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Spillover Effects of Cryptocurrency Volatility on Green Finance

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This study investigates the risk spillover between clean and dirty cryptocurrencies and their impact on green finance indexes (solar, wind, and nuclear energy) and regional economic indexes (Baltic Dry Index and CRB Index), with data processed using the diagonal BEKK model. The results identify several dirty cryptocurrencies such as: Ethereum Cash (ETC), Litecoin (LTC), and Bitcoin (BIT) as potential diversifiers and hedges with specific green energy and economic indexes. Our findings show that news from the cryptocurrency markets predominantly have a positive, significant effect on the covariance with green finance indices. The study also presents the covolatility spillover effect, showcasing the impact of a return shock in one market, such as the cryptocurrency market or the green finance market, on the co-volatility between markets, including regional economic indices like the Baltic Dry Index and CRB Index. The analysis reveals differential spillover patterns between clean and dirty cryptocurrencies and various green finance indices, highlighting the complexity of their interactions and the varying degrees of influence on regional economic indicators.

Keywords: *Co-Volatility; Cryptocurrency; Green Finance; Economic Indexes; Diagonal BEKK Model; Spillover Effects.*

Introduction

Cryptocurrencies and green finance have both emerged as transformative forces in the modern financial landscape (Al-Sheryani & Nobanee, 2020; Ozili, 2022) . While they may initially seem disparate, a deeper exploration reveals intriguing interconnections and shared implications for investors, regulators, and the broader economy (Ren & Lucey, 2022b). The development of 'clean' and 'dirty' cryptocurrencies, a classification largely dependent on their associated environmental impacts, has further complicated this relationship, invoking discussions around sustainability in the crypto market.

The concepts of clean and dirty cryptocurrency, unofficially, are also called "black/dirty" and "green/clean", related to the degree of energy use (Long *et al.*, 2023). Green cryptocurrencies emerged to minimize the carbon footprint, creating alternative, environmentally friendly variants. Dirty cryptocurrencies are considered to be insecure, with a lot of risks for their holders, however legal the operations may be (Aleksandrov, 2021). How each investor makes the action decisions in this market is governed by his own rules and knowledge (Bikhchandani & Sharma, 2000). Furthermore, the volatility of cryptocurrency markets has spillover effects that impact various economic sectors, including green finance.

As the market for 'clean' cryptocurrencies grows, we may see a more significant integration with green finance (Xu & Yao, 2023). Blockchain, the technology underpinning most cryptocurrencies, offers immense potential for the green finance sector (Chan *et al.*, 2020). Its inherent characteristics of transparency, security, and decentralization can be harnessed to improve the traceability of green investments and enhance the credibility of environmental claims, fostering trust among stakeholders (Kotey *et al.*, 2023). In particular, the distinction between 'clean' and 'dirty' cryptocurrencies has given rise to intriguing risk dynamics and volatility spillovers (Gallersdorfer, Klaaßen & Stoll, 2020) that can impact both green finance indexes and regional economic indexes (Sharif *et al.*, 2023).

The objective of this study is to investigate the risk spillover between clean and dirty cryptocurrencies and their impact on green finance indexes (solar, wind, and nuclear energy) as well as regional economic indexes (Baltic Dry Index and CRB Index). Additionally, the study aims to analyze the covolatility spillover effect, highlighting how a return shock in one market can influence the co-volatility between different markets.

Cryptocurrency price fluctuations affect green finance and the economy by altering the cost of capital for green projects, impacting investor sentiment, and thereby influencing both investment flows and the market valuation of green assets (Arfaoui *et al.*, 2023). Research has suggested a significant influence of cryptocurrency price fluctuations on stock returns, indicating potential contagion between cryptocurrency markets and other types of financial markets (Caferra & Vidal-Tomas, 2021). This highlights the importance of monitoring and analyzing cryptocurrency spillovers, particularly given the increased volatility of these markets (Diebold & Yilmaz, 2012). The ripple effects of cryptocurrency markets on green finance and the economy include shifts in risk perception, leading to increased volatility and changes in asset allocation that can affect funding for sustainable energy projects and economic stability (Kamal & Hassan, 2022).

The spillover effects from cryptocurrency volatility on green finance are an important aspect for investors. Also, investor anticipation and mass-media sentiment is essential for cryptocurrency volatility spillovers (Akyildirim, Aysan, Cepni, & Serbest, 2024), especially for the spillover effects between cryptocurrencies and the exchange markets (Wu, Wang, & Yang, 2024). The unprecedented volatility of cryptocurrency markets can have ripple effects that permeate the entire economy (Jiang *et al.,* 2022). Studies have shown strong correlations between the volatility of cryptocurrency and established market indices (Rao, Gupta, Sharma, Mahendru, & Agrawal, 2022) or regional financial indices (Joseph, Jahanger, Onwe, & Balsalobre-Lorente, 2024). We have not identified any study that analyzes the spillover effect of cryptocurrencies on the three main green finance indexes (solar, wind, and nuclear energy) and regional economic indexes (Baltic Dry Index and CRB Index).

The main interest of the paper is to investigate the risk spillover between clean and dirty cryptocurrencies and their impact on green finance indexes (solar, wind, and nuclear energy) and regional economic indexes (Baltic Dry Index and CRB Index). The study also presents the covolatility spillover effect, showcasing the impact of a return shock in one market on the co-volatility between markets.

This paper investigates the following fundamental question: *There is a significant risk spillover between clean and dirty cryptocurrencies and green finance indexes (solar, wind, and nuclear energy) and regional economic indexes (Baltic Dry Index and CRB Index)?* Furthermore, a secondary question is: *Is there a co-volatility spillover effect between cryptocurrencies and green finance indices?* The next images may show some insights in this objective.

Figure 1 shows that the upward trend in the first two trimesters of 2021 is reflective of the growing interest (market sentiment) and mainstream adoption of cryptocurrencies during this period. Large institutional investments, celebrity endorsements, and growing public awareness contributed to the surge in cryptocurrency values. In this period more businesses are accepting cryptocurrencies as payment, further strengthening the market sentiment (Rao *et al.,* 2022).

On the other hand, BIT, a representative of dirty cryptocurrencies, faced significant backlash over its carbon footprint during this period (I U Haq, 2022). Significantly, in May 2021, the head of a car manufacturing company declared that the electric vehicle firm would stop accepting BIT for transactions, citing environmental issues. This decision sparked a substantial market adjustment (in relation to environmental factors). Furthermore, cryptocurrencies are recognized for their high price fluctuations. Hence, the observed market trends could just represent the inherent peaks and troughs typical of this asset class.

