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The Impact of Dow Jones Sustainability Index, Exchange Rate and Consumer Sentiment Index on Carbon Emissions

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Abstract: The objective of this study is to examine, over the last 20 years, the short-run and long-run effect on global carbon dioxide (CO_2) emissions of the stock returns, exchange rates and consumer confidence. Stock markets contribute to environmental degradation; as a result, we employed, for the first time, Dow Jones Sustainability World Index to use stock returns of socially responsible companies. The euro to US dollar exchange rate is used, as the forex market is the largest financial market and considers it as the largest major pair. The Consumer Sentiment Index is used as a proxy to consumer confidence, since consumer behavior is, also, considered as a major factor linked to environmental degradation. The basic testing procedures employed include the Augmented Dickey–Fuller stationarity test, cointegration analysis and Vector Error Correction Model (VECM). The results establish that stock returns of companies listed on the Dow Jones Sustainability World Index exert a significant negative (positive) impact on the global CO_2 emissions in the short (long) term. The inverse, i.e., a significant positive (negative) impact on the short (long) run holds for the both other variables, i.e., US consumers' confidence and euro to US dollar exchange rates. From the outcomes obtained, policy initiatives that could assist companies to mitigate environmental degradation are recommended.

Keywords: stock returns; CO_2 emissions; Dow Jones Sustainability World Index; consumers' confidence; ESG criteria; exchange rates

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1. Introduction

Global warming has many different implications for humanity, and our societies must confront these in order to achieve not only their growth but political stability and their very own survival [1,2] It is generally accepted that global warming is due to the growth of greenhouse emissions, and in particular, the rise of carbon dioxide (CO_2) emissions [3]. The key driver of this increase is fossil fuels, such as oil, coal and gas, that when combusted lead to climate-changing CO_2 emissions with significant future but also contemporaneous repercussions, such as for example on human health with more than seven million people being killed every year due to respiratory illnesses [4–6]. According to the IPCC [7] the concentration of CO_2 in 2019 was higher than at any time in at least 2 million years, while CO_2 was increased by 47% since 1975. A number of different initiatives, such as the Kyoto protocol and the Paris agreement, have been developed to demand the industrialized economies implement specific policies to reduce greenhouse emissions [8].

A plethora of empirical studies intend to investigate the relationship between CO_2 emissions and macroeconomic factors such as international trade, GDP [4], nuclear energy [5], consumption of renewable energy [9,10], and foreign direct investment [11] so as to understand the behavior of CO_2 emissions.

Specifically, the variable of stock returns is considered as a prominent economic indicator and, in particular, it is employed as a proxy of economic growth and development in order to investigate the impact on CO_2 emissions. In this context, we consider the hypothesis of the Environmental Kuznets Curve (EKC), N-shaped relationship or any linear relationship between CO_2 emissions and stock returns. Originally, the EKC hypothesis proposes that there is an inverted U-shape relationship between economic output per capita (i.e., GDP per capita or stock returns) and environmental degradation (i.e., CO_2 emissions), supporting that economies first give priority to their economic development and then to environmental quality. When they grow, however, they focus on environmentally friendly technologies. In addition, there are studies that investigate the N-shaped relationship between CO_2 and economic output levels. In particular, the N-shaped curve suggests that environmental degradation will start to rise again beyond a certain point of economic output [12]. Social responsibility indexes and consumer sentiment are not incorporated in the Environmental Kuznets Curve. To overcome the above gaps, this study focus on validating the EKC hypothesis between stock returns of socially responsible companies and CO_2 and consumer confidence and CO_2. Several socially responsible indexes have been elaborated to integrate companies that consider non-financial initiatives in their business operations such as DJSI, FTSE4good and MSCI KLD. Among the most well-known socially responsible indexes is the DJSI that tracks the stock performance of the world's leading companies based on economic, environmental and social criteria comprising global, regional and country benchmarks (DJSI Index Family: https://www.spglobal.com/esg/performance/indices/djsi-index-family (accessed on 7 June 2021)). For the purpose of the study, the DJSI world stock returns is used, for the first time, as a proxy of world economic growth taking into account socially responsible initiatives.

In accordance with the consumer-based approach, consumer confidence depicting their willingness to buy is the third potential determinant of the global concentration of CO_2 emissions. To our knowledge, it is the first time that consumers' confidence variable is employed to understand the behavior of CO_2 emissions, and it is used as a proxy of consumers' perception of the state of the economy and their own financial situation [13], and thus, it is important in explaining their behavior as investors. In this context, it is intended to validate the EKC hypothesis, the N-shape or any linear relationship between consumer confidence and CO_2.

Based on Rothman [14], this study intends to explain the CO_2 emission behavior considering two different approaches: the first one concerns the production-based approach by explaining how the economic growth via stock returns of socially responsible companies can affect CO_2 emissions, whereas the second one concerns the consumption intention via consumers' confidence. Finally, the third potential determinant that could affect the concentration of CO_2 emissions is considered to be the exchange rate of euro to US dollar, as the US dollar is considered the world's currency and is used as invoice, funding and reserve currency, affecting international trade transactions. It is employed in the proposed model to ascertain whether the strong or weak value of the US dollar affects the CO_2 emissions. Furthermore, limited empirical studies scrutinize the relationship between exchange rate and CO_2 emissions [15].

The study employs the VECM, as it is considered the most suitable approach to measure causality [16] identify long-run relationships [17] and obtain temporal dynamic changes in explanatory variables [18–20]. Kayani et al. [17] constructed a VECM model to explore the causal relationships between financial development and CO_2 emissions. The results reveal unidirectional long-term causality from CO_2 emissions to financial development. The results of Mizra and Kanwal's [21] study indicate the presence of bidirectional causalities between economic growth and the CO_2 emissions in a VECM framework. Similarly, the VECM causality analyses of Rahman and Vu [22] showed the long-run bidirectional causality among CO_2 emissions, economic growth, and renewable energy consumption in Australia and Canada.

To sum up, there are no empirical studies using, as explanatory factors for the CO_2, stock returns of socially responsible companies, the consumers' confidence and exchange rates. Our study intends to fill this gap, using the DJSI World as a proxy for world economic growth, the Consumer Sentiment Index as a proxy for consumer's confidence, and the exchange rate of euro to US dollar as a proxy for financial markets. Our results suggest that the explanatory factors have a different effect on CO_2 emissions in the short run compared to the long run, which is a fact that policy makers should consider in their planning process. In addition, the results of the study have significant implications to socially responsible investors, as they might understand the determinants of the global CO_2 emissions and how the concentration of CO_2 emissions could be reduced. In light of the above discussion, to investigate the potential determinants of global CO_2 emissions among socially responsible companies, consumers' confidence and exchange rates is of great value to scientific knowledge.

The rest of the paper is structured as follows. Section 2 provides a literature review regarding the potential effect of our determinants on the global CO_2 emissions, while the next section describes the data and the methodology. Section 4 provides and discusses the results, while the final section analyzes their implications and mentions ideas for further research.

2. Literature Review

This section describes the potential factors that affect the concentration of CO_2 emissions and focuses on the rationale for considering stock returns of socially responsible companies, consumer confidence and exchange rates.

