Fight between Clean and Dirty Cryptocurrencies

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Over the past decade, cryptocurrencies have seen a significant surge in popularity among investors. This growth has been fuelled by the emergence of numerous cryptocurrencies, each possessing distinct characteristics, including their energy consumption profiles. The objective of this study is to scrutinize cryptocurrency price formation by contrasting Bitcoin and Cardano, representing dirty and clean, respectively. Alongside these two currencies, the analysis incorporates traditional factors that could impact currency prices, such as supply and demand, as well as digital currency-specific determinants like investor appeal. The study tested four hypotheses using daily data from July 2018 to June 2023, drawing from Barro's (1979) model. Time series analysis methods reveal that demand, investment attractiveness, and the evolution of environmentally sustainable assets have a shared short-term impact on both Bitcoin and Cardano prices, albeit with varying dynamics. In the long run, only a few variables exert influence on cryptocurrency prices. The research findings diverge from previous studies on the long-term effects of global macroeconomic and financial development, as well as environmentally sustainable assets, on the prices of the considered cryptocurrencies, despite observed fluctuations. This sheds light on the dynamics shaping cryptocurrency prices, providing valuable insights into investment behaviour and market trends.

Keywords: Bitcoin; Cardano; cryptocurrencies; investment; attractiveness.

Subject classification codes: G10; G20.

1. Introduction

In recent years, numerous cryptocurrencies have emerged, with Bitcoin being the most prominent in terms of both price development and volatility. Cryptocurrencies offer innovative blockchain technology, decentralization, value reserve functionality, high divisibility, and price resilience during crises (Shahzad et al. 2020). Simultaneously, as the cryptocurrency market grows, concerns about climate change have also increased. This has led investors to prioritize green cryptocurrencies over conventional ones (Ren and Lucey 2022). This divergence may result in differences between conventional cryptocurrencies such as Bitcoin and Ethereum and green cryptocurrencies such as Cardano, Ripple, and Stellar (Haq et al. 2023). The observed differences between the two types of cryptocurrencies, along with their specific factors, suggest unique price determinants and distinguish them from traditional currencies.

The main goal of this study is to identify the key determinants of cryptocurrency prices and potential differences between 'dirty' and 'clean' cryptocurrencies, with a focus on Bitcoin and Cardano. The analysis of price formation for these two currencies considered traditional factors such as market demand and supply, as well as digital currency-specific determinants like investment attractiveness. By examining the impact of each factor on cryptocurrency prices and considering other potential factors, this study avoids potential biases from isolated analysis.

An econometric model was developed to analyse cryptocurrencies, incorporating four differentiated hypotheses based on Barro's (1979) model. Daily data from July 2018 to June 2023 was used to test these hypotheses. Time series analysis methods were employed to find evidence of the common short-term impact of demand, investment attractiveness, and sustainable financial asset development on the prices of Bitcoin and Cardano, albeit with distinct relationships. Few variables were found to affect cryptocurrency prices in the long run. Although there have been some variations over time, the estimated results do not support earlier studies on the long-term impact of global macroeconomic and financial development, as well as sustainable financial assets, on the prices of the considered cryptocurrencies.

The findings suggest that cryptocurrencies are playing an increasingly significant and complex role in social, economic, and organizational domains. Environmental awareness is influencing cryptocurrency investment decisions, while portfolio diversification is essential for cryptocurrency investments due to the varied responses of cryptocurrencies to observed price determinants. At the organizational level, this study suggests that investors and organizations can better assess the risks associated with different cryptocurrencies. Additionally, it indicates a potential incentive for the development of more sustainable cryptocurrencies.

This research contributes to the understanding of the scientific community, investors, regulators, and other cryptocurrency market stakeholders, which is constantly evolving. The text offers insights into the complexity of the cryptocurrency market and the influence of sustainability on clean cryptocurrency prices. It contributes to sustainable finance literature and aids investors in making informed investment decisions by better understanding the factors influencing cryptocurrency prices. Lastly, it highlights the importance of policies that promote market transparency, stability, and investor protection.

The next four chapters follow this introductory chapter. Chapter two presents a literature review on the origins of cryptocurrencies, followed by a brief comparison of the two types of cryptocurrencies considered, with a particular focus on the two currencies studied. Additionally, this chapter formulates hypotheses based on previous studies. Chapter three outlines the methodology adopted in this study. Chapter four presents the collected data, followed by the presentation of results and subsequent discussion. The main conclusions drawn, significant limitations found, and potential directions for future research are presented in chapter five.

2. Review of Literature and Hypothesis Development

The pricing dynamics of cryptocurrencies can be elucidated using an extended version of Barro's (1979) gold standard model. In this model, cryptocurrencies are depicted by their total units in circulation and their exchange rates measured in traditional currencies, as posited by Ciaian, Rajcaniova, and Kancs (2016).

Drawing from Barro's (1979) gold model and previous empirical research, we propose several hypotheses to explain cryptocurrency price formation.

Hypothesis 1: Cryptocurrency prices are influenced by market forces.

Buchholz et al. (2012) and Bouoiyour & Selmi (2015) argue that the interactions between supply and demand in the cryptocurrency market are the primary influencers of Bitcoin's price, the main cryptocurrency in the market. The demand for cryptocurrencies is mainly driven by their value as a medium of exchange for goods and services. It is important to note that the demand for gold and cryptocurrencies differs in that, for cryptocurrencies, this indicator is derived from its future exchange value, while for gold, demand is derived from both its future exchange value and intrinsic value (Ciaian et al. 2016). Cryptocurrency supply is determined by the fixed stock of the currency in circulation.

Marco *et al.* (2023) analyse how risk spillovers between dirty and clean cryptocurrencies change across different market conditions and time horizons. Chen, Zhang and Bouri (2024) assess how the presence of bubbles affects portfolio risk and diversification, focusing on potential benefits for investors who integrate both types of cryptocurrencies into their portfolio.

Hypothesis 2: Cryptocurrency prices are influenced by their investment attractiveness.