As more investors bought into cryptocurrencies during the upward trend, the market may have overheated, and a correction was due (market volatility and investor sentiment) (Attarzadeh & Balcilar, 2022). Finally, the performance of cryptocurrencies is also often linked to the performance of traditional financial markets and economic indicators. The COVID-19 pandemic has injected significant uncertainty into global financial markets, with potential impacts on cryptocurrency markets as well (Khalfaoui *et al.,* 2022).

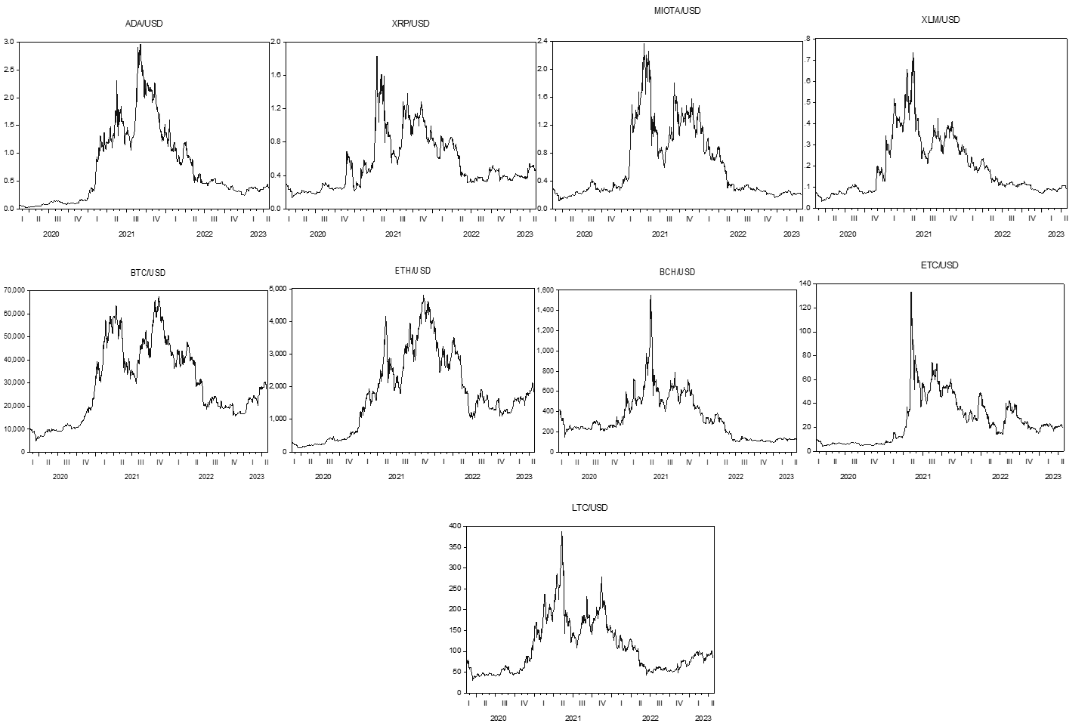

Figure 1. Daily Closing Price of Selected Clean (ADA, XRP, MIOTA and XLM) and Dirty (BIT, ETH, BTC, ETH and LTC) cryptocurrencies from 17/02/2020 to 27/04/2023

In figure 2, we have exposed daily closing prices of selected green finance indexes, for a period of over 3 years, observing an uprising trend in the first trimester of 2021 (Figure 2.), except for nuclear energy index, which registered an upward trend after a major drop, in the middle of 2020. The drop could be due to the pandemic-induced disruptions affecting the global energy market, combined with longstanding concerns about nuclear energy's safety. However, the subsequent rise is linked to renewed interest in nuclear energy as a clean and efficient power source, advancements in technology making it safer and more efficient, or specific market events favorable to the nuclear energy industry. The pandemic caused widespread disruption to global supply chains, labour markets, and energy demand, negatively impacting the nuclear sector (Long *et al.*, 2023). Regarding the other two green finance indexes (solar and wind), the general upward trend in the first trimester of 2021 could be associated with the increased focus on green energy sources and sustainable practices, driven by the global push towards combating climate change (Spano et al., 2023). Many governments implemented policies encouraging renewable energy generation, thereby fostering increased investment in the sector.

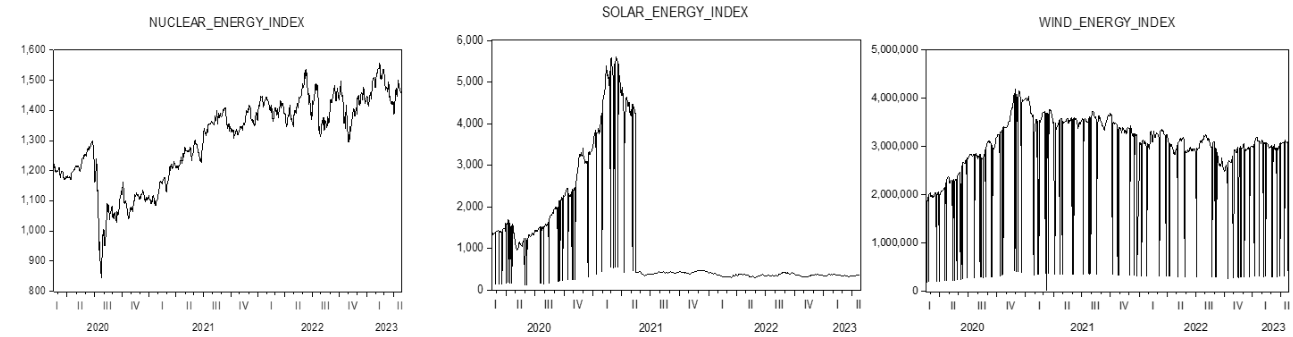

Figure 2. Daily Closing Price of Selected Green Finance Indexes from 17/02/2020 to 27/04/2023

Next images also show daily closing values (Figure 3.) of the Baltic Dry Index and CRB Index. The observed upward trend in the Baltic Dry Index at the beginning of 2021 followed by a peak in the middle of the year is attributed to the rebound in global economic activity as countries emerged from the COVID-19 pandemic and demand for goods (and hence shipping) increased (Abakah, Abdullah, Dankwah & Lee, 2024). This period marked the start of a significant recovery from the pandemic in many parts of the world, leading to increased demand for shipping and thus driving up shipping costs reflected in the Baltic Dry Index (Chen, Xu, & Miao, 2023).

The observed peak in the CRB Index in the second trimester of 2022 could be linked to a few factors. One primary factor could be inflation. In times of high inflation, commodities often serve as a "store of value," and their prices can rise. During this period (2022), many economies were experiencing increased inflationary pressure due to post-pandemic recovery efforts, possibly leading to higher demand for commodities and thus pushing the CRB Index higher.

