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How do global financial markets affect the green bond markets? Evidence from different estimation techniques

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ABSTRACT
The green bond market has significantly improved in recent years thanks to the development of financial instruments and the rising climate change concerns. Given this backdrop, this paper investigates the effects of returns in different financial markets, i.e. the United States Treasury Bonds, the Standard & Poor's stock market, the United States Dollar, Gold, Crude Oil, and Bitcoin on the Green Bond returns (the Standard & Poor's Green Bond Index) from September 17, 2014, to September 1, 2022. The results from the robust linear and machine learning estimators indicate that the returns of the United States Treasury Bonds and the United States Dollar are negatively related to the Green Bond returns. Meanwhile, Gold returns positively affect Green Bond returns. The quantile regression estimations of Machado–Santos Silva also show that these findings are valid in different quantiles. The paper also discusses policy implications related to climate change and the development of financial instruments to promote green investments.

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1. Introduction

Climate disasters and risks can decrease lower-growth economic performance with higher financial instability and volatility of asset returns (Dikau & Volz, 2021). Previous papers have demonstrated that fossil fuels-related financial assets significantly affect bond markets, exchange rates, and stock markets (MacAskill *et al.*, 2021). Climate change can also affect financial markets by increasing the price volatility of commodities. At this stage, two tools can provide enough sources for green change in climate policies: carbon taxation and green bonds (Semmler *et al.*, 2021; Su *et al.*, 2022b). Green bonds are a helpful financial instrument to finance a low-carbon economy. However, the carbon tax does not provide enough resources to promote green transition (Ren *et al.*, 2022a; Zerbib, 2019).

The green bond market significantly enhanced in the late 2010s (Reboredo, 2018). However, it is essential to note that attracting investors and traders depend on the

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returns of green bonds and removing market regulations in investment in green products (Gianfrate & Peri, 2019; Su *et al.*, 2023c). Green investments generally depend on long-term projects with a higher level of technology and take several years to be completed (Acemoglu *et al.*, 2012). Therefore, investors in green bonds need to be patient as they are long-term investments. Theoretically, this issue must motivate future returns or lower investment costs (Li *et al.*, 2020).

Another issue is that green bonds need to be less risky assets than traditional bonds in the central banks' interest rate decisions. Overall, higher future gains and fewer investment costs and risks can make green bonds more attractive than traditional bonds (Flammer, 2021). Most papers have shown that public attention to fighting against climate change is secondary to individual investments. However, as discussed in the Literature Review section, firms can invest in green assets for sustainability, environmental, social, corporate governance (ESG), and corporate social responsibility (CSR). Therefore, we need to better understand the determinants of green bond markets and how other financial markets affect the returns of green bond markets. Thus, we can provide several implications for solving the problems of green investment by promoting financial development. Promoting the green bond markets can also be an essential policy tool for central banks to help governments fight against the negative consequences of climate change on economic performance, government debt, and inflation (Blanchard, 2019). It is well known that climate change can slow economic growth and increase inflation by putting pressure on food and transportation costs (Nordhaus, 2008).

Given these backdrops, we investigate the effects of returns in different financial markets (the US Treasury Bonds, the S&P 500 Stock Market, the US Dollar, Gold, Crude Oil, and Bitcoin) on the Green Bond returns (the S&P Green Bond Index) from September 17, 2014, to September 1, 2022. For this purpose, we utilize the Robust Linear Ordinary Least Squares (RLOLS) method of Liu *et al.* (2018) and the Kernel-based Regularized Least Squares (KRLS) estimations of Hainmueller and Hazlett (2014). Thus, we address the potential issues of outlier observation and biased regression problems without relying on linearity assumptions in regressions. To the best of our knowledge, this is the first paper in the empirical literature to consider different estimation techniques for investigating the role of global financial markets in the green bonds market.

We also use the data from September 17, 2014, to September 1, 2022, which captures various periods with higher uncertainty, such as the Covid-19 pandemic and the Russia-Ukraine War. According to the results from the RLOLS and the KRLS estimations, the returns of the US Treasury Bonds and the US Dollar are negatively related to the Green Bond returns. Meanwhile, Gold returns positively affect Green Bond returns. The quantile regression estimations of Machado–Santos Silva also show that these findings are valid in different quantiles.