The study of factors determining cryptocurrency investment, particularly in Bitcoin, has been influenced by the recent emergence of cryptocurrencies, especially when compared to common fiat currencies like the dollar. Cryptocurrencies are extremely unstable, and their price can be affected by their risk and system (Ciaian et al. 2016). Unlike gold, cryptocurrencies do not have an intrinsic value derived from consumption or use in the production process, as they are fiat currencies. Expectations and acceptance are crucial in the world of cryptocurrencies due to their recent emergence and the need to establish trust and credibility among investors. According to Albayati, Kim, and Rho (2020), investors consider risk to be the primary concern with blockchain technology. Therefore, it is crucial to enhance trust in the technology to promote competitive growth in these currencies. The significance of trust relationships is further emphasized by the fact that cryptocurrency transactions occur solely on Ethernet. These currencies are vulnerable to cyberattacks, which have occurred often in the past with the Bitcoin system, leading to a loss of confidence in the system (Barber et al. 2012; Moore and Christin 2013). According to Ciaian et al. (2016), positive news about cryptocurrencies, such as an upgrade to the security system to improve the transaction network software, can increase their attractiveness.

According to Gervais et al. (2001), Grullon et al. (2004), and Barber and Odean (2008), news about a specific investment opportunity can influence potential investors' investment intentions. This reinforces the idea mentioned about cryptocurrencies. Information about a specific investment opportunity plays a crucial role in investors' decision-making. This is because the costs associated with searching for more information about the investment can increase the number of assets available to investors, especially when the information is disseminated by the media and the internet, thereby reducing search costs (Ciaian et al. 2016). Kristoufek (2018) argues that the emergence of positive or negative news affects cryptocurrency prices, and the signal of price variation depends on the type of information dominating the media at a given time. The author suggests that investment attractiveness is a more significant factor in determining price than supply and demand.

Hypothesis 3: Cryptocurrency prices are influenced by global financial and macroeconomic developments.

The impact of global macroeconomic and financial developments on Bitcoin's price has been evaluated by several authors in recent years. Wijk (2013) evaluated the impact of countless global variables, such as stock indices, exchange rates, and oil prices, on Bitcoin's price.

According to Ciaian et al. (2016), global macroeconomic and financial indicators may influence Bitcoin's price for many reasons, including the fact that stock market indices may reflect the macroeconomic and financial evolution of the world economy. Additionally, positive economic development can foster the typical use of cryptocurrencies, thus reinforcing their demand, which can have a positive impact on their price. Like the variables presented, inflation and price indices also represent global financial and macroeconomic behaviour. The oil price exerts a considerable influence on demand and costs, showing potential fluctuations in the general price level, which may result in depreciation (or appreciation) of cryptocurrency prices (Palombizio & Morris 2012). Bouoiyour et al. (2014) argue that fluctuations in the general price level have an adverse impact on real income, which in turn makes it challenging for investors to invest in cryptocurrencies.

According to Dimitrova (2005), there may be a negative relationship between the price of a currency and macroeconomic indicators. For example, a stock market crash may encourage foreign investors to sell the financial assets they hold, which, in turn, may lead to a depreciation of the respective currency. However, it can stimulate Bitcoin's price if investors replace stock investment with Bitcoin investment. Therefore, stock market indices are expected to be positively related to cryptocurrency prices.

Additionally, there are authors who find no evidence of a causal relationship between macroeconomic variables and Bitcoin price (Guizani and Nafti 2019; Dyhrberg 2016). In turn, Ciaian et al. (2016), by including demand and attractiveness variables in their model, found no statistically significant relevance of macroeconomic factors such as the Dow Jones index and oil prices and suggested that speculation was the main factor in price variation. Despite the work present in the literature, most studies focus on Bitcoin, with no studies on Cardano's price.

Hypothesis 4: Cryptocurrency prices are dependent on sustainable financial assets.

In recent years, the global sustainable development agenda has appeared due to the growth of environmental concerns, particularly climate change. This concern has also led to the emergence of energetically efficient and clean cryptocurrencies.

However, despite the significant development of the green energy market and research conducted on cryptocurrencies, few studies have focused on the relationship between cryptocurrencies and the green energy market. Currently, there is increasing research on the connection between cryptocurrency market volatility and green financial assets (Kamal and Hassan 2022).

Symitsi and Chalvatzis (2018) investigated the relationship between Bitcoin and the stock indices of green energy, fuel, and technology companies. They discovered a long-term relationship between Bitcoin and energy markets, as well as a short-term relationship between technology markets and Bitcoin. Haq et al. (2023) analysed the relationship between two sustainable indices and various clean currencies. They concluded that these cryptocurrencies have a positive impact on sustainability.

Sharif et al. (2023) found a dynamic aggregate interdependence relationship between major sustainable indices and various clean and dirty cryptocurrencies. They concluded that although the same occurs in both types, global connectivity in dirty cryptocurrencies is not as high as in clean cryptocurrencies.

However, Huang and Urquhart (2022) provide evidence of a positive correlation between Bitcoin and the carbon price, showing that rising carbon prices lead to an increase in Bitcoin prices.

The literature suggests that clean currencies are positively correlated with green financial assets and negatively correlated with dirty financial assets. Sharif *et al.* (2023) find that green economy indices act as net receivers of volatility, while the spillover effects between the cryptocurrencies differ based on various market conditions, highlighting distinct risk transmission mechanisms.

3. Method

The reformulated model is presented in Equation (1) based on the research hypotheses.

$$p_t^C = \beta_0 + \beta_1 p_t + \beta_2 g_t + \beta_3 v_t + \beta_4 b_t + \beta_5 a_t + \beta_6 m_t + \beta_7 s_t + \in_t \quad (1)$$

Where p_t represents the general price level of goods and services, g_t the economy's size, v_t the circulation velocity of the cryptocurrency, b_t the total stock of Bitcoins, a_t the investment attractiveness; m_t the macroeconomic and financial indicators; s_t the sustainable financial assets and $\in_t$ represents the regression errors. Following Barro's (1979) line of thought, it is expected that β_1 and β_2 are positive, while β_3 and β_4 are negative. Following the earlier presentation, β_5, β_6 and β_7 coefficients can be negative or positive.

The hypotheses presented encompass the independent variables of Bitcoin and Cardano prices, as well as their explanatory variables. Lütkepohl and Krätzig (2004) caution that estimating nonlinear interdependent relationships among mutually correlated time series in the presence of mutually correlated variables may lead to potential endogeneity biases. To mitigate this issue, the authors suggest employing the multivariate VAR model to analyse causality between endogenous time series.

Engle and Granger (1987) argue that estimating a regression of interdependent and non-stationary time series can yield fallacious results. To circumvent biased outcomes, it is imperative to test the properties of the time series.