Reexamining the effect of economic growth on the environment is considered a crucial issue as the results of empirical studies, such as those of Nguyen et al. [23] suggest. To this end, stock returns are used as a proxy of economic growth and development from a production-based approach [14]. The rationale behind the employment of stock returns is that when companies expand their operations, they consume more energy contributing substantially to the concentration of CO_2 emissions and leading to industrial pollution and environmental degradation [24,25].

In general terms, the EKC curve is a well-known hypothesized relationship between economic growth and environmental degradation. Greater economic growth leads to an increase in environmental degradation, but beyond some level of economic growth, the trend reverses, so that the economic growth leads to environmental improvement. The above relationship can be depicted as an inverted U [26,27]. In addition, there are empirical studies that tend to investigate the N-shaped relationship between economic growth and CO_2 emissions. Considering the N-shaped curve, at first, the environmental degradation worsens; then, the environmental degradation is improved. However, as the economic growth continues to increase, the environmental degradation worsens again [28].

Furthermore, this study incorporates companies that have assimilated socially responsible initiatives in their operations, as the need for sustainable financial products is now more imperative than ever. Different sustainability stock indexes have been elaborated to evaluate companies considering socially and environmentally responsible criteria under environmental, social and governance aspects [29].

There are a few empirical studies that investigate the impact of stock markets on CO_2 emission levels [15]. Analytically, Nguyen et al. [23] focus on Canada, France, United Kingdom, Italy, Japan, and the United States for the period 1978–2014 to examine the explanatory variables of CO_2 emissions. They confirm that stock market capitalization has a negative but weak impact on CO_2 emissions. Based on data from 18 countries, Chang et al. [30] investigate the relationship of stock returns and CO_2 emissions using Granger causality tests. There appears to be a unidirectional impact from stock market returns to CO_2 emissions but not the reverse. Ullah and Ozturk [15] find that for Pakistan in the long term, positive and negative shocks of the stock market, in terms of total value of stock trade, have a positive significant impact on CO_2 emissions. Al-mulali et al. [31] find that in Malaysia, in the short (long) run, rises (falls) in stock markets increase (decrease) CO_2 emissions, implying that stronger stock markets contribute to environmental degradation. Examining this relationship, Paramati et al. [32] focus on 23 developed and 20 emerging markets based on the Morgan Stanley Capital International. The results confirmed the presence of the EKC hypothesis between stock markets and CO_2 emissions, albeit at varying levels across developed and emerging market economies.

Paramati et al. [33] investigated the impact of stock market growth on CO_2 emissions focused on a sample of G20 member countries using data from 1991 to 2012. The results revealed that stock market development has both a negative and positive effect on the concentration of CO_2 emissions of development and developing economies, respectively. Zhang [34] illustrated for China that stock markets have a relatively larger influence on CO_2 emissions in comparison with other variables, while the influence of stock market efficiency on CO_2 emissions seems fairly weaker. To the contrary, taking into account Brazil, Russia, India and China, Tamazian et al. [25] use panel data to find that the stock market value significantly decreases CO_2 in the above countries. Tiwari et al. [35] explore the dynamic spillover effects among green bond, renewable energy stocks and carbon markets during the COVID-19 pandemic and conclude that during bearish markets conditions, the connection between CO_2 and the renewable energy market increases. Similarly, Hanif et al. [36] investigate the dependence and connectedness between carbon pricing and renewable energy stock and observe a positive dependence and strong spillover between CO_2 and renewable energy indices in the short run and in the long run. Table 1 summarizes the main aspect of the literature review regarding the effect of stock market on CO_2 emissions.

The study of Rothman [14] introduced the second, consumption-based, approach to investigate the environmental impact from consumption activities to validate the EKC hypothesis. Consumers can be a considered as a major factor linked to environmental degradation, both directly, when deciding to use a polluting car, and indirectly, when linked to the production activities that are undertaken to satisfy their demand. For instance, Schipper et al. [37] illustrate that approximately half of the total energy consumed in US is influenced by consumer behavior for personal transportation, personal services, and homes, while Bin and Dowlatabadi [38] state that more than 80% of the energy used and the CO_2 emissions emitted in the US derive from consumer demand and the required economic activities that are necessary to support this demand.

Lifestyle consumption is an important potential factor from the consumption-based approach so as to investigate the impact of consumers' consumption on environmental degradation. For instance, Bin and Dowlatabadi [38] adopted the concept of Consumer Lifestyle Approach to investigate the relationship between consumer behavior and CO_2 emissions. The results pointed out that the consumer behavior is an important aspect for effective policies in order to mitigate CO_2 emission, which was consistent with the findings of Moran et al. [39]. Similarly, Habib et al. [40] indicated that consumers' behavior and lifestyles are crucial determinants to understand CO_2 emissions in the United Kingdom. However, this study intends to implement a different aspect of consumer's behavior based on their perception for economic growth and development of economy by adopting the CSI, which represents consumers' willingness to buy and to predict their subsequent discretionary expenditures. This measure considers consumers' personal finances, general business conditions, and market conditions or prices. Thus, when there is positive consumer confidence, consumption increases and there is economic growth, while when the consumer is negative, consumption is decreased, leading to the downsizing of economic activity [41].

Table 1. Summary of literature review.

Authors	Type of Data	Period	Methodology	Country/Region	Type of Relationship	Stock Market Indicator	Relationship: Stock Market—CO_2
Tiwari et al. (2022) [35]	Time series	2015–2020	Time-varying parameter vector autoregression (TVP-Var)	Global	Linear relationship	Renewable energy stock market	Strong connectedness between stock market and CO_2 emissions
Hanif et al. (2021) [36]	Time series	2011–2020	Vector autoregression method	Europe	Nonlinear relationship	Renewable energy stock market	Asymmetric tail dependence between the carbon prices and renewable indices
Nguyen et al. (2021) [23]	Panel data	1978–2014	Fully modified ordinary least squares, dynamic ordinary least squares	G-6 countries	EKC is not clear	Stock market capitalization: stock market capitalization to GDP ratio	Stock market has weak and negative impact on CO_2 emissions
Ullah and Ozturk (2020) [15]	Time series	1985–2018	A nonlinear autoregressive distributed lag (ARDL)	Pakistan	Asymmetry relationship	Stocks traded: total value (% of GDP)	Positive and negative shocks in the stock market have a positive significant effect on CO_2 emissions
Chang et al. (2020) [30]	Time series	1971–2017	Unidirectional Granger causality, regressions with dummy variables	18 countries	Linear relationship	Stock returns	Unidirectional causality from stock market to CO_2 emissions
Al-mulali et al. (2019) [31]	Time series	1980–2017	A nonlinear autoregressive distributed lag (ARDL)	Malaysia	Asymmetry relationship	Percentage of stock traded to total GDP	Increases in stock markets will increase CO_2 emissions
Paramati et al. (2018) [32]	Panel data	1992–2011	Panel cointegration methodology, common correlated effects	Developed and emerging market economies	Confirms EKC hypothesis	Total market capitalization divided by the total population of the country, total stocks traded divided by the total population of the country	The effect of stock market indicators varies across developed and developing economies
Paramati et al. (2017) [33]	Panel data	1991–2012	Fisher-type Johansen cointegration test, fully modified ordinary least square method	G20 countries	Linear relationship	Stock market capitalization: market capitalization of listed companies as a percentage of GDP	Stock market capitalization increases CO_2 emissions of full sample and developing economies, and it reduces in developed economies
Zhang (2011) [34]	Time series	1992–2009	Granger causality, Johansen cointegration test, VECM	China	Linear relationship	Stock market scale: the ratio of stock market capitalization to the GDP and stock market efficiency: the ratio of stock market turnover to GDP	Both stock market scale and efficiency influence the volatility CO_2 emissions
Tamazian et al. (2009) [25]	Panel data	1992–2004	Random effect	Bric (Japan and US)	Confirms EKC hypothesis	Stock market value (total shares traded on the stock market exchange to GDP in country)	Stock market value significantly decreases CO_2