The rest of the paper is organized as follows. Section 2 reviews the previous empirical papers on green finance and green bonds. Section 3 provides the background of the data, the empirical model, and the econometric methodology. Section 4 discusses the empirical findings. Section 5 provides the robustness check with policy implications. Section 6 concludes.

2. Previous papers on green finance and green bonds

2.1. The role of climate change and sustainability

Hmaittane *et al.* (2019) examined whether corporate social responsibility influences the cost of equity capital of firms operating in controversial industry sectors (alcohol, tobacco, gambling, military, firearms, nuclear power, oil and gas, cement, and biotechnology) from 1991 to 2012. The authors found that corporate social responsibility engagement significantly reduces the implied cost of equity capital in all controversial industry sectors. It is also further noticed that this effect is more pronounced when the firm belongs to the alcohol and tobacco industry sectors. Gao *et al.* (2021) evaluated the performance of the Chinese equity securities investment funds from 2003 to 2020 using a bootstrap methodology to distinguish skill from luck. The authors observed that the evidence does not support the existence of 'genuine' skilled fund managers. It is found that poor performance is mainly attributable to poor stock-picking skills. Taghizadeh-Hesary *et al.* (2021) examined the determinants of the Russian and Asia-Pacific energy trade using the quarterly data from 2010 to 2017 in 17 selected Asia-pacific economies. The authors found that economic growth in these countries enhanced Russian energy exports. The findings supported the Linder hypothesis that economies with similar per capita income levels have more overlapping demand, which should induce them to trade more intensively.

On the other hand, Dorfleitner and Grebler (2022) studied the impact of corporate social responsibility on systematic firm risk at the global level. The author found that the impact of corporate social responsibility on systematic firm risk varies across regions. Product responsibility is the key driver of systematic firm risk in North America and Japan. Ji *et al.* (2021a) assessed the attractiveness of renewable investments by comparing the performance of alternative energy-focused equity funds against their conventional counterparts. The author used the panel data from 2010 to 2019, covering 3,886 funds across 19 Eurozone countries. The author found that renewable energy funds underperform traditional peers and market benchmarks and lack market and volatility timing. It is also observed that investors willing to opt for environment-friendly investment funds have to pay a premium for their choice, negatively reflecting financial attractiveness.

2.2. The role of financial assets and financial development

Umar *et al.* (2021b) studied the impact of the resource curse on banking profit efficiency, asset quality, and solvency in 12 oil-producing countries from 2001Q1 to 2019Q4. The author found that during episodes of the price boom, banking efficiency declines, credit infection worsens, and the probability of default surges. These findings confirm the presence of a resource curse and validate why countries with excess reliance on natural resources tend to have lower financial development. Naqvi *et al.* (2021) studied green funds' financial performance, managerial abilities, and their conventional peers. A comprehensive data set of 2,339 funds across 27 emerging market economies indicated that traditional energy funds outperform renewable funds. The authors also indicated that the performance of renewable funds degraded during the

Covid-19 pandemic. Umar *et al.* (2021a) studied the impact of carbon-neutral lending on credit risk in the Eurozone. Exposure to carbon-neutral lending is also found to be negatively related to default risk. The author used the quarterly data for 344 lending institutions in 19 member states from 2011 to 2020.

Using monthly data between 2011 and 2019, Ji *et al.* (2021b) considered 6,519 actively managed mutual funds in BRICS after sorting them into black, brown, and green categories based on their investment holdings. The authors indicated that green funds outperform their counterparts for the entire sample and within-country assessment. It is also observed that Chinese green funds perform better than other countries. Lobato *et al.* (2021) studied the risk-adjusted performance of socially responsible exchange-traded funds (SR ETFs) compared to conventional exchange-traded funds. The authors observed that the performance of the SR ETFs differs from that of conventional exchange-traded funds. Berger (2022) examined the relationship between sentiment and financial market returns through conditional mean and regression analyses and found that periods of high retail sentiment precede poor subsequent market returns. The authors found the most substantial impact on subsequent returns within difficult-to-value or difficult-to-arbitrage firms. Using the entire dataset of non-financial ratings, Ferrat *et al.* (2022) examined the cross-sectional returns of the US and the European sustainability-leading and lagging corporations between 2007 and 2019. The authors found that responsible investment growth's impact depends on the timeframe. It is also observed that the return spread is negative over long horizons and increases over time. Karim *et al.* (2022) investigated whether bond markets offer hedging facilities to uncertainty indices of cryptocurrencies from June 2014 to April 2021. The authors found that bond markets are neither hedges nor safe havens against cryptocurrencies during economic fragility.