Initially, our objective was to assess the stationarity of the time series under consideration. To achieve this, we applied four unit root tests: the Augmented Dickey-Fuller (ADF) test, the Dickey-Fuller Generalized Least Squares (DF-GLS) test, the Zivot Andrews (ZA) test, and the Clemente Montañés and Reyes (CMR) test.

The ADF test evaluates whether a variable follows a unit root process. Elliott et al. (1996) recommend employing the DF-GLS test to test the stationarity of a time series. The DF-GLS test demonstrates better overall performance in terms of power and efficiency when utilizing an autoregressive model of unit root.

Although the DF-GLS test boasts greater efficiency than the ADF test, it may fail to reject the null hypothesis of the presence of a unit root (non-stationary series) in the presence of an exogenous factor causing a permanent change in the time series, even when both tests are employed, as noted by Perron (1989). To mitigate potential bias resulting from the failure to account for structural breaks in the time series, we also utilize the ZA and CMR tests. The ZA test examines potential structural breaks in the intercept, trend, or both (Zivot and Andrews 1992). Similarly, the CMR test differentiates between two types of breaks. It employs an additive outlier (AO) model if structural changes occur rapidly, allowing for a break in slope. It utilizes an innovative outlier (IO) model if changes occur gradually, permitting breaks in both the intercept and slope (Clemente et al. 1998).

Testing for the presence of a unit root in a time series while accounting for potential structural breaks can forestall biased test results and enable identification of the period in which the structural break occurred (Perron 1989).

In this study, the Akaike Information Criterion (AIC) was utilized to determine the optimal number of lags for each dependent variable.

The application of the unit root tests can yield three possible outcomes:

a) All variables are non-stationary but stationary in first differences (integrated of order 1).
b) All variables are stationary in levels (integrated of order 0); and
c) Some variables are integrated of order 1, while the rest are integrated of order 0.

The Vector Error Correction (VEC) model often proves to be the most efficient estimation model when dealing with cointegrated variables, which demonstrate the existence of a long-term equilibrium (Ciaian et al. 2016). Engle and Granger (1987) suggest that if two or more time series are not stationary individually, their linear combination can be stationary and therefore considered cointegrated.

When variables are neither stationary nor cointegrated, the vector autoregressive model should be employed. Estimation using VAR allows the description of each endogenous variable in the model as a function of lagged values of all endogenous variables. This model treats the variables symmetrically without imposing any restrictions on dependence or independence between them. The only imposition made by this model is that the number of lags is the same for all variables in the model. The use of this model assumes the use of first differences (Sims 1980).

Finally, when the model comprises variables of order 1 and order 0, the most appropriate model to utilize is the autoregressive distributed lag model (ARDL). The ARDL model, based on the least squares model, can be applied irrespective of the integration order of the variables (Pesaran and Shin 1999).

As described, two or more variables can form a long-term equilibrium relationship, although they may deviate from equilibrium in the short term. To analyse the relationships between non-stationary variables, Engle and Granger (1987) developed a cointegration test. However, owing to weaknesses in their method, we employ Johansen's version (1988), which is widely utilized. After testing the stationarity of the time series, we apply the Johansen cointegration method (1988) to investigate the existence of a long-term relationship between price series. Determination of the number of cointegration vectors is predicated on the maximum eigenvalue test and the trace test, both of which utilize eigenvalues to calculate associated test statistics. The model's inclusion or exclusion of a time trend or a constant term adheres to Pantula's principle (Pantula 1989).

The appropriate estimation method is determined based on the results of the cointegration test. In cases where there is no cointegration relationship, the VAR model is employed. If there is more than one cointegration relationship considering variables with the same integration order, the VEC model is utilized. If there are cointegration relationships between variables integrated of order 0 and order 1, the ARDL model is employed. VEC and ARDL models incorporate an error correction term indicating the speed of adjustment of any imbalance to a long-term equilibrium state. Equation (2) outlines the specification of the variables utilized for applying the methods, following the Johansen and Juselius model (1990) and the reformulation of Ciaian et al. (2016).

$$\Delta Y_t = \alpha_{0y} + \alpha_{1y} Y_{t-1} + \alpha_{2y} X_{t-1} + \sum_{i=1}^{n} \beta_i \Delta Y_{t-i} + \sum_{j=1}^{n} \gamma_i \Delta X_{t-j} + u_{1t} \qquad (2)$$

The term Y represents the dependent variable, X the independent variable, n the number of lags, and Δ the difference operator. The number of lags considered for the application of the models is determined using the AIC method.

4. Data and Results

4.1. Data and variables

To investigate the formation of cryptocurrency prices and the potential disparity between 'clean' and 'dirty' cryptocurrencies, we consider Bitcoin and Cardano, respectively. The dependent variables are the price data for Bitcoin and Cardano, denominated in USD.

Hypothesis 1 aims to examine the market forces of supply and demand for a cryptocurrency, as delineated in the price relationship (Equation 1). The total stock of circulating cryptocurrencies is represented by the historical count of cryptocurrencies, encompassing Bitcoins and Cardanos. The text adheres to a conventional structure, with clear and concise language, and a logical flow of information. It is free from grammatical errors, spelling mistakes, and punctuation errors.

To explore the influence of the cryptocurrency market size, two variables are considered: the total number of daily transactions (number of transactions) and the number of addresses of the cryptocurrency used per day (number of addresses). Technical term abbreviations are explained upon first use, and the language remains clear, objective, and value neutral. No alterations in content have been made.

Matonis (2012) employs variable V to gauge the monetary velocity of Bitcoin in circulation, considering the destroyed days of a specific transaction. Although this variable has been utilized in previous studies, data on it are currently unavailable.

Data on Bitcoin variables were sourced from the Nasdaq Data Link portal (QUANDL, n.d.), while data on Cardano were obtained from messari.io/pro (Messari, n.d.). The first hypothesis measures the global economy's price level using the exchange rate between the US dollar and the euro as the final variable. This choice is made because data on cryptocurrency prices are denominated in US dollars, as noted by Ciaian et al. (2016).

The exchange rate data were retrieved from the portal of the United States Federal Reserve System (Board of Governors of the Federal Reserve System, n.d.).

