economy.

However, this study is subject to certain limitations. It focuses on a specific set of variables — green bonds, CO_2 emissions, investor sentiment, and financial stress — while other potentially influential factors such as monetary policy shifts, geopolitical events, or technological innovation in clean energy were not included. Future research could expand the scope by incorporating a broader range of variables and applying alternative modeling techniques to further enhance the robustness and generalizability of the findings.

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ABOUT THE AUTHOR / ИНФОРМАЦИЯ ОБ АВТОРЕ

Souha Boutouria — PhD in finance, Associate Professor, Probability and Statistics Laboratory, University of Sfax: Higher Institute of Business Administration, Sfax, Tunisia
Суха Бутурия — PhD в области финансовых наук, доцент лаборатории теории вероятностей и статистики, Университет Сфакса: Высший институт делового администрирования, Сфакс, Тунис
https://orcid.org/0009-0004-9051-1337
souha.boutouria@isaas.usf.tn

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