2.3. Previous empirical papers on green bonds

Since 2020, there has been an increasing number of papers on the determinants of green bond returns. The paper by Reboredo and Ugolini (2020) is among the first to examine the relationship between green bonds and financial markets. The authors considered the Structural Vector Autoregressive (SVAR) model and found that the green bond market is significantly linked to the Treasury Bills and currency markets. There is a weak relationship between green bonds and stock and energy markets. Hammoudeh *et al.* (2020) also used the time-varying causality approach to examine the causal relationship between green bond markets and other financial indicators from 2016 to 2020. The authors found that the US 10-year Treasury bond returns are the primary determinant of green bond returns. Pham and Nguyen (2021) also investigated the tail-dependence between green bonds and energy, stocks, and traditional bond markets using the cross-quantilogram method from October 2014 to February 2021. The authors obtained mixed evidence as the spillover between the financial and green bonds market significantly changes across different quantiles. Mensi *et al.* (2022) observed that green bonds are relatively less volatile than financial markets during extreme events. The energy market is the primary determinant of the green bonds market, especially during times of crisis, such as the Covid-19 pandemic.

In addition, Chatziantoniou *et al.* (2022) used the quantile frequency connectedness approach for different green investment measures, including the S&P Green Bond Index. The findings from November 28, 2008, to January 12, 2022, indicated that the S&P Green Bond Index is the net receiver of external shocks. Elsayed *et al.* (2022) also investigated the interdependence between green bonds and financial markets with the time-frequency domain approach. The authors found a significant linkage between green bonds and financial markets where the green bond market is a net receiver of spillover from financial markets. Naeem *et al.* (2022) also implemented a quantile-connectedness method from 2008 to 2020 to examine the relationship between green bonds and financial markets, including agriculture and energy commodities. The authors found a significant bidirectional risk spillover between green and traditional bonds, giving investors opportunities to diversify their portfolios.

Overall, there are previous papers on the effects of financial markets on green bond markets. Most of these studies have observed that traditional bond returns are the primary driver of green bond returns. In this paper, we contribute to this empirical literature by utilizing novel estimation techniques, such as the RLOLS method of Liu *et al.* (2018) and the KRLS estimations of Hainmueller and Hazlett (2014). Thus, we address the potential issues of outlier observations and biased regression problems without relying on linearity assumptions in regressions. To the best of our knowledge, this is the first paper to address these potential issues in the empirical literature on the role of global financial markets in green bond returns.

3. Data, model, and methodology

3.1. Data

This paper focuses on the daily data for green bonds and several financial markets from September 17, 2014, to September 1, 2022. We have 2,010 observations for each indicator, and the related data are obtained from Bloomberg. Each indicator is used in natural logarithmic returns.

The S&P Green Bond Index (*lnSP_GBI*) is the benchmark indicator of the green bonds market. For financial markets, we use the US 10-Year Treasury Bond (*lnUSB*), the US Dollar Index, January 2006 = 100 (*lnDXY*), Brent Crude Oil Spot Price per Barrel in the USD (*lnBRENT)*, Gold Spot Price per Ounce in the USD (*lnGOLD*), the S&P 500 Index (*lnSP_500*), and Bitcoin Price in the (*lnBTC*). Table 1 reports a summary of descriptive statistics.

Table 1 shows that green bonds and crude oil have negative average daily returns, while other assets have positive returns. The highest average daily returns are observed in Bitcoin, followed by the S&P 500 Index. Regarding standard deviations, Bitcoin is the riskiest asset, followed by the US 10-Year Treasury bonds and Crude Oil. The S&P Green Bond Index has the lowest standard deviations. Table 2 provides the correlation matrix.

Table 2 indicates that the S&P Green Bond Index returns negatively correlate with the DXY and the US 10-Year Treasury bond returns. Its correlation with other financial markets' returns is found to be positive. Bitcoin is positively correlated with every

Table 1. Summary of descriptive statistics (September 17, 2014–September 1, 2022).