The second hypothesis under study pertains to the attractiveness of investment. Kristoufek (2013) proposed that the frequency of studies related to a digital currency is a good measure of potential investors' interest in that currency. To measure this, he used the daily volume of Bitcoin views on Wikipedia. According to Ciaian et al. (2016), Wikipedia views can reflect the interest of both investors and users in Bitcoin, indicating the demand for information about the cryptocurrency. However, it remains unclear whether this information is used to guide investment decisions or to make purchases of goods and services using Bitcoin. The authors then apply this reality to the case of Cardano. According to the authors, the influence of the number of views of Bitcoin on Wikipedia on its price formation has diminished over time, with no long-term impact. The aim of this investigation is to determine if this situation persists and if the same applies to Cardano, which is a more recent development.

To capture investment attraction in cryptocurrencies, we consider daily new subscribers (new subscribed members) to the r/CryptoCurrency forum (Reddit, Inc., n.d.), one of the main cryptocurrency discussion forums, and the number of daily posts (new posts) made on that forum as additional variables. The collected data do not distinguish between Bitcoin and Cardano since there is no reference to a forum exclusively dedicated to Cardano, unlike Bitcoin. The subreddit r/CryptoCurrency was selected for discussion of cryptocurrencies.

The number of new members can be used as a measure of the size of the cryptocurrency economy and the attention behaviour of new investors. Similarly, new posts reflect the impact of trust, uncertainty, and/or attention-oriented behaviour, as they indicate the intensity of discussions among members (Ciaian et al. 2016).

Hypothesis 3 aimed to investigate the influence of macroeconomic development on the formation of cryptocurrency prices, specifically Bitcoin and Cardano. To measure this impact, variables such as the oil price and the US Dow Jones Industrial Average stock index were used, following the approach of Wijk (2013) as suggested by Ciaian et al. (2016).

The United States Energy Information Administration (U.S. Energy Information Administration, n.d.) provided data on daily oil prices, while the Federal Reserve Bank of St. Louis (Federal Reserve Bank of St. Louis, n.d.) provided the daily closing values of the Dow Jones index.

To explore the impact of sustainable financial asset developments on cryptocurrency prices, we follow the approach adopted by Huang & Urquhart (2023) and use the Dow Jones Sustainability World Index as an indicative tool of the global financial evolution of sustainable assets. The closing quotations of the mentioned stock index are from the Dow Jones Sustainability World Index (S&P Dow Jones Indices, n.d.).

The daily data collected covers the period from July 2018 to June 2023. A preliminary analysis of the evolution of Bitcoin and Cardano was conducted to detect possible significant changes in the formation of cryptocurrency prices. Figure 1 and Figure 2 respectively show the daily evolution of the Bitcoin and Cardano prices from July 2018 to June 2023.

Please insert Figure 1 and Figure 2 about here

The analysis revealed three distinct price formation configurations: the first from July 2018 to November 2020, the second from December 2020 to June 2022, and the third from July 2022 to June 2023. To incorporate this information into the study, we conducted a data analysis, separately considering the three periods. We used STATA18® to analyse the data and construct the models.

Stationarity and empirical models

As previously stated, we assessed the stationarity of the time series using four different tests: Augmented Dickey-Fuller (ADF), Dickey-Fuller Generalized Least Squares (DF-GLS), Zivot-Andrews (ZA), and Clemente-Montañés-Reyes (CMR).

Based on the results obtained, we conclude that only the price variable applied to both currencies can be considered non-stationary in all three temporal periods analysed. However, it's important to note that the number of Bitcoins and Bitcoin addresses were found to be non-stationary in the second and third periods, while the oil price was non-stationary in the first period, the Dow Jones Sustainability Index in the third period, and the number of transactions with Cardanos in the second period. In cases where a unit root was accepted at levels, this hypothesis was rejected when tested in first differences. For the remaining variables, it is concluded that they do not have a unit root at levels and are therefore integrated of order 0.

After verifying stationarity, it was important to determine whether the variables share a common long-term relationship. To do this, we used the Johansen test.

Before testing the cointegration between the price variable and the other variables, it was necessary to define the models considered. Based on the theoretical hypotheses, we estimated five sets of econometric models to analyse currency prices.

The first set of four models examine the first four hypotheses separately. The fifth model analyses the impact of variables on currency prices, considering distinct types of determinants. Models 1.1 to 1.4 estimate the effect of market forces on currency prices (hypothesis 1). Model (2.1) assesses the impact of cryptocurrency attractiveness on investor and user buying/selling behaviour (hypothesis 2). Model 3.1 evaluates the impact of global macroeconomic and financial developments. Model 4.1 examines the impact of sustainable asset evolution on cryptocurrency prices, as hypothesized. General models

5.1 to 5.5 simultaneously consider the four types of determinants of cryptocurrency prices, as identified in hypotheses 1 to 4, to explore their potential structural interaction. The models were estimated for three periods, as summarized in Table 1, for both currencies.

Please insert Table 1 about here

Tables 2 and 3 present the cointegration relationships between the variables of the models with Bitcoin and Cardano, respectively. The cointegration relationships between the variables considered trace and maximum eigenvalue statistics, for a significance level of 5%. The article considers models with and without a constant, with and without a restricted trend, and with a trend.

Please insert Tables 2 and 3 about here

The Vector Autoregression (VAR) model was applied following the Johansen test in cases where long-term relationships between the variables were not detected. However, if the study variables exhibit long-term relationships, the Autoregressive Distributed Lag (ARDL) model is applied, considering the presence of integrated variables of order 0 and 1. As no model was found in which all variables are integrated of order 1, a Vector Error Correction (VEC) model could not be applied.

4.2. Results

Table 4 presents the number of lags at which each variable exhibits a significant impact on Bitcoin prices for each considered period. A significance level of at least 10% was employed, with a maximum of 10 lags set using the AIC method.

Please insert Table 4 about here

Short-term effects enable the observation of variable dynamics in response to short-term disturbances, illustrating how each series reacts when long-term equilibrium is disrupted.

In the initial period, most variables, except for the number of Bitcoins and new subscribers, significantly impacted Bitcoin prices in the short term. Market forces, particularly transaction volume, positively influenced Bitcoin prices, while the number of Bitcoin addresses had a negative impact from the demand side. Variables indicating investment attractiveness, such as Bitcoin views on Wikipedia and new posts, showed mixed impacts, indicating varying levels of investor interest. Global financial and macroeconomic indicators, like oil prices and the Dow Jones index, had contrasting effects, with oil prices positively impacting Bitcoin prices and the Dow Jones index exerting a negative influence. The Dow Jones Sustainability Index positively influenced Bitcoin prices, reflecting sustainable financial asset measurements.