The third potential determinant of CO_2 emissions is considered to be the exchange rate of euro to US dollar. One of the most important developments in ecological macroeconomics is the study of financial markets and their role in the non-financial sectors [42]. In this study, the exchange rate is chosen, as the forex market is the world's largest financial market. The exchange rate exerts significant impact on environmental quality via its influence on economic and technological activities [43]. The role of the US dollar for the global economy is crucial because it is used as an invoice, funding and reserve currency, and it is an important factor affecting the international trade transactions [4,43–45]. A few empirical studies investigate the role of the exchange rate on CO_2 emissions. Ullah and Ozturk [15] look into the role of exchange rate volatility between Pakistan and USA on CO_2 emission as a proxy of environmental pollution. In the long run, the findings revealed that both positive and negative shocks in exchange rate volatility affect CO_2 emissions negatively. In the short run, positive shocks in exchange rate volatility reduce CO_2 emissions, while negative shocks in exchange rate volatility have a positive significant effect on CO_2 emissions. Moreover, Omoke et al. [4] who investigate the role of financial development on environmental degradation in Nigeria over the period 1973–2014, use among other variables, exchange rates. The results showed that exchange rate depreciation in terms of LCU per USD contributes to environmental degradation in the form of CO_2 emissions. In addition, Zhang and Zhang [43] point out that a stronger RMB exchange rate against the dollar renders China's exports less competitive as the total value of exports fall, leading to lower levels of CO_2 emissions.

3. Data and Methodology

3.1. Data

The aim of this study is to explore the relationship among the CO_2 emissions and the exchange rate of euro to US dollar, stock returns of socially responsible companies and US consumers' confidence using monthly time-series data for the period 1 April 2001 to 1 July 2020. The original data are sourced from the S&P Global and the Thomson Reuters Database as well as the National Ocean and Atmospheric Administration and the Federal Reserve Economic Data. In addition, all the variables adopted were transformed into logarithmic form. On the one hand, this transformation in logarithms facilitates the interpretation of the estimated coefficients, which are read as elasticities. On the other hand, it can control the heteroscedasticity problem [46]. Based on VECM, the study employs global CO_2 emissions as a dependent variable, and the exchange rate of euro to dollar, the DJSIW's stock returns, and the US Consumer Sentiment Index (CSI) as independent variables. While our main interest is in the relationship among carbon emissions, EUR/USD, DJSI and CSI, in accordance with the relative literature, we include the US GDP [47–51] (and global energy index [25,47,51,52] as control variables potentially correlated with CO_2.

3.2. Methodology

In order to verify the correctness of the U-shaped and N-shaped EKC hypothesis, we follow the principles of the EKC hypothesis and introduce the squared and cubic term of DJSI and CSI into the model as independent variables, as seen below:

$$CO_{2tt} = \beta_0 + \beta_1 DJSIW_t + \beta_2 DJSIW_t{}^2 + \beta_3 DJSIW_t{}^3 + \beta_4 EUR/USD_t + \beta_5 CSI_t + \beta_6 GDP\_US_t + \beta_7 ENERGY_t \quad (1)$$

$$CO_{2t} = \beta_0 + \beta_1 CSI_t + \beta_2 CSI_t{}^2 + \beta_3 CSI_t{}^3 + \beta_4 EUR/USD_t + \beta_5 DJSIW_t + \beta_6 GDP\_US_t + \beta_7 ENERGY_t \quad (2)$$

where CO_2 are global carbon dioxide emissions, DJSIW is the Dow Jones Sustainability Index World stock returns, EUR/USD is the exchange rate of Euro to US dollar, CSI is the US Consumer Sentiment Index, GDP_US is the Gross Domestic Product of the US and ENERGY is the global price of the energy index.

The validity of the EKC hypothesis can be tested by the β_1, β_2, and β_3 coefficients [53]. Specifically,

If $\beta_1 > 0$, $\beta_2 < 0$ and $\beta_3 = 0$, it indicates a quadratic inverse U-shaped relationship.

If $\beta_1 < 0,\ \beta_2 > 0$ and $\beta_3 = 0$, it indicates a U-shaped quadratic relationship.

If $\beta_1 > 0,\ \beta_2 < 0$ and $\beta_3 > 0$, it indicates the N-shaped cubic polynomial relationship.

If $\beta_1 < 0,\ \beta_2 > 0$ and $\beta_3 < 0$, it indicates the inverse N-shaped cubic polynomial relationship.

The central contribution of this research is to examine the dynamic relationship among carbon emissions, DJSI, EUR/USD and CSI in an integrated framework. The equation of the EKC hypothesis explores the U-shaped and N-shaped relationship between CO_2 and DJSI. In order to investigate the linear relationship and causal relationship among CO_2 emissions and other variables, we construct a Vector Error Correction Model (VECM).

Given that in this study, the time-series EUR/USD, DJSIW, CSI and CO_2 are encountered as endogenous, we use as required a simultaneous equation system [54–56]. Similarly, Kayani et al. [17], Kivyiro and Arminen [57], Sebri and Salha [58] and Zeb et al. [59] investigate the relationship among CO_2, renewable energy and economic growth and treat all the variables as endogenous. One of the most popular simultaneous equation systems is the Vector Autoregressive Model (VAR), as the researcher does not need to specify which variables are endogenous or exogenous—all are endogenous. VAR was popularized in econometrics by Sims [60], as a natural generalization of the univariate autoregressive model AR to a multivariate autoregressive time-series model.

The test of stationarity in the time series is essential not only to ascertain the order of integration of a variable to prevent spurious analysis and erroneous policy implications [61] but also in order to use the VAR model. The augmented Dicky–Fuller (ADF) test [62] is one of the most commonly used unit root tests [63–66]. The lag-length criteria are selected through the Akaike Information Criteria (AIC), Schwartz Information Criteria (SIC) and Hannan–Quinn Criteria (HQ) [67,68]. According to the VAR model, every variable depends on different combinations of the previous values of all variables and error terms. The autoregressive term refers to the lagged dependent variable, while the vector refers to the number of variables. The simplest case that can be entertained is a bivariate VAR, where there are only two variables and one lag. This could be written as:

$$Y_t = a_0 + A_1 Y_{t-1} + \varepsilon_t \tag{3}$$

where $Y_t = \begin{pmatrix} Y_{1t} \\ Y_{2t} \end{pmatrix}$, $Y_{t-1} = \begin{pmatrix} Y_{1,\,t-1} \\ Y_{2,\,t-1} \end{pmatrix}$, $\alpha_0 = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix}$, $A_1 = \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}$, $\varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$, and ε_t are stochastic error terms, which are also called impulses or schocks and are white noise disturbance terms with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t, \varepsilon_s{}') = \Omega\ ,\ \gamma\iota\alpha\ t = s$

$$E(\varepsilon_t, \varepsilon_s{}') = 0,\ \gamma\iota\alpha\ t \neq s$$

Ω is the matrix of variance–covariance:

$$\Omega = \begin{pmatrix} V(\varepsilon_{1t}) & Cov(\varepsilon_{1t}, \varepsilon_{2t}) \\ Cov(\varepsilon_{1t}, \varepsilon_{2t}) & V(\varepsilon_{2t}) \end{pmatrix}$$

An extension of model VAR with k variables and p lags is:

$$Y_t = a_0 + A_1 Y_{t-1} + A_2 Y_{t-2} + \ldots + A_p Y_{t-p} + \varepsilon_t \tag{4}$$

where matrix $A_i, i = 1, \ldots, p$ is the matrix of coefficients α_{ij} with dimensions $K \times K_{i,j} = 1, 2, \ldots, K$.