Indicator	Measurement	Form	Abbreviation	Data Source	Mean	Std. Dev.	Min	Max.	Observation
S&P Green Bond Index	Index, USD	Log. Return	lnSP_GBI	Bloomberg	−0.006	0.338	−2.409	2.012	2,010
US 10-Year Treasury Bond	USD	Log. Return	lnUSB	Bloomberg	0.009	3.310	−36.16	35.84	2,010
US Dollar Index	(Index, January 2006 = 100)	Log. Return	lnDXY	Bloomberg	0.012	0.428	−2.244	2.222	2,010
Brent Crude Oil (Spot Price)	USD per Barrel	Log. Return	lnBRENT	Bloomberg	−0.001	2.694	−31.23	18.82	2,010
Gold Spot Price	USD per Ounce	Log. Return	lnGOLD	Bloomberg	0.015	0.880	−6.560	4.701	2,010
S&P 500 Index	Index, USD	Log. Return	lnSP_500	Bloomberg	0.033	1.162	−12.76	8.968	2,010
Bitcoin Price	USD per Unit	Log. Return	lnBTC	Bloomberg	0.188	4.607	−46.47	22.51	2,010

Source: The authors' estimations.

Table 2. Correlation matrix (September 17, 2014–September 1, 2022).

Indicator	lnSP_GBI	lnUSB	lnDXY	lnBRENT	lnGOLD	lnSP_500	lnBTC
lnSP_GBI	1.000	–	–	–	–	–	–
lnUSB	−0.091	1.000	–	–	–	–	–
lnDXY	−0.687	0.034	1.000	–	–	–	–
lnBRENT	0.002	−0.035	−0.048	1.000	–	–	–
lnGOLD	0.383	−0.029	−0.385	0.091	1.000	–	–
lnSP_500	0.029	−0.021	0.011	0.066	−0.023	1.000	–
lnBTC	0.014	0.020	0.004	0.014	−0.025	0.208	1.000

Source: The authors' estimations.

asset except Gold. The US 10-Year Treasury bond is positively correlated with the DXY; however, its correlation is negative with other assets. (Figure 1)

Finally, Figure 1 demonstrates the quantile plots for each variable in the dataset.

3.2. Empirical model and econometric methodology

We estimate the following model to examine the effects of different financial markets on the green bonds market.

$$\text{lnSP\_GBI}_t = \beta_0 + \beta_1 X_t + \varepsilon_t \tag{1}$$

Note that lnSP_GBI_t are the returns of the S&P Green Bond Index in time t and $X_{,t}$ is several financial markets in time t provided in Table 1. In addition, ε_t represents the error term. The model in Eq. (1) is estimated by the RLOLS method of Liu *et al.* (2018) and the KRLS approach of Hainmueller and Hazlett (2014). The KRLS is based on a machine learning approach to address biased regression problems without relying on linearity assumptions in regressions. The RLOLS technique solves potential issues with the outlier observations in the model estimations. For instance, Yu *et al.* (2022) studied the credit rating of 355 Eurozone eco-friendly firms from 2010 to 2019. The author found that classification and regression trees have the most credit rating predictions using the machine learning method.

Following Chatziantoniou *et al.* (2022), we also utilize the quantile regression estimations of Machado and Santos Silva (2019) to analyze the effects of financial