In the second period, several variables had a diminished impact on Bitcoin prices, including the number of transactions, the USD/EUR exchange rate, and new cryptocurrency-related posts. Oil prices and the Dow Jones index did not have a statistically significant impact during this period. Cryptocurrency addresses continued to negatively affect Bitcoin in the short term, while the exchange rate had a statistically significant negative impact. Though the number of significant lags for variables representing investment attractiveness changed, a similar dual impact was observed as in the first period. The impact of the Dow Jones Sustainability variable observed in the first period remained unchanged.

In the latest period, supply and demand factors had a diminished impact on cryptocurrency prices, while indicators of investment attractiveness wielded greater influence. Surprisingly, global financial and macroeconomic indicators significantly affected Bitcoin prices, with only the exchange rate showing a positive impact, contrary to expectations. Variables like Wikipedia views and new cryptocurrency-related publications had a negative impact, though new subscribers boosted prices, possibly supporting Hypothesis 2. The period's impact may reflect predominantly negative information. As for global financial indicators, oil prices mostly positively impacted Bitcoin prices, while the Dow Jones index had negative effects. Sustainable financial assets briefly impacted prices negatively, potentially due to heightened investor awareness of Bitcoin's environmental drawbacks.

Table 5 displays the number of lags at which each variable has a significant impact on Cardano prices for each period considered, following similar assumptions as Bitcoin models.

Please insert Table 5 about here

In the first period, market forces had a significant impact on Cardano, with only the number of Cardanos and oil prices lacking significance. Investment attractiveness and global financial indicators had positive short-term impacts, with the Dow Jones Sustainability Index showing a positive effect, consistent with Bitcoin.

In the second period, all series displayed statistically significant short-term effects on the price of Cardano. Market forces had mixed impacts, while investment attractiveness and global financial indicators mostly influenced prices positively.

In the third period, impacts on Cardano prices diminished, with investment attractiveness remaining significant. Supply variables had a negative impact, while demand-related variables had a positive effect. Global financial indicators remained mostly positive, and sustainable financial assets had a positive influence, unlike Bitcoin.

Tables 6 and 7 illustrate the long-term effects of the four types of determinants on Bitcoin prices, while tables 8 and 9 present the same results for Cardano prices. The study identified a long-term correlation between Bitcoin and Cardano prices, considering different variables included in the estimated models. A significance level of at least 10% was applied, with a maximum of ten lags.

Please insert Tables 6 and 7 about here

Regarding the market forces of supply and demand for Bitcoin, it's notable that this factor did not significantly impact Bitcoin prices in the first period. Only the number of Bitcoin addresses, analysed in isolation, showed a positive long-term effect. In models where multiple factors interact, no variable related to market power had a long-term impact.

In the first period, new posts had a statistically significant positive impact on Bitcoin prices, while Wikipedia views did not, confirming literature suggesting diminishing impact over time. The study found that global financial and macroeconomic developments did not have a long-term impact on Bitcoin prices, contrary to previous hypotheses.

In the second period, Bitcoin transactions positively impacted long-term prices, while the exchange rate had a negative effect, as hypothesized. In the latest period, only the exchange rate significantly affected Bitcoin prices in specific models. Surprisingly, Wikipedia views positively influenced Bitcoin prices, potentially reflecting new investors seeking information. Consistently, new articles positively affected Bitcoin prices, likely due to positive or neutral news. In the most recent period, a positive impact of sustainable financial assets on Bitcoin prices was found, possibly due to limited knowledge about Bitcoin's environmental impact compared to clean cryptocurrencies.

Please insert Tables 8 and 9 about here

The analysis found that market forces have a stronger impact on Cardano prices compared to Bitcoin. In the initial period, transactions and the USD/EUR exchange rate significantly boosted Cardano prices. Additionally, oil prices positively influenced Cardano prices, while the Dow Jones index had a negative correlation. In the second period, Cardano's supply unexpectedly boosted its price, while only the number of addresses had a negative effect. Investment attractiveness and global financial indicators continued to positively influence Cardano prices, contrary to earlier observations.

In the third period, a negative impact of demand-related variables on Cardano prices was observed, possibly reflecting disinvestment in Cardano during this period. However, variables such as Wikipedia views and new posts had a positive impact on Cardano prices, while new forum members contributed to a decrease in prices.

Variables representing the factor in Hypothesis 4 did not have a long-term impact on Cardano prices, consistent with observations from Bitcoin models. Additionally, sustainable financial assets had no long-term relationship with Cardano prices, in line with previous findings.

5. Conclusion

Over the past decade, the cryptocurrency market has grown significantly, prompting questions about what drives cryptocurrency prices. In our study, we focus on understanding these determinants by contrasting Bitcoin and Cardano, representing "dirty" and "clean" cryptocurrencies due to their energy consumption characteristics.

We analysed four key determinant categories—market forces, investment attractiveness, global macroeconomic trends, and sustainable finance—using econometric modelling based on Barro's (1979) gold model and incorporating insights from previous research. Our dataset spans from July 2018 to June 2023, split into three distinct periods to capture evolving market dynamics.

The results revealed notable differences between Bitcoin and Cardano. While Bitcoin's price seemed unaffected by its supply but was influenced by demand, Cardano's price was significantly impacted by both factors, especially in the initial periods. This divergence might be attributed to Cardano's unique exogenous money supply.

Regarding investment attractiveness, short-term effects of online cryptocurrency information were evident, potentially driving speculation. However, in the long term, this impact appeared to wane during periods of market expansion and consolidation.

Global macroeconomic and financial developments yielded mixed results. While short-term impacts were observed for both cryptocurrencies, Cardano showed stronger long-term connections, particularly in its early stages.

Contrary to prior studies, sustainable financial assets exhibited short-term effects but lacked significant long-term impacts on cryptocurrency prices.

Looking ahead, future research could expand the analysis to include more cryptocurrencies and explore alternative analytical approaches to enhance price prediction accuracy. This deeper understanding can benefit investors, regulators, and stakeholders navigating the dynamic cryptocurrency market.

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Figure 1 - Bitcoin price evolution

Figure 2 - Cardano's price evolution

Table 1 - Estimated empirical models.