Most of the time, series are non-stationary at the levels and then stable after first differences [69]. In this case, VAR can capture only the short-term relationship between variables; otherwise, this could have led to the estimation of spurious relations. The estimation of a long-term relationship, employing the variables in levels, would result in non-robust estimators unless the series were cointegrated. If it is stationary, then the series are considered to be cointegrated and form a long-run relationship with each other [69]). Cointegration tests reveal whether a long-term equilibrium relationship exists between non-stationary sequences. The Johansen cointegration test is suitable for the multi-period cointegration time-series analysis [70]. A Vector Error Correction Model (VECM) is used to examine the short-term and long-term relationships between variables if all variables are co-integrated I(1) (Equation (5)).

$$\Delta y_t = \beta_1 \Delta x_t + \beta_2 (y_{t-1} - \gamma x_{t-1}) + \varepsilon_t \quad (5)$$

where x_t and y_t are cointegrated, and coefficient $y_{t-1} - \gamma x_{t-1}$ is the error correction term. Every variable is, separately, I(1), while the linear combination $y_{t-1} - \gamma x_{t-1}$ is I(0).

The target variable of VECM is CO_2. Equation (6) is the cointegration equation of VECM. Coefficients β_i represent the long-term relationship among CO_2 and other variables, where X is a series of control variables.

$$ECM_{t-1} = CO_2 - \beta_0 - \beta_1 \frac{EUR}{USD}_{t-1} - \beta_2 DJSI_{t-1} - \beta_3 CSI_{t-1} - \sum_{i=4}^{5} \beta_i X_i \quad (6)$$

The VECM model designed for the variable of interest is described as follows:

$$\begin{aligned} D(CO_{2t}) = \varphi_1 ECT_{t-1} + \sum_{i=1}^{n} \alpha_{1i} D(CO_{2t-1})) + \sum_{i=1}^{n} \delta_{1i} D(EUR/USD_{t-i}) + \sum_{i=1}^{n} \theta_{1i} D(DJSI_{t-i}) \\ + \sum_{i=1}^{n} \omega_{1i} D(CSI_{t-i}) + \sum_{i=1}^{n} \beta_i X_i + \varepsilon_{1t} \end{aligned} \quad (7)$$

$$\begin{aligned} D(EUR/USD_t) = \varphi_2 ECT_{t-1} + \sum_{i=1}^{n} \alpha_{2i} D(CO_{2t-1}) + \sum_{i=1}^{n} \delta_{2i} D(EUR/USD_{t-i})) + + \sum_{i=1}^{n} \theta_{2i} D(DJSI_{t-i}) \\ + \sum_{i=1}^{n} \omega_{2i} D(CSI_{t-i}) + \sum_{i=1}^{n} \beta_i X_i + \varepsilon_{2t} \end{aligned} \quad (8)$$

$$\begin{aligned} D(DJSI_t) = \varphi_3 ECT_{t-1} + \sum_{i=1}^{n} \alpha_{3i} D(CO_{2t-1}) + \sum_{i=1}^{n} \delta_{3i} D(EUR/USD_{t-i}) + \sum_{i=1}^{n} \theta_{3i} D(DJSI_{t-i})) + \sum_{i=1}^{n} \omega_{3i} D(CSI_{t-i}) \\ + \sum_{i=1}^{n} \beta_i X_i + \varepsilon_{3t} \end{aligned} \quad (9)$$

$$\begin{aligned} D(CSI_t) = \varphi_4 ECT_{t-1} + \sum_{i=1}^{n} \alpha_{4i} D(CO_{2t-1}) + \sum_{i=1}^{n} \delta_{4i} D(EUR/USD_{t-i}) + \sum_{i=1}^{n} \theta_{4i} D(DJSI_{t-i}) + \sum_{i=1}^{n} \omega_{4i} D(CSI_{t-i})) \\ + \sum_{i=1}^{n} \beta_i X_i + \varepsilon_{4t} \end{aligned} \quad (10)$$

where i represents the number of lags, coefficients $\varphi_j, \alpha_{ji}, \delta_{ji}, \theta_{ji}, \omega_{ji}, \ and\ \beta_{ji}$ (j = 1, 2, 3) are parameters to be estimated and ε_{ji} are white noise error terms. Especially, ECT is the error correction term derived from the corresponding long-run equilibrium relationship, and the coefficients φ_j of the ECTs represent the deviation of the dependent variables from the long-run equilibrium.

The error correction term (ECT) in this study reflects the strength of the self-correction mechanism at work in CO_2 emissions. If the coefficients of ECT_{t-1} are statistically significant, VECM makes it possible to estimate the short-term relationships and to indicate the existence of long-term relationships. The coefficients of ECT have to be negative, as they represent the speed of adjustment of the system and constrain the endogenous variables to converge to cointegration relationships while allowing for short-term dynamic adjustments. The ECT implies that the variations of the endogenous variables are a function of the level of imbalance in the cointegration relation that it recovers [18,20,71]. Coefficients $\alpha_{ji}, \delta_{ji}, \theta_{ji}, \ \omega_{ji},$ and β_{ji} indicate the short-run causal relationship among the dependent variables, its lag and other independent and control variables.

The VECM model indicates 3 types of causality: short-run, long-run and strong causality. If $\alpha_{ji}, \delta_{ji}, \theta_{ji},$ and ω_{ji} are statistically significant, they indicate short-run causality among dependent and other variables. If φ_j is statistically significant, it indicates long-run causality among dependent and other variables, and finally, if both coefficients φ_j and

$\alpha_{ji}, \delta_{ji}, \theta_{ji}, \omega_{ji}$ are statistically significant, they indicate a strong causality among dependent and other variables.

4. Results

4.1. Descriptive Statistics

The following Table 2 depicts the descriptive statistical measures of the variables. GDPUS has the lowest mean (−0.000148), while DJSIW has the highest price (0.001203). The lowest deviation from the mean value based on the standard deviation is (0.003318) and appears to be in CO_2, while ENERGY has the highest price (0.078589). All the variables have a negative asymmetry, while the curvature is positive, which proves it to be slender shaped.

Table 2. Descriptive statistics.