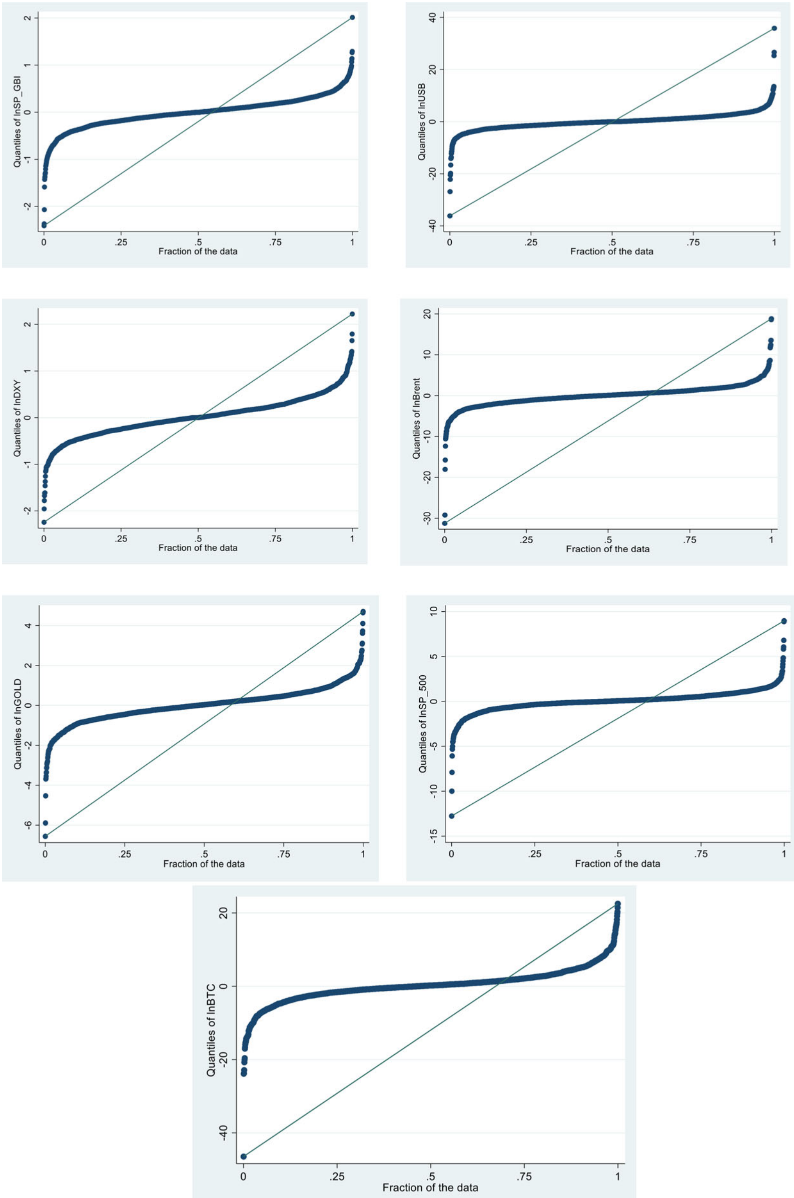

Figure 1. Quantile plots for each variable in the dataset.
Source: The authors' estimations.

markets on green bond returns in each quantile. These results can provide policy implications related to climate change and the development of financial instruments.

It is important to note that all variables need to follow the stationary process in these estimation techniques. For this purpose, we consider the unit root test of Clemente *et al.* (1998). This unit root method considers one structural break in the time series with the null hypothesis of stationarity. If the test statistic exceeds the critical value, the series follows the unit root process. The corresponding critical values are provided by Perron and Vogelsang (1992).

4. Empirical findings

4.1. Preliminary test: unit-root test of Clemente et al. (1998)

Table 3 provides the findings of the unit-root test of Clemente *et al.* (1998) from September 17, 2014, to September 1, 2022. Note that the results are based on the single mean shift. Following Clemente *et al.* (1998) and Perron and Vogelsang (1992), we select the maximum lag as six lags, and the Trimmer rate is 0.10.

The findings indicate that all variables (*lnSP_GBI*, *lnUSB*, *lnDXY*, *lnBRENT*, *lnGOLD*, *lnSP_500*, and *lnBTC*) follow the stationary process, i.e. I(0). Interestingly, the structural break in the time series occurred in March 2020 when the Covid-19 pandemic started to spread globally (Hasnaoui *et al.*, 2021). Specifically, *lnSP_GBI*, *lnUSB*, *lnDXY*, *lnSP_500*, and *lnBTC* experienced a structural break in March 2020. *lnGOLD* had a structural break in January 2019. The Omicron coronavirus variant has pushed Covid-19 cases to higher levels, but governments decided to reduce the restrictions. In early 2019, Gold prices escalated to different sources of uncertainty, such as the trade war between the United States and China, Brexit uncertainty, extreme debt levels, and the United States government shutdown. Finally, lnBRENT had a structural break in January 2021 due to the lack of production capacity and limited investment in the oil sector (Ren *et al.*, 2022b; Su *et al.*, 2023a). Nevertheless, global supply chain problems and slowing economic recovery from the pandemic occurred in many developed economies in early 2021 (Paul *et al.*, 2021).

4.2. The RLOLS estimations

Table 4 reports the results of the RLOLS estimations of Liu *et al.* (2018) from September 17, 2014, to September 1, 2022. The first column includes only *lnUSB*. The second column uses *lnUSB* and *lnDXY*. The third column also considers *lnUSB*, *lnDXY*, and *lnBRENT*. The fourth column includes *lnUSB*, *lnDXY*, *lnBRENT*, and *lnGOLD*. The fifth column uses *lnUSB*, *lnDXY*, *lnBRENT*, *lnGOLD*, and *lnSP_500*. Finally, the sixth column includes all variables: *lnUSB*, *lnDXY*, *lnBRENT*, *lnGOLD*, *lnSP_500*, and *lnBTC*.