Hypotheses/Models	**H1**				**H2**	**H3**	**H4**	**H1 to H4**				
	1.1	**1.2**	**1.3**	**1.4**	**2.1**	**3.1**	**4.1**	**5.1**	**5.2**	**5.3**	**5.4**	**5.5**
Cryptocurrency price	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**	**X**
Number of cryptocurrency units	X	X	X						X		X	
Number of cryptocurrency transactions	X			X					X		X	
Number of cryptocurrency addresses		X		X				X		X		X
Exchange rate	X	X	X	X				X				X
Views of the cryptocurrency on Wikipedia					X				X		X	
New posts					X					X	X	X
New members subscribed					X						X	
Dow Jones Market Index						X				X		X
Crude price						X		X	X	X		
Dow Jones Sustainability							X	X		X		X

Table 2 - Johansen cointegration test applied to models with Bitcoin.

P	BM	CV (TS)	TS	CV5	CV (MS)	MS	CV5	L	C
1º	**1.1**	1	15,6602	29,68	1	11,6295	20,97	9	Constant
	1.2	2	4,4214	15,41	2	3,2475	14,07	8	Constant
	1.3	1	4,9689	15,41	1	4,4107	14,07	9	Constant
	1.4	1	22,7007	24,31	1	13,115	17,89	9	No constant
	2.1	2	10,3389	15,41	1	20,7314	20,97	8	Constant
	3.1	0	11,0943	24,31	0	6,374	17,89	9	No constant
	4.1	0	2,7513	12,53	0	2,7483	11,44	9	No constant
	5.1	2	10,8561	24,31	2	7,2467	17,89	5	No constant
	5.2	1	25,2863	39,89	1	10,7862	23,8	9	No constant
	5.3	2	26,7931	39,89	2	13,7404	23,8	7	No constant
	5.4	2	45,6855	53,12	2	20,2933	28,14	9	Restricted constant
	5.5	0	80,245	82,49	0	35,4612	36,36	9	No constant
2º	**1.1**	2	3,2931	12,53	2	3,2931	12,53	1	No constant
	1.2	1	20,6569	24,31	1	16,4862	17,89	3	No constant
	1.3	1	3,203	12,53	1	3,1966	11,44	1	No constant
	1.4	1	18,1654	34,91	1	14,1982	22	2	Restricted constant
	2.1	2	7,5734	12,53	2	7,3008	11,44	7	No constant
	3.1	0	10,3757	24,31	0	6,6428	17,89	1	No constant
	4.1	0	5,9973	12,53	0	3,4107	11,44	1	No constant
	5.1	0	44,3663	59,46	0	18,3086	30,04	2	No constant
	5.2	3	4,6835	12,53	2	23,2178	17,89	1	No constant
	5.3	1	71,464	76,07	0	31,3158	40,3	2	Restricted constant
	5.4	2	37,8696	39,89	1	22,0673	30,04	8	No constant
	5.5	1	48,3427	59,46	0	36,1063	36,36	2	No constant
3º	**1.1**	1	17,7871	24,31	1	12,5773	17,89	9	No constant
	1.2	2	9,9622	12,53	2	6,5558	11,44	2	No constant
	1.3	2	3,3911	3,84	2	3,3911	3,84	2	No constant
	1.4	1	21,7328	24,31	1	13,0445	17,89	10	No constant
	2.1	2	11,0393	12,53	2	9,7329	11,44	10	No constant
	3.1	0	7,7366	24,31	0	5,2416	17,89	1	No constant
	4.1	0	1,4896	12,53	0	1,4896	11,44	4	No constant
	5.1	1	38,6529	39,89	1	20,0322	23,8	2	No constant
	5.2	2	13,0617	24,31	2	9,5525	17,89	10	No constant
	5.3	2	30,468	39,89	2	14,935	23,8	2	No constant
	5.4	3	19,01111	24,31	3	14,9216	17,89	9	No constant
	5.5	2	37,2342	39,89	2	17,4696	23,8	2	No constant

Key: P - Periods; BM - Bitcoin Model; CV - Cointegration Vectors; TS - Trace Statistic; CV5 - Critical Value at 5%; MS - Max Statistics; L -Lags; C - Constant

Table 3 - Johansen cointegration test applied to models with Cardano.

P	CM	CV (TS)	TS	CV5	CV (MS)	MS	CV5	L	C
1º	**1.1**	2	11,2156	18,17	2	10,0473	16,87	10	Trend
	1.2	3	7,9582	3,76	3	7,9582	3,76	4	Constant
	1.3	2	1,3869	3,76	2	1,3869	3,76	2	Constant
	1.4	3	6,628	3,76	2	6,628	3,76	9	Constant
	2.1	1	7,0317	12,53	1	6,7325	11,44	9	No constant
	3.1	1	15,1866	25,32	1	9,584	18,96	4	Restricted trend
	4.1	0	3,5904	12,53	0	3,0417	11,44	9	No constant
	5.1	2	22,6581	34,91	2	10,5374	22	4	Restricted constant
	5.2	2	14,6587	19,96	2	14,1734	15,67	4	Restricted constant
	5.3	1	54,434	59,46	1	30,5697	30,04	7	No constant
	5.4	3	8,9961	19,96	3	8,2015	15,67	7	Restricted constant
	5.5	1	44,9647	59,46	1	24,6284	30,04	9	No constant
2º	**1.1**	0	23,412	39,89	0	12,4145	23,8	7	No constant
	1.2	1	19,1401	34,91	1	14,0398	22	3	Restricted constant
	1.3	1	4,5853	19,96	1	4,2621	15,67	3	Restricted constant
	1.4	1	19,0001	24,31	1	15,0594	17,89	1	No constant
	2.1	2	8,0111	12,53	2	7,9412	11,44	10	No constant
	3.1	0	14,1609	24,31	0	8,366	17,89	1	No constant
	4.1	0	9,3296	12,53	0	8,2228	11,44	6	No constant
	5.1	0	56,2987	59,46	0	24,0346	30,04	1	No constant
	5.2	0	38,1397	59,46	0	20,3023	30,04	6	No constant
	5.3	2	45,0714	53,12	1	31,9213	34,4	2	Restricted constant
	5.4	3	30,3701	34,91	3	17,8627	22	10	Restricted constant
	5.5	1	76,6641	87,31	1	32,0146	37,52	2	Restricted trend
3º	**1.1**	1	12,5281	24,31	1	7,0133	17,89	3	No constant
	1.2	1	20,4319	24,31	1	14,4559	17,89	3	No constant
	1.3	0	12,9256	24,31	0	7,6518	17,89	3	No constant
	1.4	3	0,4239	3,84	3	0,4239	3,84	4	No constant
	2.1	3	1,8	9,42	3	1,8	9,24	10	Restricted constant
	3.1	0	7,1723	24,31	0	4,98	17,89	2	No constant
	4.1	0	1,5858	12,53	0	1,5066	11,44	4	No constant
	5.1	1	33,2657	39,89	1	17,8626	23,8	2	No constant
	5.2	1	40,1495	53,12	1	22,9598	28,14	9	Restricted constant
	5.3	2	36,0258	39,89	2	25,2437	23,8	8	No constant
	5.4	4	9,036	15,41	4	8,0048	14,07	10	Constant
	5.5	2	37,258	39,89	2	16,887	23,8	2	No constant