Variables	CO_2	EUR/USD	DJSIW	CSI	GDPUS	ENERGY
Mean	0.000499	0.001002	0.001203	−0.001202	−0.000148	0.001039
Median	0.001587	0.000730	0.008142	−0.002709	0.000127	0.010122
Maximum	0.006352	0.096276	0.115841	0.148694	0.019420	0.237459
Minimum	−0.006549	−0.102355	−0.200314	−0.240043	−0.049122	−0.403523
Std. Dev	0.003318	0.027920	0.042303	0.056380	0.004648	0.078589
Skewness	−0.554356	−0.305116	−1.103941	−0.506764	−5.709579	−1.208289
Kurtosis	1.965248	4.507465	5.672819	4.922114	66.80467	7.224504

A GARCH model is employed to verify the correctness of the EKC hypothesis. The results show that all the coefficients except CSI are not significantly important (see Tables A1 and A2 in Appendix A). When including the quadratic and cubic variable, the other determinants lose significance. This means that including the quadratic and cubic terms just brings distortion to the model and should not be considered. In this way, inverted U-shaped and N-shaped functional forms are also discarded.

4.2. Test of Stationary

According to Table 3 and the Augmented Dickey–Fuller (ADF) unit root test, it is concluded that the time series remains stable in all levels, except for CO_2, while all variables remain stable I(1) at first differences at the 1% level of significance.

Table 3. ADF stationary test.

Variables	Level Values	First Differences
	t-Statistic	t-Statistic
CO_2	−0.735269	−13.51329 *
EUR/USD	−12.16529 *	−9.039720 *
DJSIW	−12.72848 *	−10.43915 *
CSI	−9.051139 *	−8.835164 *
GDPUS	−7.447519 *	−11.70490 *
Energy	−10.38490 *	−11.64283 *

Notes: For the level, critical *t*-values were taken as –2.575011, –1.942205 and −1.615784 for the significance levels of 1%, 5% and 10%, respectively. For the first differences, critical *t*-values were taken as –2.575144, −1.942224 and −1.615772 for the significance levels of 1%, 5% and 10%, respectively. * is the significance level of 1%.

The existence of structural breaks in the dataset may lead the above unit root test results to be misleading. In order to capture structural breaks, we will use a Breakpoint Unit Root Test. The null hypothesis is H_0: the variable has a unit root. The results of the test are presented in Table 4.

According to Table 4, the null hypothesis can be rejected at a 1% significance level; as a result, all the variables do not have the unit roots with structural breaks. Combining with the results in Table 3, it can be concluded that the six variables analyzed are not stationary at level but stationary at their first differences.

Table 4. Results of unit root with structural breaks test.

Variables	Intercept	Trend and Intercept
	t-Statistic	t-Statistic
CO_2	−5.368745 *	−5.392604 *
EUR/USD	−15.88910 *	−15.86313 *
DJSIW	−13.29994 *	−13.47101 *
CSI	−16.40341 *	−16.25841 *
GDPUS	−12.69829 *	−12.67187 *
Energy	−11.35777 *	−11.51268 *

Notes: For the intercept, critical *t*-values were taken as –4.949133, –4.443649 and −4.193627 for the significance levels of 1%, 5% and 10%, respectively. For the trend and intercept, critical *t*-values were taken as –5.347598, −4.859812 and −4.607324 for the significance levels of 1%, 5% and 10%, respectively. * is the significance level of 1%.

4.3. Cointegration Analysis

In order to estimate the long-run relationship through the VECM approach, there are pre-requisite tests for the selection of the appropriate lag selection criteria [72,73]. Table 5 presents the prices of the LR, FPE, AIC, SC and HQ criteria, as a result of the unrestricted VAR model. Following the literature [74,75] according to the AIC criteria, we select three lags. To capture dynamic results, the AIC criterion is considered superior and more effective as compared to SC and HQ, as it provides more reliable results [16]

Table 5. Lag length criteria.

Lag	LR	FPE	AIC	SC	HQ
0	NA	4.18×10^{-21}	−29.89712	−29.80660	−29.86060
1	326.4540	1.30×10^{-21}	−31.06383	−30.43013 *	−30.80812
2	120.9319	1.02×10^{-21}	−31.31175	−30.13489	−30.83687 *
3	95.39607	8.84×10^{-22} *	−31.45320 *	−29.73318	−30.75915
4	38.08187	1.01×10^{-21}	−31.32445	−29.06136	−30.41132
5	57.00695 *	1.04×10^{-21}	−31.29822	−28.49187	−30.16581

Note: * indicates lag order selected by the criterion. LR: sequential modified LR test statistic (each test at 5% level); FPE: final prediction error; AIC: Akaike Information Criterion; SC: Schwarz Information Criterion; and HQ: Hannan–Quinn Information Criterion.

We employ the Johansen cointegration test in order to examine the existence of cointegration among the CO_2 emissions, the exchange rate EUR/USD, the Dow Jones Sustainability Index, the Consumer Sentiment Index, the GDP US and the energy index. The results are reported in Table 6.

Table 6. Johansen cointegration results for CO_2 with, EUR/USD, DJSIW, CSI, GDPUS, ENERGY.

Hypothesized No CE(s)	Trace Test			Maximum Eigenvalue Test	
	Trace Statistic	0.05 Critical Value	Prob **	Max-Eigen Statistic	0.05 Critical Value
None *	487.8425	95.75366	0.0001	122.0161	40.07757
At most 1 *	365.8264	69.81889	0.0001	110.1060	33.87687

* denotes rejection of the hypothesis at the 0.05 level. ** MacKinnon–Haug–Michelis (1999) *p* values.

They demonstrate that the first two null hypotheses are rejected, since trace and eigenvalue tests are greater than the critical bounds of the 0.01 level of significance. This indicates that there is one cointegrating equation at the 0.01 level. As a result, we confirm that the CO_2 emissions, EUR/USD, DJSIW, CSI, GDP US and ENERGY, have a long-term stable cointegration relationship at the 1% level.

Based on the existence of a cointegrated relationship among variables, the VECM is implemented to reveal long-term equilibrium relationships between non-stationary series. Results of the VECM used in this study are summarized in Tables 7–9.

Table 7. Cointegration equation of VECM.

Cointegrating Equation	$CO_{2(-1)}$	$EUR/USD_{(-1)}$	$DJSIW_{(-1)}$	$CSI_{(-1)}$	$GDPUS_{(-1)}$	$ENERGY_{(-1)}$	C
CointEq1	1.00000	0.028048	−0.037012	0.082171	0.201637	−0.003883	−0.000378
		(0.01967)	(0.01257)	(0.01177)	(0.11536)	(0.00720)	
		[1.42627]	[−2.94390]	[9.34048]	[1.74795]	[−0.53931]	

Standard errors in ( ) and t-statistics in [ ].