The findings indicate that *lnUSB*, *lnDXY*, and *lnBRENT* are negatively related to *lnSP_GBI*. Among these variables, *lnUSB* and *lnDXY* are statistically significant at the 1% significance level ($p < 0.01$). *lnGOLD*, *lnSP_500*, and *lnBTC* positively affect *lnSP_*

Table 3. Results of the unit-root test of Clemente *et al.* (1998) (September 17, 2014–September 1, 2022).

Indicator	t-test Statistic & (Lag)	Structural Break Date	Evidence
lnSP_GBI	−28.77*** & (1)	March 26, 2020	I(0)
lnUSB	−21.53*** & (6)	March 11, 2020	I(0)
lnDXY	−19.43*** & (5)	March 27, 2020	I(0)
lnBRENT	−13.64*** & (6)	January 12, 2021	I(0)
lnGOLD	−14.07*** & (0)	January 6, 2019	I(0)
lnSP_500	−17.61*** & (6)	March 13, 2020	I(0)
lnBTC	−16.38*** & (6)	March 11, 2020	I(0)

Notes: The results are based on the single mean shift. The maximum lag is 6. The Trimmer rate is 0.10.
***$p < 0.01$.
Source: The authors' estimations.

Table 4. Results of the Robust Linear Ordinary Least Squares (RLOLS) Estimations of Liu *et al.* (2018) (September 17, 2014–September 1, 2022).

Dependent Variable = lnSP_GBI	RLOLS (I)	RLOLS (II)	RLOLS (III)	RLOLS (IV)	RLOLS (V)	RLOLS (VI)
lnUSB	−0.009*** (0.002)	−0.006*** (0.002)	−0.006*** (0.002)	−0.006*** (0.002)	−0.006*** (0.002)	−0.006*** (0.002)
lnDXY	–	−0.540*** (0.017)	−0.542*** (0.017)	−0.499*** (0.018)	−0.499*** (0.018)	−0.499*** (0.018)
lnBRENT	–	–	−0.004 (0.003)	−0.005* (0.002)	−0.005** (0.002)	−0.005** (0.002)
lnGOLD	–	–	–	0.054*** (0.009)	0.054*** (0.009)	0.054*** (0.009)
lnSP_500	–	–	–	–	0.011* (0.006)	0.011* (0.006)
lnBTC	–	–	–	–	–	0.001 (0.001)
Constant Term	−0.006 (0.007)	0.001 (0.001)	0.001 (0.005)	−0.001 (0.005)	−0.001 (0.005)	−0.001 (0.005)
Observation	2,010	2,010	2,010	2,010	2,010	2,010
Adjusted R-squared	0.007	0.476	0.478	0.495	0.496	0.496

Notes: The robust standard errors are in ().
***$p < 0.01$, **$p < 0.05$, and *$p < 0.10$.
Source: The authors' estimations.

GBI. Among these variables, *lnGOLD* and *lnSP_500* are statistically significant at the 1% ($p < 0.01$) and 10% ($p < 0.10$) significance levels, respectively.

4.3. The KRLS estimations

Table 5 provides the findings of the KRLS estimations of Hainmueller and Hazlett (2014) from September 17, 2014, to September 1, 2022. Again, the first column uses only *lnUSB*. The second column considers *lnUSB* and *lnDXY*. The third column also includes *lnUSB*, *lnDXY*, and *lnBRENT*. The fourth column considers *lnUSB*, *lnDXY*, *lnBRENT*, and *lnGOLD*. The fifth column uses *lnUSB*, *lnDXY*, *lnBRENT*, *lnGOLD*, and *lnSP_500*. Finally, the sixth column includes all variables: *lnUSB*, *lnDXY*, *lnBRENT*, *lnGOLD*, *lnSP_500*, and *lnBTC*.

The results show that *lnUSB*, *lnDXY*, and *lnBRENT* are negatively associated with *lnSP_GBI*. Among these variables, *lnUSB*, *lnDXY,* and *lnBRENT* are statistically significant at the 1% significance level ($p < 0.01$). *lnGOLD* increases *lnSP_GBI,* which is statistically significant at the 1% ($p < 0.01$) significance level.