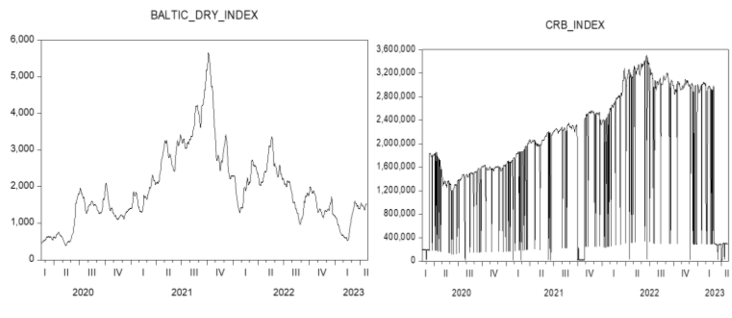

Figure 3. Daily Closing Values of Selected Economical Signal Indexes from 17/02/2023 to 27/04/2023

In order to analyze the cryptocurrencies volatility and its spillover over the green finance and economical indexes volatility, we have presented the daily closing returns of selected cryptocurrencies, categorized in clean and dirty cryptocurrencies (Figure 4.). Figure 5 presents the Daily Closing Returns of Selected Green Finance Indexes, while Figure 6 displays the Daily Closing Prices of Selected Economic Signal Indexes.

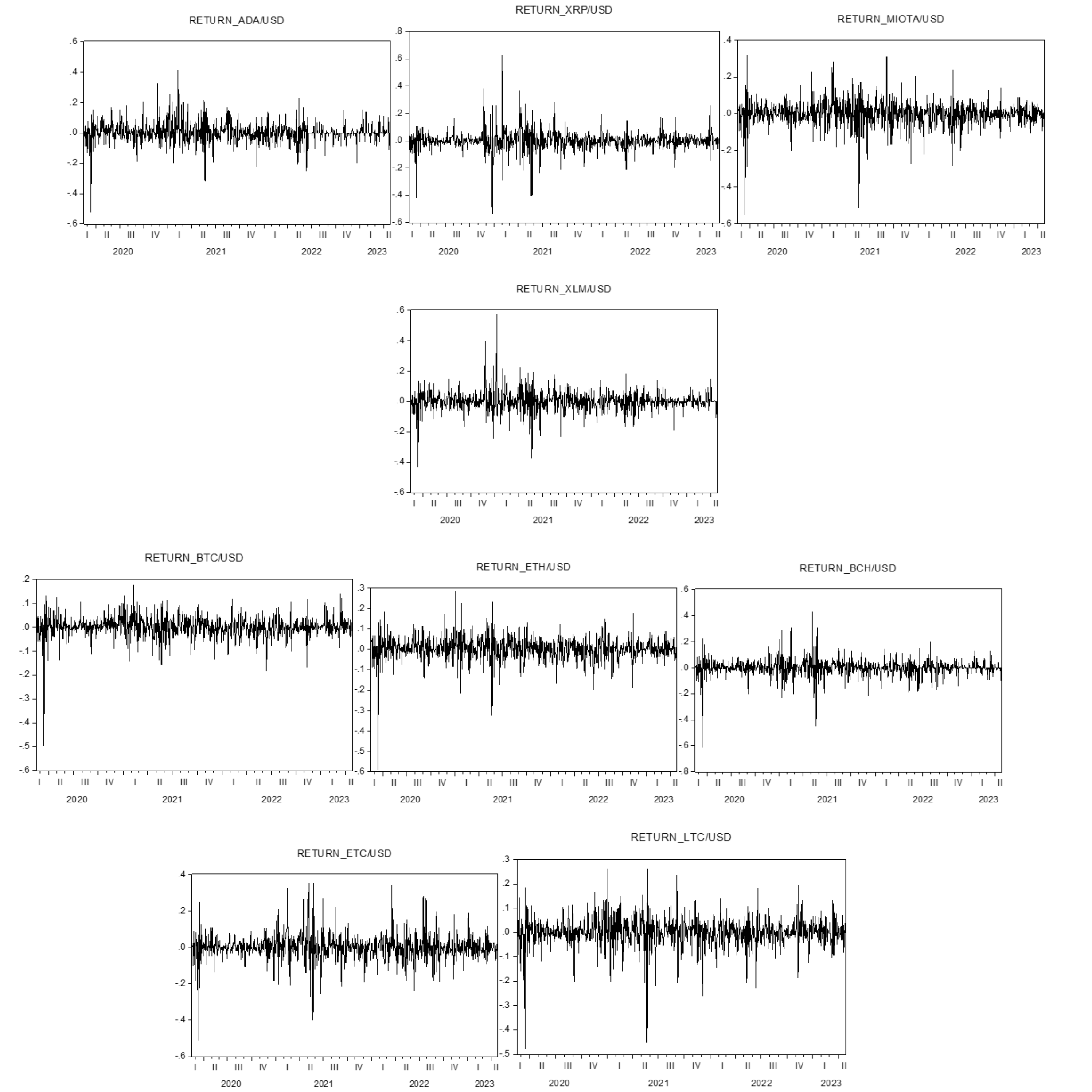

Figure 4. Daily Closing Returns of Selected Clean (ADA, XRP, MIOTA and XLM) and Dirty (BIT, ETH, BTC, ETC and LTC) cryptocurrencies, from 17/02/2020 to 27/04/2023

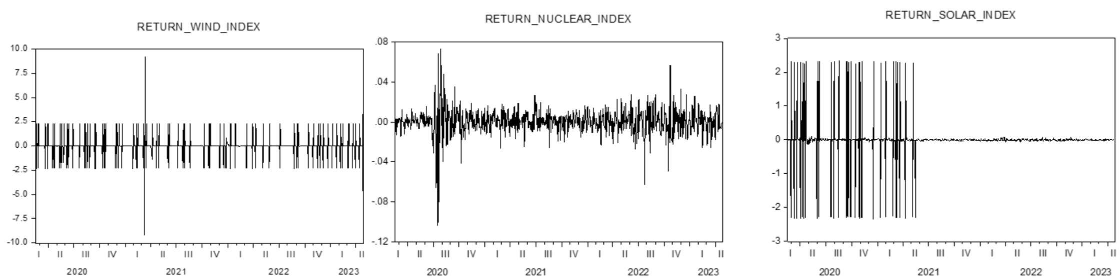

Figure 5. Daily Closing Returns of Selected Green Finance Indexes from 17/02/2020 to 27/04/2023