According to Table 7, the cointegration equation is:

$$ECM_{t-1} = 1.00000\, CO_{2_{(-1)}} + 0.028048\, EUR/USD_{(-1)} - 0.037012 DJSI_{(-1)} + 0.082171 CSI_{(-1)} \\ + 0.201637 GDPUS_{(-1)} - 0.003883 ENERGY_{(-1)} - 0.000378 \quad (11)$$

Error Correction Modeling (ECM) is the simplest univariate modeling. It depicts the long-term relationship among CO_2 and other variables. The coefficients are statistically significant and reveal a long-run positive relationship between CO_2 emissions, DJSIW and ENERGY. As shown in Equation (11), DJSI has the largest contribution to CO_2 emissions at 0.037012, which is followed by ENERGY at 0.003883. In other words, a 1% increase in DJSIW will increase CO_2 by 3.7% and a 1% increase in ENERGY will, respectively, increase CO_2 by 0.3%. A long-run negative relationship appeared among CO_2 and EUR/USD, CSI and GDP US at −0.028048, −0.082171 and −0.201637, respectively. It is very interesting that a 1% increase in GDPUS will decrease CO_2 by 20.1%. This is in line with Mohsin et al. [76], who conclude that GDP is negatively contributing to carbon dioxide emissions for the long run. Regarding the other variables, a 1% increase in CSI will decrease CO_2 by 8.2%, and a 1% increase in EUR/USD will decreases CO2 by 2.8%.

Table 8 shows that ECT coefficients for the EUR/USD, DJSIW, CSI, GDPUS and ENERGY are found to be −0.3596, −0.2953, −8.0342, −0.1438 and −1.1659, respectively, and they are statistically significant at the 1% level.

These results validate the presence of a long-run causal relationship among the variables. The error correction term (ECT) in this study reflects the strength of the self-correction mechanism at work in CO_2 emissions. In this case, the ECT is found to be −0.3596, which is a result that indicates that when there exist short-term dynamic deviations in CO_2 from the long-term equilibrium, the next phase of CO_2 emissions will be reversed by external changes to bring the unbalanced state back to equilibrium at 35.9%.

Finally, the results of the first and second lagged values reveal that there is a short-run causal relationship among the variables.

In Table 9, we isolate the first equation of VECM (first column of the Table 8) with CO_2 emissions as a dependent variable, EUR/USD, DJSIW and CSI as independent variables and GDPUS and ENERGY as control variables to investigate the short-run and long-run causal relationships among the variables and perform some necessary diagnostic tests.

In accordance with Table 9, the equation of error correction with the CO_2 emissions as the dependent variable is:

$$\begin{aligned} D(CO_2) \; &= -0.359692 ECT_{t-1} + 0.397294 D\left(CO_{2_{(-1)}}\right) + 0.245313 D\left(CO_{2_{(-2)}}\right) \\ &+ 0.009703 D\left(EUR/USD_{(-1)}\right) + 0.008406 D\left(EUR/USD_{(-2)}\right) - 0.006705 D\left(DJSI_{(-1)}\right) \\ &- 0.001935 D\left(DJSI_{(-2)}\right) + 0.022277 D\left(CSI_{(-1)}\right) + 0.008440 D\left(CSI_{(-2)}\right) \\ &+ 0.011328 D\left(\mathrm{GDPUS}_{(-1)}\right) - 0.034395 D\left(\mathrm{GDPUS}_{(-2)}\right) - 0.001785 D\left(ENERGY_{(-1)}\right) \\ &- 0.000435 D\left(ENERGY_{(-2)}\right) - 1.69E - 05 \end{aligned} \quad (12)$$

Table 8. VECM estimates.

Error Correction	**[1] D(CO_2)**	**D(EUR/USD)**	**D(DJSIW)**	**D(CSI)**	**D(GDPUS)**	**D(ENERGY)**
CointEq1	−0.359692 *	−0.295379	−0.951541	−8.034263 ***	−0.143863 **	−1.165925
	(0.04245)	(0.61671)	(0.83613)	(1.12951)	(0.07988)	(1.52539)
	[−8.47382]	[−0.47896]	[−1.13802]	**[−7.11305]**	**[−1.80099]**	[−0.76434]
$D(CO_{2(-1)})$	0.397294 *	0.367120	−0.907101	5.902574	0.108877	0.683075
	(0.06085)	(0.88404)	(1.19859)	(1.61914)	(0.11451)	(2.18663)
	[6.52930]	[0.41527]	[−0.75681]	[3.64550]	[0.95083]	[0.31239]
$D(CO_{2(-2)})$	0.245313 *	−0.294326	1.111206	4.259699	−0.67197	3.365139
	(0.06971)	(1.01276)	(1.37311)	(1.85489)	(0.13118)	(2.50501)
	[3.51917]	[−0.29062]	[0.80926]	[2.29647]	[−0.41225]	[1.34336]
$D\left(\frac{EUR}{USD}\right)_{(-1)}$	0.009703 *	−0.706992 *	0.058300	0.258379 **	−0.001121 ***	−0.019915
	(0.00443)	(0.06434)	(0.08723)	(0.11784)	(0.00833)	(0.15914)
	[2.19105]	**[−10.9881]**	[0.66832]	**[2.19259]**	**[−0.13446]**	[−0.12514]
$D\left(\frac{EUR}{USD}\right)_{(-2)}$	0.008406 *	−0.398249 *	−0.034946	0.206211 **	−0.005796 **	0.068271
	(0.00436)	(0.06339)	(0.08594)	(0.11610)	(0.00821)	(−0.15679)
	[1.92651]	**[−6.28249]**	[−0.40661]	**[1.77614]**	**[−0.70593]**	[0.43542]
$DJSIW_{(-1)}$	−0.006705 *	−0.030714 ***	−0.560285 *	0.104281 ***	−0.004454 *	−0.010112
	(0.00357)	(0.05180)	(0.07023)	(0.09487)	(0.00671)	(0.12813)
	[−1.88063]	**[−0.59294]**	**[−7.97773]**	**[1.09917]**	**[−0.66381]**	[−0.07892]
$DJSIW_{(-2)}$	−0.001935 ***	−0.041600 ***	−0.356622 *	0.096446 **	−0.009892 *	−0.185411 ***
	(0.00329)	(0.04782)	(0.06483)	(0.08758)	(0.00619)	(0.11827)
	[−0.58780]	**[−0.86997]**	**[−5.50078]**	**[1.10125]**	**[−1.59715]**	**[−1.56764]**
$D(CSI)_{(-1)}$	0.022277 *	0.020025	**0.005590**	**−0.270270 ****	**0.002792 ****	**0.121799 *****
	(0.00309)	(0.04492)	(0.06090)	(0.08227)	(0.00582)	(0.11110)
	[7.20544]	[0.44581]	[0.09178]	**[−3.28519]**	**[0.47989]**	**[1.09627]**
$D(CSI)_{(-2)}$	0.008440 *	0.015445 ***	−0.033704 ***	−0.127762 **	−0.002722 *	−0.107916 ***
	(0.00239)	(0.03465)	(0.04698)	(0.06347)	(0.00449)	(0.08571)
	[3.53857]	**[0.44572]**	**[−0.71739]**	**[−2.01307]**	**[−0.60649]**	**[−1.25908]**
$D(GDPUS)_{(-1)}$	0.011328	−0.108338	4.216318	3.285028	−0.130227 **	3.123381
	(0.00239)	(0.54532)	(0.73935)	(0.99877)	(0.07063)	(1.34882)
	[0.30182]	[−0.19867]	[5.70273]	[3.28908]	[−1.84368]	[2.31563]
$D(GDPUS)_{(-2)}$	−0.034395	0.441676	−0.439166	2.693038	−0.050379	−5.881146
	(0.03725)	(0.54113)	(0.73366)	(0.99108)	(0.07009)	(1.33844)
	[−0.92346]	[0.81622]	[−0.59860]	[2.71727]	[−0.71877]	[−4.39402]
$D(ENERGY)_{(-1)}$	−0.001785	0.044541 **	0.021036	−0.023764	0.015246 *	−0.349104 *
	(0.00187)	(0.02712)	(0.03677)	(0.04967)	(0.00351)	(0.06708)
	[−0.95621]	**[1.64226]**	[0.57205]	[−0.47840]	**[4.33970]**	**[−5.20390]**
$D(ENERGY)_{(-2)}$	−0.000435	0.023242 **	−0.011843	−0.142056 **	0.008325 *	−0.209877 **
	(0.00195)	(0.02832)	(0.03839)	(0.05186)	(0.00367)	(0.07004)
	[−0.22341]	**[0.82074]**	[−0.30845]	**[−2.73896]**	**[2.26952]**	**[−2.99640]**
C	-1.69×10^{-5}	0.000306	6.54×10^{-5}	−0.000802	9.27×10^{-5}	0.001265
	(0.00014)	(0.00210)	(0.00285)	(0.00385)	(0.00027)	(0.00520)
	[−0.11698]	[0.14534]	[0.02291]	[0.20805]	[0.34028]	[0.24306]