5. Additional robustness checks and discussion

5.1. Quantile regression estimations of Machado and Santos Silva (2019)

Table 6 reports the findings of the Quantile Regression estimations of Machado and Santos Silva (2019) from September 17, 2014, to September 1, 2022, in different quantiles ($\tau = 0.10$, 0.25, 0.50, 0.75, and 0.90). The estimations include all variables: *lnUSB*, *lnDXY*, *lnBRENT*, *lnGOLD*, *lnSP_500*, and *lnBTC*.

The results demonstrate that *lnUSB*, *lnDXY*, and *lnBRENT* are negatively related to *lnSP_GBI* in every quantile. Among these variables, *lnUSB* and *lnDXY* are statistically significant at the 1% significance level ($p < 0.01$) in each quantile. The coefficients of

Table 5. Results of the Kernel-based Regularized Least Squares (KRLS) Estimations of Hainmueller and Hazlett (2014) (September 17, 2014–September 1, 2022).

Dependent Variable = lnSP_GBI	KRLS (I)	KRLS (II)	KRLS (III)	KRLS (IV)	KRLS (V)	KRLS (VI)
lnUSB	−0.003***	−0.007***	−0.007***	−0.007***	−0.006***	−0.006***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
lnDXY	–	−0.511***	−0.511***	−0.451***	−0.442***	−0.436***
		(0.013)	(0.013)	(0.014)	(0.014)	(0.014)
lnBRENT	–	–	−0.011***	−0.011***	−0.010***	−0.010***
			(0.002)	(0.002)	(0.002)	(0.002)
lnGOLD	–	–	–	0.054***	0.056***	0.056***
				(0.007)	(0.007)	(0.007)
lnSP_500	–	–	–	–	0.011*	0.009
					(0.005)	(0.006)
lnBTC	–	–	–	–	–	0.001
						(0.001)
Observation	2,010	2,010	2,010	2,010	2,010	2,010
R-squared	0.004	0.511	0.530	0.551	0.575	0.580

Notes: The constant term is included. The robust standard errors are in ().
***$p < 0.01$, **$p < 0.05$.
Source: The authors' estimations.

lnUSB and *lnDXY* slightly decrease as the quantiles increase. Similarly, *lnBRENT* is negatively associated with the *lnSP_GBI*; however, its coefficient of 0.10 quantile is statistically insignificant. In addition, as the quantile increases, the negative impact of *lnBRENT on lnSP_GBI* is also increased.

On the other hand, *lnGOLD*, *lnSP_500*, and *lnBTC* positively affect *lnSP_GBI*. Among these variables, *lnGOLD* is statistically significant at 1% ($p < 0.01$) in each quantile. The *lnSP_500* and *lnBTC* are also positively related to *lnSP_GBI*. The coefficient of *lnGOLD* decreases as the quantile increases. However, *lnBTC* is statistically insignificant in each quantile estimation. In addition, *lnSP_500* has a statistically insignificant coefficient of 0.90 quantiles. The coefficient of lnSP_*500* increases as the quantile increases.

Overall, *lnUSB* and *lnDXY* are negatively related to *lnSP_GBI,* while *lnGOLD* increases *lnSP_GBI*. These results are valid in every quantile, and all coefficients are statistically significant at the 1% level. These findings are in line with the RLOLS and the KRLS estimations.

5.2. Discussion and policy implications

Our results from different estimation techniques show that the US Treasury Bonds and the US Dollar returns are negatively related to the Green Bond returns. Meanwhile, Gold returns positively affect Green Bond returns.

The main results indicate that the changes in the USD returns are one of the leading determinants of green bond returns. This evidence aligns with the flight-to-quality hypothesis (Gubareva *et al.*, 2023). Mainly there will be bear market expectations. The USD has become the leading instrument to hedge risk in financial markets because of its reserve and trading currency features. Our results indicate that the higher returns of the DXY (stronger USD) motivate traders to invest in less risky assets. This evidence is in line with the previous findings of Kocaarslan and Soytas (2019). They found that a stronger USD makes traders avoid risky assets, such as

Table 6. Results of the quantile regression estimations of Machado and Santos Silva (2019) (September 17, 2014–September 1, 2022).