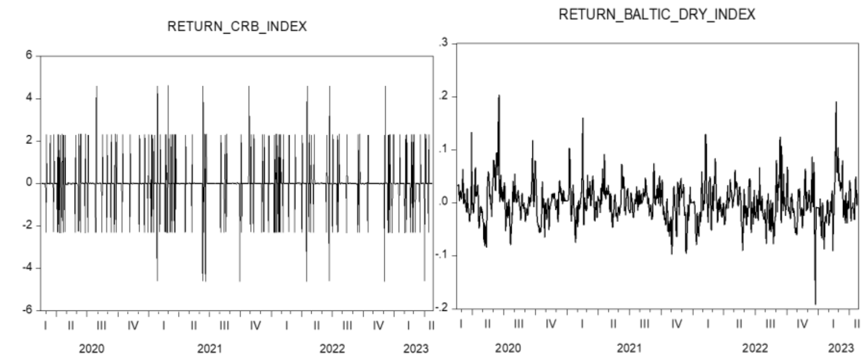

Figure 6. Daily Closing Price of Selected Economical Signal Indexes from 17/02/2020 to 27/04/2023

The findings of the study have implications for the existing body of literature in several distinct ways. Unlike many existing studies, this research provides a comprehensive, multidimensional analysis, linking cryptocurrencies, green finance indexes, and regional economic indexes. Most current research tends to isolate these areas, but our study shows how they interconnect and influence one another. Second, by highlighting the potential for risk and co-volatility spillover between different markets, this study underscores the importance of a systemic approach to financial market analysis and regulation. It adds to the recent literature on the financial stability implications of cryptocurrencies and the spillover effects they can have on broader markets. Third, it carries tangible, pragmatic implications for decision-makers, investors, and regulators.

The research demonstrates how shifts in the cryptocurrency arena can influence other sectors, emphasizing the necessity to establish regulatory structures that take into account the complex relationship between digital assets, green finance, and economic growth. Finally, this study aids in shaping effective strategies for managing the risks and opportunities associated with the rise of cryptocurrencies and their intersection with green finance and regional economic development.

The structure of the study is as follows: Section 2 contains the review of the specialized literature; Section 3 explains the data and econometric models used; Section 4 provides results; Section 5 offers a Discussion and presents policy implications; Section 6 concludes the study.

Theoretical Background

Definition of Cryptocurrencies

Cryptocurrencies are digital financial assets whose ownership is obtained through a cryptographic and decentralized technological phenomenon (Giudici, Milne, & Vinogradov, 2020). Their emergence has been a real challenge for traditional financial institutions. The regulation of their operation is still a major concern for all countries involved; therefore, some countries want to support their operation, but in other cases, they intend to ban them or adopt restrictions. They have been called virtual financial instruments characteristic of the Millenium generation (Ivan & Bădele, 2021), and one of their particular features is that the investor's identity can be anonymized.

Functions of Cryptocurrencies

Academic papers analyze their role and functions, and it is considered that the emergence of cryptocurrencies could be considered a factor favoring the growth of economic welfare, given their ability to recover quickly after periods of crisis.

Furthermore, some research tests through various and elaborate statistical models whether cryptocurrencies could supplant the functions of money, being a medium of exchange or a securities depository (Ammous, 2018; Levulyte & Sapkauskiene, 2021) but their volatility and unstable demand as well as global uncertainties (Yousaf, Riaz, & Goodell, 2023) cannot ascribe this attribute to the whole family of currencies. Like any other asset, cryptocurrencies also carry efficiency and stability issues and risks, and the position of anonymity conferred to investors may encourage undesirable practices in a financial market, such as tax evasion and money laundering activities or financial support for terrorism (Nica, Piotrowska, & Schenk-Hoppp, 2017).

The main functions held by cryptocurrencies, which so far insufficient literature in the field notes, are as follows: equity diversifier and refuge in times of recession to hedge market risk (Goodell & Goutte, 2021), diversification for placing rational investments represented by non-volatile stock indices, a hedge for representative bond markets as well as a dual role for other relevant stock index categories (Barbu, Boitan, & Cepoi, 2022). Cryptocurrencies are also considered an alternative to traditional investments by some authors (Wilson, 2019), who support the thesis that cryptocurrencies are assuming this role in emerging market economies, given the returns they offer in comparison to traditional investments under conditions of risk and uncertainty.

Moreover, it represents a means of investment, a role assigned since cryptocurrencies have gone through a very rapid capitalization process in the last decade, and their existence in the risk portfolio has even come to be appreciated as a genuine guarantor of improved investment returns. Results shown in Zhao, Goodell, & Shen (2024) provide evidence that smaller cryptocurrencies have significant inbound links and therefore have a significant impact on the larger cryptocurrencies. This means that even small-cap cryptocurrencies cannot be ignored in the spillover analysis. Crisis periods bring major risk-generating effects in terms of contagion risk propagation, and targeting investors towards green investments will be able to prevent contagion risk propagation and profit neutrality (Sharma *et al.*, 2022).

At the same time, cryptocurrencies represent a means of refuge in certain periods - a role that cryptocurrencies hold in terms of their ability to be able to hedge the market risk implied by fluctuating financial dynamics with global uncertainties and to drive economic benefit by adjusting the portfolio to risk factors (Omane-Adjepong & Alagidede, 2020). From this position, cryptocurrencies materialize their role as actual transmitters and receivers of shocks in the stock market.

Finally, hedging capabilities - another relevant function that cryptocurrencies have is that they can act as a protective shield for hedging unforeseen economic and commercial elements that may arise in the investors' activity (Inzamam Ul Haq *e al.*, 2021) while also contributing to increased risk-adjusted performance for the entire set of potentially return-enhancing assets in the portfolio (Widarto, Muharam, Wahyudi, & Pangestuti, 2022).

Type of Cryptocurrencies and its Vary Effects on Green Finance

Almost a decade and a half after the first decentralized virtual currency emerged, this phenomenon has grown unexpectedly, attracting an increasing number of investors. Green cryptocurrencies have emerged to minimize the carbon footprint, creating alternative, environmentally friendly variants. Dirty cryptocurrencies are considered unsafe, with many risks for their holders, no matter how legal the operations are (Aleksandrov, 2021). The way each investor makes action decisions in this market is governed by their own rules and knowledge.

A recent study has outlined the link between responsible social investment and the propagation of clean and dirty cryptocurrencies, showing the importance that knowledge of these types of information can have in the work of investors in meeting climate goals (Patel, Kumar, Bouri, & Iqbal, 2023). Another study found that clean energy reserves do not provide sufficient protection for cryptocurrencies but can still provide a minimum level of refuge for both types of cryptocurrency markets (Ren & Lucey, 2022a).