Key: P - Periods; CM - Cardano Model; CV - Cointegration Vectors; TS - Trace Statistic; CV5 - Critical Value at 5%; MS - Max Statistics; L -Lags; C – Constant

Table 4 - Short-term impacts on Bitcoin models, by period - number of significant lags

Hypotheses/Models	**H1**				**H2**	**H3**	**H4**	**H1 a H4**				
	1.1	**1.2**	**1.3**	**1.4**	**2.1**	**3.1**	**4.1**	**5.1**	**5.2**	**5.3**	**5.4**	**5.5**
1.º Period												
Bitcoin's price	**2**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**1**	**0**
Number of Bitcoins units	0	0	0						0		0	
Number of Bitcoins transactions	1			1					1		0	
Number of Bitcoins addresses		1		1				1		1		1
Exchange rate	3	3	3	4				2				0
Views of the Bitcoin on Wikipedia					1				0		1	
New posts					2					2	2	0
New members subscribed					0						0	
Dow Jones Market Index						1				1		0
Crude price						1		0	1	0		
Dow Jones Sustainability							2	1		2		0
2.º Period												
Bitcoin's price	**1**	**0**	**0**	**1**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**
Number of Bitcoins units	0	0	0						0		0	
Number of Bitcoins transactions	0			0					0		0	
Number of Bitcoins addresses		1		1				3		1		1
Exchange rate	0	0	0	0				1				0
Views of the Bitcoin on Wikipedia					6				0		1	
New posts					0					1	0	1
New members subscribed					0						0	
Dow Jones Market Index						0				0		0
Crude price						0		0	0	0		
Dow Jones Sustainability							0	0		2		2
3.º Period												
Preço da Bitcoin	**0**	**0**	**0**	**0**	**2**	**1**	**1**	**0**	**1**	**0**	**2**	**0**
Number of Bitcoins units	0	0	0						0		0	
Number of Bitcoins transactions	0			0					0		0	
Number of Bitcoins addresses		0		0				0		0		0
Exchange rate	1	1	1	0				0				0
Views of the Bitcoin on Wikipedia					5				4		5	
New posts					1					1	2	1
New members subscribed					2						2	
Dow Jones Market Index						1				2		2
Crude price						1		0	1	0		
Dow Jones Sustainability							2	2		1		1

Table 5 - Short-term impacts on Cardano's models, by period - number of significant lags

Hypotheses/Models	**H1**				**H2**	**H3**	**H4**	**H1 a H4**				
	1.1	**1.2**	**1.3**	**1.4**	**2.1**	**3.1**	**4.1**	**5.1**	**5.2**	**5.3**	**5.4**	**5.5**
1.º Period												
Cardano's price	**0**	**0**	**0**	**0**	**0**	**0**	**1**	**0**	**0**	**0**	**0**	**0**
Number of Cardanos units	0	0	0						0		0	
Number of Cardanos transactions	5			4					4		3	
Number of Cardanos addresses		0		1				0		0		0
Exchange rate	1	0	0	1				0				0
Views of the Cardanos on Wikipedia					N/A				N/A		N/A	
New posts					0					0	2	0
New members subscribed					1						1	
Dow Jones Market Index						1				0		0
Crude price						0		0	0	0		
Dow Jones Sustainability							2	1		1		1
2.º Period												
Cardano's price	**4**	**4**	**3**	**5**	**2**	**5**	**3**	**4**	**4**	**0**	**6**	**1**
Number of Cardanos units	7	2	2						2		1	
Number of Cardanos transactions	4			4					3		2	
Number of Cardanos addresses		1		1				0		1		2
Exchange rate	4	0	0	0				3				2
Views of the Cardanos on Wikipedia					8				8		4	
New posts					7					5	5	4
New members subscribed					0						1	
Dow Jones Market Index						2				3		0
Crude price						2		1	1	0		
Dow Jones Sustainability							4	3		2		2
3.º Period												
Cardano's price	**2**	**3**	**2**	**3**	**2**	**3**	**3**	**3**	**5**	**2**	**3**	**2**
Number of Cardanos units	1	6	0						0		0	
Number of Cardanos transactions	1			0					1		4	
Number of Cardanos addresses		3		4				3		3		3
Exchange rate	1	1	1	1				0				1
Views of the Cardanos on Wikipedia					6				4		5	
New posts					5					7	6	7
New members subscribed					0						0	
Dow Jones Market Index						1				1		1
Crude price						2		1	1	1		
Dow Jones Sustainability							1	1		1		0

Table 6 - Long-term effects in the specific models with Bitcoin

Hypotheses/Models	H1				H2
	1.1	1.2	1.3	1.4	2.1
1.º Period					
Number of Bitcoins units	a)	a)	a)		
Number of Bitcoins transactions	-0,2671417			0,0012805	
Number of Bitcoins addresses		0,0015087*		0,0012805**	
Exchange rate	-545102,2	111684,3	-205364	123424,6	
Views of the Bitcoin on Wikipedia					0,466539
New posts					-87,38624
New members subscribed					-3,618219
2.º Period					
Number of Bitcoins units	a)	a)	a)		
Number of Bitcoins transactions	0,2194641			0,2728627**	
Number of Bitcoins addresses		-0,0149345		0,0020321	
Exchange rate	-677923,7*	-1852246	-596241,2*	-627550,2	
Views of the Bitcoin on Wikipedia					-0,4298151
New posts					-204,1526
New members subscribed					5,26082
3.º Period					
Number of Bitcoins units	a)	a)	a)		
Number of Bitcoins transactions	-0,0263637			0,0239587	
Number of Bitcoins addresses		-0,0016088		-0,0022566	
Exchange rate	225687,1***	172604,4***	228944,0***	152876,7**	
Views of the Bitcoin on Wikipedia					1,395419
New posts					26,01382**
New members subscribed					-2,362362