Notes: *, **, and *** denote significance levels of 1% 5% and 10%, respectively.[1] In the table of error correction, in front of the variables, there is a "D" due to the fact that at first, times series were not stable and the model VECM corrects the stationary, taking the differences. This is the reason why we use 2 lags and not 3 lags, as it was suggested by the lag length criteria. Standard errors in ( ) and t-statistics in [ ].

We will check the robustness of the equation. We have employed the Jarque–Bera test for the normality of the residuals, the LM test for the autocorrelation of the residuals and the Breusch–Pagan–Godfrey test for heteroskedacity. According to the F-statistic, the regression is statistically significant. The probability of the Jarque–Bera is 0.95 > 0.05; as a result, the null hypothesis is not rejected. According to LM test, the null hypothesis of no existence of autocorrelation is not rejected, and last but not least, according to Breusch–Pagan–Godfrey, the residuals are homoskedastic.

Table 9. Equation of CO_2.

Variable	Coefficient	Std. Error	t-Statistic	Prob
ECT_{t-1}	−0.359692 *	0.042447	−8.473820	0.0000
$D(CO_{2(-1)})$	0.397294 *	0.060848	6.529302	0.0000
$D(CO_{2(-2)}$	0.245313 *	0.069708	3.519175	0.0005
$D\left(EUR/USD_{(-1)}\right)$	0.009703 **	0.004429	2.191048	0.0295
$D\left(EUR/USD_{(-2)}\right)$	0.008406 **	0.004363	1.926508	0.0554
$D\left(DJSI_{(-1)}\right)$	−0.006705 ***	0.003565	−1.880634	0.0614
$D\left(DJSI_{(-2)}\right)$	−0.001935	0.003291	−0.587799	0.5573
$D\left(CSI_{(-1)}\right)$	0.022277 *	0.003092	7.205436	0.0000
$D\left(CSI_{(-2)}\right)$	0.008440 *	0.002385	3.538574	0.0005
$D\left(GDPUS_{(-1)}\right)$	0.011328	0.037534	0.301817	0.7631
$D\left(GDPUS_{(-2)}\right)$	−0.034395	0.037245	−0.923463	0.3568
$D\left(ENERGY_{(-1)}\right)$	−0.001785	0.001867	−0.956210	0.3400
$D\left(ENERGY_{(-2)}\right)$	−0.000435	0.001949	−0.223413	0.8234
C	-1.69×10^{-5}	0.000145	−0.116979	0.9070
R-squared	0.334763		Jarque-Bera test	0.088163
Adjusted R-squared	0.294539		(p-values)	(0.956876)
F-statistic	8.322547		LM-test	1.325039
(p-values)	0.000000		(p-values)	(0.5156)
			Breusch-Pagan-Godfrey test	8.342628
			(p-values)	(0.9731)

*, **, and *** denote significance levels of 1% 5% and 10%, respectively.

The coefficient of ECT is $c(1) = -0.3596$. Once the coefficient is significant and negative, it implies that there is at least a long-term link among CO_2 and the other variables (EUR/USD, DJSIW, CSI, GDPUS, ENERGY). In the short run, there is a positive causal relationship from the first and second lag of CO_2 to CO_2 ($c(2) = 0.3972$ and $c(3) = 0.2453$, respectively) at the 1% level of significance, and from the first and second lag of EUR/USD to CO_2 ($c(4) = 0.0097$ and $c(5) = 0.0084$, respectively) at the 5% and 10% levels of significance, respectively. The first lag of DJSIW has a negative causal relationship with CO_2 emissions at the 5% level, with direction from DJSI to CO_2 ($c(6) = -0067$)). Finally, there is a positive causal relationship from the first and second lag of CSI to CO_2 at the 1% level ($c(8) = 0.0227$ and $c(9) = 0.0084$), respectively. As for the control variables, GDPUS and ENERGY are not statistically significant at any level.

The results of the study reveal a differentiation in the long run and in the short run. Specifically, the causal relationship between CO_2 emissions and DJSIW is negative in the short run and positive in the long run. Similarly, the causal relationships among CO_2 and the variables EUR/USD and CSI are positive in the short run and negative in the long run. Furthermore, as for the control variables, in the long run, GDPUS has a negative effect on CO_2 emissions and ENERGY has a positive effect on CO_2 emissions, while in the short run, none of them are statistically significant. Regarding the correctness of the U-shaped and N-shaped EKC hypothesis, the inverted U-shaped and N-shaped functional forms are discarded, as all the coefficients except CSI are not significantly important, and when including the quadratic and cubic variable, the other determinants lose significance.

5. Conclusions and Policy Implications

As environmental degradation attracts the interest of the global community, this study intends to investigate the determinants of global CO_2 emissions. Focused on the production point of view, stock returns are employed as an indicator of economic growth and development to examine the impact on environmental degradation. Based on the consumption point of view, consumers' confidence is another plausible factor of CO_2 emission levels [14]. The third explanatory factor of environmental degradation is the exchange rate of euro to US dollar because of the importance of the US dollar for the global economy. Finally, the sample consists of socially responsible companies that integrate environmental concerns in their business operation. In particular, the sample is made up of companies listed in DJSIW considering monthly data for the period 1 April 2001 to 1 July 2020.

Based on the empirical results of the study, it is found that in the short run, the increase in stock returns contributes to the decline of global CO_2 emissions. This result implies that the growth of socially responsible companies driven by the integration of environmental initiatives in their business operations mitigates environmental degradation. This can be linked to government initiatives and policy makers' incentives that force companies to employ eco-friendly technology [32]. All the above initiatives might have significantly contributed to the short-run companies to mitigate the global CO_2 emissions.