Analysing both "clean" and "dirty" cryptocurrencies gives us a complete understanding of the crypto landscape. "Clean" coins, such as ADA or XRP, promote sustainability through low energy consumption. On the other hand, "dirty" coins like BIT or ETH, although popular and widely accepted, have a significant environmental impact due to their high energy consumption in (Ren & Lucey, 2022a). This dual analysis helps us assess different cryptocurrencies' efficiency and environmental impact.

Financial risk spillover has kept researchers' interest steady in recent years as they examine the impact of cryptocurrency volatility spillover on green finance. Linking cryptocurrency activity to green finance indices via the spillover effect outlines worldwide scientifically validated possibilities for risk prevention. Financial risk spillover requires the adoption of anticipation and control measures, which can provide precise data on transmission modes and substantiate macro-level financial risk mitigation techniques (Liu, Julaiti, & Gou, 2024; Zhang, Zhang, & Lee, 2022).

The controversy that cryptocurrency mining would cause a dangerous impact on the environment has led scholars to investigate the degree of compensation that green markets could bring to cryptocurrency markets *et al.*, 2023).

The Impact of Cryptocurrencies on Economy

The spillover effect between cryptocurrencies and the green finance index and establishing the link between volatility and returns are certificates of losses specific to a turbulent economy, with volatility shocks, especially in the case of short-term traded assets (Sharif, Brahim, Dogan, & Tzeremes, 2023).

The cryptocurrency market has established itself as an easy and advantageous way to diversify portfolios, but this also has negative environmental connotations (Krause & Tolaymat, 2018).

The first scientific contribution that provided relevant information for investors and policymakers and addressed the stock market connection between green commodities, cryptocurrencies and uncertainty was published in (Khalfaoui, Ben Jabeur, & Dogan, 2022) and signaled the neglect of the impact of financial shocks felt by green markets. An important goal is to build a climate-resilient economy (Mzoughi, Urom, & Guesmi, 2022), overcoming environmental challenges by promoting and implementing the principles of sustainable development.

The spread of total risk is reported in periods of extremely high volatility, and policymakers need to develop effective policies to promote green finance (Naeem, Conlon, & Cotter, 2022).

By studying the spillover effects of cryptocurrency volatility on solar, wind and nuclear energy indices, we can explore the interactions between the cryptocurrency market and renewable energy sectors. The results of our study can provide valuable insights into how fluctuations in the crypto market can affect investment and development in these crucial energy sectors. In addition, this study may reveal potential opportunities or risks for investors in the context of the global energy transition towards cleaner and more sustainable energy sources.

On a secondary level, by studying the spillover effects of cryptocurrency volatility on the Baltic Dry index and the CRB, we can better understand the dynamics of financial markets and the links between cryptocurrencies and other financial assets. This analysis can provide relevant insights into how fluctuations in cryptocurrency prices may influence commodity and shipping markets, which are essential to the global economy. In addition, it can reveal potential risks and diversification opportunities for investors.

The recognition of specific cryptocurrencies as possible tools for diversification or hedging indicates that both companies and individual investors have opportunities to better manage risk, in times of normal or high market instability or fluctuations. The varying effects of the 'clean' and 'dirty' categories on green finance and economic indicators offer valuable information for building investment portfolios, as the investors may find valuable hedges and diversifiers pairs of assets and cryptocurrencies.

Companies engaged in sustainability efforts or green technologies should consider the possible impact of cryptocurrencies on the financial indices of their sector, especially in the developing phase of their financing strategies. The relationship between specific cryptocurrencies and economic indicators might affect the resource allocation decisions at businesses - especially firms that deal with shipping or international trade - based on the correlation these two variables share.

Since cryptocurrencies are volatile and risky, they bear potential implications for financial reporting and disclosures, especially for businesses holding or transacting in digital assets. The covolatility effect between green and dirty cryptocurrencies and green finance indicators underscores the prospective influence that environmental policy might have over economic outcomes. Indicators can indirectly impact general economic activity or even worldwide trade dynamics. The possibility of some cryptocurrencies to act as diversifiers or hedge instruments might have an impact on the overall stability of financial systems, particularly in times of economic crises as proposed in (Aibai, Julaiti, & Gou, 2024). This would call for the consideration of cryptocurrencies by a policymaker's formulation of monetary policies.

Literature Gaps

Although previous studies have explored the impact of cryptocurrency volatility on various financial markets, there is a notable research gap regarding the specific effects of cryptocurrency spillovers on green finance indices, particularly in the context of solar, wind, and nuclear energy. Existing literature predominantly focuses on traditional financial markets or broader economic indices, often neglecting the unique dynamics between cryptocurrencies and renewable energy sectors. Our study aims to address this gap by providing a comprehensive analysis of these interactions, offering valuable insights into how fluctuations in the cryptocurrency market influence both green finance and regional economic stability.

Methodology

The present study aims to focus on the risk spillover between clean and dirty cryptocurrencies on the green finance indexes and on regional economic indexes.

To fulfil our objective, we have searched the specific literature and conclude that cryptocurrencies may be categorized in clean and dirty cryptocurrencies, in relation with the environment. For example, in (Mora *et al.,* 2018), it is mentioned that dirty cryptocurrencies might lift global warming by 2 degrees Celsius within less than 3 decades. In essence, dirty cryptocurrencies are the ones that use ‘‘Proof of Work’’ (PoW) consensus, while clean cryptocurrencies use more eco-friendly technologies (Ren and Lucey, 2022a). Estimates suggest that a single Bitcoin transaction utilizes a significant amount of energy due to the computationally intensive Proof-of-Work mechanism.

Specifically, it is approximated that each transaction requires 1834.02 kWh of electricity which is equivalent to what the average American family consumes in 62 days (Ren & Lucey, 2022a).

Currently, there are numerous cryptocurrencies that prioritize energy efficiency, and more are in the process of being developed. Examples of such cryptocurrencies include Cardano, Ripple, and IOTA, all of which have been ranked among the top ten cryptocurrencies by market capitalization.

In comparison to Bitcoin's energy consumption of 707 KWh per transaction, Cardano, XRP, and IOTA boast significantly lower estimated energy consumption rates of 0.5479, 0.0079, and 0.00011 KWh per transaction, respectively (Ren & Lucey, 2022b). The power usage of dirty or green cryptocurrency has not been established in the literature as a demarcation value, thus, the main difference would be in the presence or the absence of PoW technology.

Thus, following the methodology in Ren & Lucey (2022a), we have selected five dirty cryptocurrencies and four clean cryptocurrencies, as presented in table 1. For the green energy indexes, we have also assessed the literature (Attarzadeh & Balcilar, 2022; Bhattacharya *et al.,* 2016; Frondel *et al.*, 2010; Sovacool, 2017) and identified three green energy indexes, for solar, wind and nuclear energy, which cover the three major green energy types, having their description and source presented in table 1. Besides the three green energy indexes, two economical indexes were analyzed in relation to the selected cryptocurrencies, to estimate the spillover risk between them. We have chosen the Baltic Dry Index and the CRB Commodity Index, their description and source also being presented in table 1.