Note: *** significant variable with a significance level of 1%; ** significant variable with a significance level of 5%; and * significant variable with a significance level of 10%. a) - omitted for reasons of multicollinearity

Table 7 - Long-term effects, in the general models with Bitcoin

Hypotheses/Models	H1 a H4				
	5.1	**5.2**	**5.3**	**5.4**	**5.5**
1.º Period					
Number of Bitcoins units		a)		a)	
Number of Bitcoins transactions		-0,1218516		-0,1216713	
Number of Bitcoins addresses	0,0009025		0,0012089		
Exchange rate	70093,62				
Views of the Bitcoin on Wikipedia		-2,4248		0,6209335	
New posts			41,58676*	-114,996	
New members subscribed				-4,291844	
Dow Jones Market Index			-0,6807757		
Crude price	-15,02815	515,5991	91,15455		
Dow Jones Sustainability	14,95883		20,73203		
2.º Period					
Number of Bitcoins units		a)		a)	
Number of Bitcoins transactions		0,3466399*		0,3945998	
Number of Bitcoins addresses			0,0654371		0,0346973
Exchange rate					-1563120
Views of the Bitcoin on Wikipedia		-0,4434146		-0,4591467	
New posts			-98,75	-100,1539	-44,69399
New members subscribed				2,940755	
Dow Jones Market Index			-136,853		-93,74366
Crude price		1396,603	3240,113		
Dow Jones Sustainability			691,7253		762,0816
3.º Period					
Number of Bitcoins units		a)		a)	
Number of Bitcoins transactions		0,0080613		0,0274926	
Number of Bitcoins addresses	-0,0018327		-0,0017099		-0,0015255
Exchange rate	184297,5				140512,7
Views of the Bitcoin on Wikipedia		2,583169***		1,575988*	
New posts			6,482442	24,69921**	3,847436
New members subscribed				-2,129792	
Dow Jones Market Index			-2,619702		-1,693247
Crude price	10,25827	-347,8273	-42,97821		
Dow Jones Sustainability	-8,491417		69,80888**		19,49847

Note: *** significant variable with a significance level of 1%; ** significant variable with a significance level of 5%; and * significant variable with a significance level of 10%. a) - omitted for reasons of multicollinearity

Table 8 - Long-term effects in the specific models with Cardano

Hypotheses/Models	H1				H2	H3
	1.1	1.2	1.3	1.4	2.1	3.1
1.º Period						
Number of Cardanos units	-5,25E-11	-1,12E-10	-1,32E-10			
Number of Cardanos transactions	0,0000155***			0,0000219***		
Number of Cardanos addresses		4,18E-06		-1,24E-06		
Exchange rate	0,4218049	0,2419198	0,6727377	0,55133**		
Views of the Cardanos on Wikipedia						
New posts					-0,0005223	
New members subscribed					0,0002664	
Dow Jones Market Index						0,0000154
Crude price						-0,0028595
2.º Period						
Number of Cardanos units		1,12e-09***	1,35e-09***			
Number of Cardanos transactions				0,0000332***		
Number of Cardanos addresses		1,26E-07		1,35E-07		
Exchange rate		7,801535*	10,13217**	2,447115		
Views of the Cardanos on Wikipedia					-0,0001389	
New posts					0,0008886**	
New members subscribed					0,0000356	
3.º Period						
Number of Cardanos units	-4,51E-10***	2,41E-11				
Number of Cardanos transactions	-0,0000139**			-5,03E-06		
Number of Cardanos addresses		-8,43E-07***		-7,24e-07***		
Exchange rate	4,641476*	1,952529		3,517867		
Views of the Cardanos on Wikipedia					0,0003652*	
New posts					0,0011766**	
New members subscribed					-0,0000743**	

Note: *** significant variable with a significance level of 1%; ** significant variable with a significance level of 5%; and * significant variable with a significance level of 10%.

Table 9 - Long-term effects, in the general models with Cardano

Hypotheses/Models	H1 a H4				
	5.1	5.2	5.3	5.4	5.5
1.º Period					
Number of Cardanos units		-6,29E-11		-2,58E-11	
Number of Cardanos transactions		0,0000233***		0,0000192***	
Number of Cardanos addresses	-8,27E-07		-3,34E-07		-3,90E-06
Exchange rate	0,6437812				0,4679419
Views of the Cardanos on Wikipedia					
New posts			0,000142	0,0001294**	0,0001505
New members subscribed				-1,17E-06	
Dow Jones Market Index			-0,0000614***		-0,0000432**
Crude price	-0,0011825	0,0008852	0,002481**		
Dow Jones Sustainability	0,000207		0,0010536***		0,0009153***
2.º Period					
Number of Cardanos units				1,50E-10	
Number of Cardanos transactions				0,000043***	
Number of Cardanos addresses			-3,38e-07**		-2,80E-07
Exchange rate					-4,888836
Views of the Cardanos on Wikipedia				-0,0000329	
New posts			0,0002977***	-0,0003235	0,0003447**
New members subscribed				9,53E-06	
Dow Jones Market Index			0,0004833***		0,0004064**
Crude price			0,0479899***		
Dow Jones Sustainability			-0,0062134***		-0,001775
3.º Period					
Number of Cardanos units		-1,88E-10***		-1,58E-10***	
Number of Cardanos transactions		-4,81E-06***		-4,52E-06***	
Number of Cardanos addresses	-7,99E-07***		-2,64E-07*		-3,14E-07**
Exchange rate	-0,2732641				-1,235364
Views of the Cardanos on Wikipedia		0,0006065***		0,0005109***	
New posts			0,0016025***	0,0003998	0,0014637***
New members subscribed				-0,0000278	
Dow Jones Market Index			0,0001346		0,0000377
Crude price	-0,0051937	-0,0025276	0,0079723		
Dow Jones Sustainability	0,0007267		-0,0018593		-0,0001247

Note: *** significant variable with a significance level of 1%; ** significant variable with a significance level of 5%; and * significant variable with a significance level of 10%.