In the long run, the results show that the increase in stock returns causes higher levels of CO_2 emissions. This result indicates that the continuing economic development contributes to long-run environmental degradation (i.e., responsible firms grow in good market periods but so do less responsible ones). For this reason, all governmental bodies and policy makers should intensify their initiatives, the same way they did for the short-run, so that companies are prepared for a long-run production with an eco-friendly approach. Furthermore, policy makers and governments should provide financial incentives such as tax benefits for stable renewable energy production that could minimize the CO_2 emissions level produced by companies. Governments could impose stricter fines or increased taxes to polluting companies, leading corporate management to alter their production procedures to more sustainable ones by investing in eco-friendly technology using clean or renewable energy. Finally, policy makers should encourage and promote companies to commit to sustainability networks in which companies are brought together to help each other find solutions by exchanging or sharing sustainable technological innovations and operational procedures [31,32].

As far as the consumers' confidence variable is concerned, in the short run, the results reveal a positive effect of consumer confidence on global CO_2 emissions. On the one side, the high prospects of increased consumer consumption find companies unable and unprepared to produce with sustainable approaches, leading to increased CO_2 emissions. This is probably due to the fact that companies wait before investing in environmental initiatives so as to ascertain that consumer positive prospects will not just be a short-term phenomenon but a long-run one. On the other side, negative prospects of consumer willingness to buy lead to lower sales and profits for companies, preventing them from investing in eco-friendly technology and reforming their business procedures that could mitigate CO_2 emissions.

In the long run, there is a negative effect of consumer confidence on CO_2 emissions. The positive prospects of consumers' confidence for their personal finances and general business conditions causes lower levels of CO_2 emissions. This result implies that consumers will buy more and over the long run increase company sales and profits, enforcing companies to adopt all necessary environmental initiatives that could reduce CO_2 emissions.

Finally, in the short run, the euro to US dollar exchange rate has a positive effect on the global CO_2 emissions. This result implies that when the US dollar is strengthening, the global CO_2 emissions are increasing. As the US dollar plays a crucial role in the funding of companies, when the US dollar strengthens in relation to the euro, the lending cost of companies for their investments and operations increases, imposing barriers to consider further investments to mitigate environmental degradation. Furthermore, as the US dollar is the world's preferred currency for international trade, the strengthening of the US dollar leads to higher costs of trade transactions, discouraging companies from taking into account the environmental concerns on their business operations. On the other side, the results indicate that when the US dollar is depreciated, environmental degradation increases. The depreciation of the US dollar could be considered as an overwhelmingly positive development for the US and global economies. As companies increase their sales and profits, they are able to consider and implement sustainability measures to mitigate the environmental degradation.

In the long run, the results indicate that the euro to US dollar exchange rate has a negative effect on the global CO_2 emissions. The result implies that companies have developed alternative environmental funding strategies so as to avoid the cost of the US dollar strengthening. For instance, companies collaborate with governments or economic communities that have introduced several environmental funds to promote and reduce the cost of eco-friendly investment technologies and change their business operations according to environmental standards. In addition, the strong US dollar in relation to the euro drives companies to find and integrate alternative energy resources so as to avoid the repercussions of high prices of crude oil, as it is priced in US dollars. However, the long-run depreciation of the US dollar seems to act against the US dollar's global status, leading to increased concerns for global economic stability as well impacting the development of sustainability projects that could mitigate environmental degradation. Thus, policy makers should find ways of motivating companies to consider sustainable production and to assist them with environment-related funding tools that help them during periods of adverse exchange rate impact. This study shows that the three explanations have different effects on CO_2 emission levels in the short and long run, which policy makers should consider in their planning process.

Regarding the control variables, in the long run, GDPUS has a negative effect on CO_2 emissions. This result is in line with previous studies [77,78], where the authors posited that an increase in GDP will bring about environmental efficiency by switching away from the high-carbon emission system to a low carbon-based. Mohsin et al. [76] employing a VECM model conclude, also, that GDP is negatively contributing to carbon dioxide emissions for the long run. According to the control variable ENERGY, in the long run, it has a positive effect on CO_2 emissions. Similarly, Chen et al. [47] find a positive relationship between energy intensity and CO_2 emissions and conclude that the high energy-intensive economic production mode is not conductive to CO_2 emission reduction. In the short run, both GDPUS and ENERGY are not statistically significant at any level.

This study constructs a VECM model in order to explore the determinants of CO_2 emissions, but it could not capture the asymmetric effects of the variables on carbon emissions. Future research could focus on other empirical approaches such as the Nonlinear Autoregressive Distributed Lag technique (NARDL) and employing a higher frequency dataset to construct a forecasting model. Furthermore, the subject study can be extended, for instance, by considering other regional socially responsible indexes, such as DJSI Europe, FTSE4good and MSCI KLD in order to be compared with DJSI World effects on the global CO_2 emissions. Moreover, renewable energy stocks such as global wind or solar can be included.

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Abbreviations

DJSI World	Dow Jones Sustainability Index
CSI	Consumer Sentiment Index
ADF	Augmented Dickey–Fuller
VECM	Vector Error Correction Model
CO_2	Carbon Dioxide Emissions
GDP	Gross Domestic Product
EKC	Environmental Kuznets Curve
VAR	Vector Autoregressive model
AIC	Akaike Information Criterion
SIC	Schwartz Information Criterion
HQ	Hannan–Quinn Criterion
ECT	Error Correction Term
LM	Lagrange Multiplier
ECM	Error Correction Model

Appendix A

Table A1. The results of GARCH for the EKC hypothesis (DJSIW).

Variable	Coefficient	Std. Error	z-Statistic	Prob
C	0.000710 *	0.000285	2.491411	0.0127
DJSIW	−0.001071	0.008404	−0.127440	0.8986
$DJSIW^2$	−0.004562	0.090149	−0.050606	0.9596
$DJSIW^3$	−0.110755	1.089423	−0.101664	0.9190
EUR/USD	−0.004135	0.008415	−0.491360	0.6232
CSI	0.009299 *	0.004408	2.109766	0.0349
GDP_US	−0.081281	0.074484	−1.091248	0.2752
ENERGY	0.005913 ***	0.003463	1.707557	0.0877
	Variance Equation			
C	7.84×10^{-7}	4.94×10^{-7}	1.586591	0.1126
$RESID(-1)^2$	−0.106473	0.052328	−2.034741	0.0419
GARCH(-1)	1.036902	0.050786	20.41697	0.0000

* and *** denote significance levels of 1% and 10%, respectively.

Table A2. The results of GARCH for the EKC hypothesis (CSI).

Variable	Coefficient	Std. Error	z-Statistic	Prob
C	0.002714 *	0.000161	16.88410	0.0000
CSI	0.008089 ***	0.004459	1.813915	0.0697
CSI^2	−0.019484	0.029750	−0.654912	0.5125
CSI^3	−0.129473	0.420760	−0.307712	0.7583
EUR/USD	−0.005029	0.005794	−0.867935	0.3854
DJSIW	−0.004714	0.003954	−1.191975	0.2333
GDP_US	0.004627	0.045039	0.102737	0.9182
ENERGY	0.000341	0.002505	0.136089	0.8918
	Variance Equation			
C	3.59×10^{-6}	7.02×10^{-7}	5.120570	0.0000
$RESID(-1)^2$	0.915868	0.198188	4.621206	0.0000
GARCH(-1)	−0.116314	0.033470	−3.475168	0.0005

* and *** denote significance levels of 1% and 10%, respectively.

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