The Baltic Dry index plays a crucial role in understanding global economic health and its inter-connections with various markets, including crypto currencies (Bandyopadhyay & Rajib, 2023). Previous studies have highlighted the influence of the BDI, along with commodity indices like oil and gold, on sustainability indices, establishing links between economic activity and green finance (Giannarakis *et al.*, 2017).

The Baltic Dry Index (BDI) is a leading indicator for the raw materials industry and the overall economic health. It measures the cost of transporting major raw materials like metals, grains, and fossil fuels by sea.

The BDI is a good gauge of the volume of global trade at both input levels and shipping point of view. When the BDI is high, it can be inferred that there's a high demand for raw materials, which can be a sign of an economic upturn. If the news suggests a surge in the BDI, it could indicate an improving global economy (Abakah *et al.*, 2024). This could lead to increased risk-taking behaviour, with investors potentially investing more in volatile assets such as cryptocurrencies (Zeng & Qu, 2014).

News impacting the Baltic Dry Index market affects the covariance with cryptocurrencies markets because BDI is also sometimes correlated with commodity prices. If the news leads to an increase in the BDI, it may also signal a potential increase in commodity prices. Cryptocurrencies, especially "dirty" ones like BIT that require substantial energy for mining, might be affected by changes in energy commodity prices (Kamal & Hassan, 2022). Data was obtained from tradingeconomics.com and finance.yahoo.com and was abbreviated as follows, in table 1:

Table 1

Data Source, Abbreviation and Description of the Indexes

Variable	Abbreviation	Source	Description
Cardano	ADA	tradingeconomics.com	-
Ripple	XRP	tradingeconomics.com	-
Iota	MIOTA	finance.yahoo.com	-
Stellar	XLM	tradingeconomics.com	-
Bitcoin	BIT	tradingeconomics.com	-
Ethereum	ETH	tradingeconomics.com	-
Bitcoin Cash	BTC	tradingeconomics.com	-
Ethereum Cash	ETC	finance.yahoo.com	-
Litecoin	LTC	tradingeconomics.com	-
Solar Energy Index		tradingeconomics.com	The index covers the financial trend of traded companies that activate in the solar energy economical sector, or produce supplies for the solar energy industry.
Wind Energy Index		tradingeconomics.com	The index covers the financial trend of traded companies that activate in the wind energy economical sector, or produce supplies for the wind energy industry.
Nuclear Energy Index		tradingeconomics.com	The index covers the financial trend of traded companies that activate in the nuclear energy economical sector, or produce supplies for the nuclear energy industry.
CRB Commodit y Index	CRB Index	tradingeconomics.com	The index consists of 19 commodities: Aluminum, Cocoa, Coffee, Copper, Corn, Cotton, Crude Oil, Gold, Heating Oil, Lean Hogs, Live Cattle, Natural Gas, Nickel, Orange Juice, RBOB Gasoline, Silver, Soybeans, Sugar and Wheat. Those commodities are sorted into 4 groups, with different weightings: Energy: 39%, Agriculture: 41%, Precious Metals: 7%, Base/Industrial Metals: 13%.
Baltic Dry Index		tradingeconomics.com	The index provides a benchmark for the price of moving the major raw materials by sea. The index is a composite of three sub-indices that measure different sizes of dry bulk carriers: Capesize, which typically transport iron ore or coal cargoes of about 150,000 tons; Panamax, which usually carry coal or grain cargoes of about 60,000 to 70,000 tons; and Supramax, with a carrying capacity between 48,000 and 60,000 tons. The Baltic Dry Index takes into account 23 different shipping routes carrying coal, iron ore, grains and many other commodities.

The analyzed period was 17/02/2020 to 27/04/2023, thus consisting for a total of 1165 observations for each analyzed variable. The period was chosen in concordance with the appearance of the most cryptocurrencies.

Data was imputed using linear interpolation in EViews, for a lack of 3% of the data. The closing price return was computed using dlog, in EViews, that covers the inflation rate in % based on closing prices, and has the next formula:

$$\mathrm{dlx} = \mathrm{dlog(x)}\ \mathrm{dlx} = \log(\mathrm{x}) - \log(\mathrm{x}(-1)) \qquad (1)$$

The results section starts with charts over the closing prices, for the selected cryptocurrencies, the green finance indexes and the economic indexes, while the descriptive statistics cover the mean, maximum, minimum, skewness and kurtosis for each of the cryptocurrencies, green finance indexes and economic indexes that were introduced in the present paper.

In order to test the presence of a unit root test in our data and the necessity of data transformation, we have used the Augmented Dickey-Fuller (ADF) and the Phillips–Perron (PP) test, to test for the presence of a unit root in the tested data and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test to test for an absence of a unit root in the tested data. Also, in order to analyze and test the regressive effect in the available data, we have used the ARCH LM test in EViews. The results of these tests were included in the descriptive statistics.

Because one of the characteristics of the financial market movement is the presence of conditional volatility, we have decided to exploit the property to analyze the risk spillovers between these cryptocurrencies and green finance and economic indexes. In order to choose a proper model we have searched in the literature and find that the GARCH models are suitable for the mentioned asset capability, as it was defined in Hsu et al. (2021).

For example, in (Troster *et al.*, 2019b; Trucios, 2019; Umar *et al.*, 2021), all GARCH models have been used to analyze the risk spillovers, while different versions of GRACH have been found accros literature. For example, in (Wan *et al.*, 2023) (Ren & Lucey, 2022), the DECO-GARCH model was used, in (Tiwari *et al.*, 2019b) we have found the copula-ADCC-EGARCH, the GARCH-MIDAS was found in (Conrad et al., 2018) and the DCC-MGARCH and AGRACH were found in (Canh *et al.*, 2019b). The diagonal BEKK model was found in (Allen & McAleer, 2018; Hsu *et al.*, 2021; Omane-Adjepong & Alagidede, 2019b), while a multiscale wavelet method was also used (Omane-Adjepong & Alagidede, 2019b), in order to analize the risk spillover among cryptocurrencies. Also, in (Chaim & Laurini, 2019), a multivariate stochastic volatility model with and Monte-Carlo simulations were used to measure and forecast the risk spillovers among cryptocurrencies.

The Diagonal BEKK was chosen firstly because, in contrast with its counterpart (the simple BEKK model), the regularity conditions can be verified, so that the asymptotic properties of the Quasi-Maximum Likelihood Estimates (QMLE) allow valid statistical tests of volatility spillovers (Chang, Li, & McAleer, 2018). We have also found that the BEKK model is used to forecast conditional covariances, although it can be used to forecast also conditional correlations indirectly, as stated in (Caporin & Mcaleer, 2012).