Quantile	Coefficient	Standard Error
$\tau = 10^{th}$		
lnUSB	−0.007***	(0.002)
lnDXY	−0.555***	(0.022)
lnBRENT	−0.003	(0.003)
lnGOLD	0.058***	(0.011)
lnSP_500	0.020**	(0.008)
lnBTC	0.003	(0.002)
$\tau = 25^{th}$		
lnUSB	−0.007***	(0.002)
lnDXY	−0.523***	(0.016)
lnBRENT	−0.004**	(0.002)
lnGOLD	0.056***	(0.008)
lnSP_500	0.015**	(0.006)
lnBTC	0.002	(0.001)
$\tau = 50^{th}$		
lnUSB	−0.006***	(0.001)
lnDXY	−0.497***	(0.014)
lnBRENT	−0.005***	(0.002)
lnGOLD	0.054***	(0.007)
lnSP_500	0.010**	(0.005)
lnBTC	0.001	(0.001)
$\tau = 75^{th}$		
lnUSB	−0.006***	(0.001)
lnDXY	−0.492***	(0.015)
lnBRENT	−0.006***	(0.002)
lnGOLD	0.053***	(0.007)
lnSP_500	0.006	(0.005)
lnBTC	0.003	(0.014)
$\tau = 90^{th}$		
lnUSB	−0.005***	(0.002)
lnDXY	−0.446***	(0.020)
lnBRENT	−0.007**	(0.003)
lnGOLD	0.051***	(0.010)
lnSP_500	0.002	(0.007)
lnBTC	0.001	(0.001)

Notes: The dependent variable is lnSP_GBI. The robust standard errors are in ().
***$p < 0.01$, **$p < 0.05$.
Source: The authors' estimations.

renewable energy stocks, technology stocks, and crude oil. Our paper enhances this finding by including green bonds, which seem risky assets to investors and traders.

Along with the stronger USD, higher treasury bond returns are the leading indicators of worsening business and economic expectations, thus reducing the returns of green bonds. Similarly, traditional bond returns are negatively related to green bond returns. We observe a substitution effect between green and traditional bonds (Hachenberg & Schiereck, 2018). Again, the rise of the returns of traditional bonds (in the United States) is a strong indicator of lessened risk appetite (Arif *et al.*, 2021). This finding is in line with the previous results provided by Reboredo and Ugolini (2020).

Gold is typically used to hedge risky assets under uncertain economic conditions and is labelled safer in financial markets. In addition, gold returns are positively related to green bond returns. The positive impact of Gold returns on green bond returns can be seen as the potential hedging instrument of Gold against Green Bonds.

The Covid-19 pandemic has negatively affected consumer demand and has distorted global supply chain dynamics (Mirza *et al*., 2020; Su *et al*., 2023b). Since early 2022, central banks have raised interest rates due to the escalating impact of the Russia-Ukraine War on inflation. Especially FED's rise of the benchmark interest rates causes stronger USD and higher returns the traditional bonds. In addition, Gold prices are also in a downtrend. According to our results, these issues have caused lower returns in green bonds. However, green bonds are essential to transition from the fossil fuel economy to the green economy (Sartzetakis, 2021) and financing renewable energy investments (Qin *et al*., 2022; Su *et al*., 2022a). Therefore, the leading policy implication from our findings is that central banks should support green bonds even though they implement contractionary monetary policy (Ren *et al*., 2023). We also suggest that central banks and other regulatory institutions should have duties in fighting against the negative consequences of climate change (Fatica *et al*., 2021).

6. Conclusion

In this paper, we examined the effects of returns in different financial markets (the US Treasury Bonds, the S&P 500 Stock Market, the US Dollar, Gold, Crude Oil, and Bitcoin) on the Green Bond returns, measured by the S&P Green Bond Index, from September 17, 2014, to September 1, 2022. We utilized the robust regression of Liu *et al*. (2018) and the machine learning estimator of Hainmueller and Hazlett (2014). We found that the returns of the US Treasury Bonds and the US Dollar decreased to the Green Bond returns. However, Gold returns positively affect Green Bond returns. We also ran the quantile regression estimations of Machado and Santos Silva (2019). We observed that the findings are valid in different quantiles. These results provide policy implications related to climate change and the development of financial instruments.

However, it is essential to note that our results are limited to specific financial global markets and the S&P Green Bond Index. Therefore, future papers can focus on firm-level green bond assets to examine the effects of financial markets on green markets. Another research agenda is to include uncertainty measures as the determinants of green bond markets. Different econometric and machine learning methods can also be considered at this stage.

Disclosure statement

No potential conflict of interest was reported by the authors.

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