The conditional mean equation of the financial return series is given as follows:

$$R_t = E(R_t | I_{t-1}) + \varepsilon_t \quad (2)$$

where R_t is financial returns, $R_t = (R_{1t,\cdots}R_{mt})'$, I_{t-1} is the information set available at time $t-1$, and ε_t is the shocks on returns, $\varepsilon_t = (\varepsilon_{1t},\cdots\varepsilon_{mt})$, following the methodology in (Bollerslev, 2009; Chang *et al.*, 2018; Hsu *et al.*, 2021).

The vector random coefficient autoregressive process of order one takes the following form:

$$\varepsilon_t = \Phi_t \, \varepsilon_{t-1} + \eta_t \quad (3)$$

where ε_t and η_t are m×1 vectors, and Φ_t is an m×m matrix of random coefficients, and $\Phi_t \sim iid(0, A)$, $\eta_t \sim iid(0, QQ')$ (Chang et al., 2018).

After ARCH (Engle, 1982), the GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) model was first introduced in (Bollerslev, 1986), and includes p lags of the conditional variance in the linear ARCH(q) conditional variance equation, as presented in (Bollerslev, 2009), while BEKK (Baba, Engle, Kraft & Kroner, 1995) model is a specific parameterization of the multivariate GARCH model developed in (Engle & Kroner, 1995), while the simplest BEKK representation for the N×N conditional covariance matrix Ω_t takes the form:

$$\Omega_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'\Omega_{t-1}B + D'^{v_{t-1}v_{t-1}'}D \quad (4)$$

where C denotes an upper triangular N×N matrix, and A, B and D are unrestricted N×N matrices. The coefficients do not estimate directly the "impact of the different lagged terms on the elements of Ht", as stated in (Bauwens et al., 2006), thus their interpretation is complex. Ωt denotes a time-varying variance and covariance matrix as to X_t and Y_T. This quadratic representation automatically guarantees that Ωt is positive definite, as stated in (Bollerslev, 2009).

The covolatility spillover effect which represents the impact of the return shock of financial asset i at time $t-1$ on the subsequent co-volatility between two financial assets i and j at time t, as stated in (Hsu et al., 2021), was defined as in (Chang et al., 2018), as follows:

$$\partial H_{ijt} / \partial \varepsilon_{kt-1}, i \neq j, k = either\ i\ or\ j \quad (5)$$

Besides the knows capabilities of cryptocurrencies (diversifier and refuge in times of recession to hedge market risk; alternative to traditional investments; a way of investment; means of refuge in certain periods; actual transmitters and receivers of shocks in the stock market) (Baur & Lucey, 2010; Baur & McDermott, 2010); Goodell and Goutte 2021; Letho, Chelwa, and Alhassan 2022; Tzouvanas, Kizys, and Tsend-Ayush 2020) in (Hsu *et al.*, 2021), the diagonal BEKK model allows the measure of the covolatility spillover effect, thus the capabilities of financial assets were extended, thus the assets are categorized in diversifiers and hedges, in comparison with results of the covolatility spillover results.

The second reason why the diagonal BEKK was chosen is the possibility of measuring, through its three coefficients, the next aspects of the financial market:

(1) A(1,1)*A(1,2) and A(2,1)*A(2,2) - **the effect of news** from the first market on the covariance (volatility spillover) between the two markets. Interpretation of the A coefficient follows the next rules: the positive, respectively negative, significant coefficient between the two markets denotes similar, respectively opposable movements of the price of both markets after news report.

(2) D(1,1)*D(1,2), D(1,2)*D(2,1)+D(1,1)*D(2,2) and D(2,1)*D(2,2) - **the asymmetry effect** of the first market on the volatility spillover between the two markets. If the coefficient has significant and positive, respectively negative, results, the positive shocks in the first market will positively, respectively negatively, affect the covolatility between the two markets. In contrast

(3) B(1,1)*B(1,2), B(2,1)*B(2,2) and B(1,2)*B(2,1)+B(1,1)*B(2,2) - the effect of the **persistence** on the volatility spillover between the two markets. Volatility persistence is the strength of the volatility feedback effect: high persistence means that volatility shocks will be felt further in the future, albeit to a lesser extent (Wang and Yang, 2017). Positive and significant results show that high persistence in the first market will uprise the volatility spillovers between the two markets. In contrast, negative and significant coefficient result shows that high persistence in the first market lowers the volatility spillovers between the two markets.

(4) **The covolatility spillover coefficient**, thus identifying diversifiers and hedges pairs of assets. If the two coefficients between two markets are positive, then the assets are considered to be diversifiers, so that the positive performance of one market could neutralize the negative performance of the other market. In contrast, if both the coefficients among the two assets are negative, then the two assets can be considered hedging instruments, because losses in one asset can be diminished by the positive returns in another asset (Bouri *et al.*, 2017; Hsu *et al.*, 2021).

The both coefficients of the diagonal BEKK model and the covolatility spillover effect were estimated in EViews, as exemplified in (Guidolin & Pedio, 2018).

Results

In Table 2, descriptive statistics, unit root tests and ARCH test results for closing daily returns are presented. It can be observed that all means oscillate near zero, while negative skewness and excess kurtosis is found in the majority of cases. Thus, all of the series are asymmetric and leptokurtic. From the unit root test, specifically the Augmented Dickey-Fuller (ADF) and the Phillips–Perron (PP) test, all of the analyzed series are stationary, as all of the teste statistics are significant at 1% level, thus no differentiating or transformation was applied to the closing daily returns series. For the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, the test statistic was higher than the asymptomatic critical values for the 1% level, in all of the cases, thus accepting the null hypothesis that the series are stationary. The ARCH LM test gives us an important overview on the regressive effects of the analyzed series (Bailey, 1909). Most of the series denotes the presence of the ARCH effects, as the ARCH LM is statistically significant at 1 %, 5 % and 10 % level, with except for ADA and BIT Classic.

Table 2

Descriptive Statistics, Unit Root Tests and ARCH Test for Closing Daily Returns

Variables	Descriptive statistics						Unit root test			ARCH
	Mean	Maximum	Minimum	SD	Skewness	Kurtosis	ADF	PP	KPSS	LM
ADA/USD	0.002194	0.41	-0.52	0.07	-0.13	10.58	-30.99*	-30.92*	0.55˚	2.46
XRP/USD	0.000530	0.63	-0.54	0.07	0.22	17.86	-30.80*	-30.74*	0.08˚	28.87*
MIOTA/USD	-0.000412	0.32	-0.55	0.07	-1.03	12.09	-31.77*	-31.69*	0.26˚	6.11**
XLM/USD	0.000288	0.57	-0.43	0.07	0.40	14.85	-30.15*	-30.14*	0.22˚	10.74**
BTC/USD	0.001263	0.18	-0.50	0.05	-1.66	20.36	-30.49*	-30.49*	0.29˚	0.34
ETH/USD	0.002371	0.28	-0.59	0.06	-1.41	17.20	-30.67*	-30.63*	0.30˚	3.44***
BCH/USD	-0.001486	0.43	-0.61	0.07	-1.05	17.93	-34.02*	-34.02*	0.11˚	3.10***
ETC/USD	0.000841	0.35	-0.51	0.08	0.05	10.50	-30.23*	-30.20*	0.13˚	68.29*
LTC/USD	0.000197	0.26	-0.48	0.06	-1.24	12.27	-32.47*	-32.38*	0.11˚	3.29***
SOLAR ENERGY INDEX	-0.001621	2.34	-2.33	0.61	-0.04	14.05	-20.49*	-142.52*	0.06˚	56.55*
WIND ENERGY INDEX	0.000526	9.21	-9.21	1.08	0.01	17.24	-13.67*	-276.03*	0.27˚	54.79*
NUCLEAR ENERGY INDEX	0.000212	0.07	-0.10	0.01	-1.14	15.95	-17.26*	-29.89*	0.04˚	47.90*
BALTIC DRY INDEX	0.001477	0.20	-0.19	0.04	0.71	7.00	-9.35*	-13.39*	0.17˚	113.75*
CRB INDEX	0.000484	4.61	-4.63	1.21	0.00	6.63	-21.18*	-125.80*	0.09˚	32.70*

*Notes: * denotes significance at the 1% level, ** denotes significance at the 5% level, *** denotes significance at the 5% level.*
˚ denotes that the KPSS test statistic is higher than the asymptomatic critical value for 1% level.

In Table 3, the diagonal elements of A, from the BEKK model results are exposed, along with their level of significance. Most of the coefficients have a level of significance of 10 % and are positive, showing a positive, strong effect of the news from one market on the covariance between the two markets. Overall, news from the solar energy index positively affects the covariance with the cryptocurrency markets. In contrast, the effect of the news on the cryptocurrency markets do not significantly affect the covariance between this markets and wind energy index, except for ADA, BIT Classic, BTC and ETC, which registered all positive coefficients for A(1,1), while nonsignificant coefficients in case of A(2,2), thus the news on the wind index market does not affect the covariance with the mentioned cryptocurrencies.

For the third green finance index, the nuclear energy index, news on the cryptocurrencies markets significantly and positively affects the covariance with the nuclear energy index, except for XRP and BIT Classic, where the coefficient is significant, but negative (for example, these two markets may have divergent investor bases, with news that excites cryptocurrency investors potentially concerning those focused on nuclear energy, leading to opposing market movements), and XLM and LTC, where the coefficient is insignificant. So, news about these cryptocurrencies does not have a substantial influence on the nuclear energy market for several reasons, including less relevance of these cryptocurrencies to energy markets or lower market capitalization and influence compared to others.

The effect of the news on nuclear energy index is significant in relation to the conditional covariance with the cryptocurrency indexes, with except for BCH.

The A(1,1) coefficients for ADA, LTC and BTC are negative, while the rest of the coefficients are positive. ADA and ETH have shown a significant but negative relationship with the nuclear energy index A(2,2), following news in the nuclear sector. This suggests that positive news about nuclear energy may lead to a decrease in covariance with these cryptocurrencies, and vice versa. The reasons behind this could vary. For instance, these cryptocurrencies may have unique market dynamics or investor bases. Also, ADA and ETH both focus on energy-efficient solutions in the blockchain space (ADA uses a Proof-of-Stake consensus mechanism, and ETH is transitioning to it), which might make their market dynamics inversely related to the developments in the nuclear energy sector (Afjal & Clanganthuruthil Sajeev, 2022).

The only coefficient that is significant on 1% level is in relationship with effect of the news between the covolatility of Baltic Dry Index and ADA, both coefficients being positive. Given that ADA is a third-generation cryptocurrency designed to address the problems of first-generation cryptocurrencies (like BIT) and second-generation ones (like ETH), it might be more sensitive to broader market and economic indicators due to its improved scalability, sustainability, and interoperability.

Same, for the Diagonal Elements of A estimated between XRP, MIOTA, XLM ETH , BIT, ETH Cash and LTC, the coefficients are both positive and significant at 10% or 5% level.

The Baltic Dry Index (BDI) is a key economic indicator that measures the cost of shipping major raw materials-such as metals, grains, and fossil fuels-by sea. A high BDI suggests strong demand for these materials, signaling a potential economic upturn. News of a surge in the BDI may indicate an improving global economy, leading investors to take more risks by investing in volatile assets like cryptocurrencies (Zeng & Qu, 2014).

Since the BDI sometimes correlates with commodity prices, news affecting it impacts its covariance with cryptocurrency markets. Therefore, increases in the BDI may signal rising commodity prices, affecting energy-intensive cryptocurrencies like Bitcoin (Kamal & Hassan, 2022).

Estimation of the diagonal elements of B matrix, in the diagonal BEKK model, presented in Table 4, denotes the contribution of the persistence from one market over the covolatility of the two markets.

From Table 4 it can be seen that the majority of the coefficients between Solar Energy index and the selected cryptocurrencies are positive and significant, at a level of significance of 10%, except for the effect of the persistence in the Solar Energy index market and the covolatility with ETH Classic, where the coefficient is significant, but negative, meaning that high persistence in the Solar Energy index market lowers the volatility spillovers between the two markets and vice versa.

When analyzing the coefficients for the Wind energy index, they appear as significant and positive, but for the coefficient B(1,1) for BTC, which is insignificant. Same for the nuclear energy index, the coefficient B(1,1) for BTC, is insignificant, while the rest of the coefficients for elements B(1,1) and B(2,2) are positive and significant.

For the CRB Index, all coefficients for element B(1,1) are positive and significant, except for XRP and XLM, which present negative coefficients and MIOTA which is insignificant. In case of the effect of the volatility persistence of the CRB index over the covolatility with the cryptocurrency markets, the coefficients are positive and significant, except for BTC and ETH cash, where the coefficients are negative, and ADA and BIT, where the coefficients are insignificant. Coefficients for the effect of the volatility persistence of XRP, MIOTA, XLM and LTC markets over the covolatility with Baltic dry index are insignificant, while the rest of the coefficients are positive and significant.

Also, the coefficients of the contribution of the persistence of Baltic Dry Index over the ADA, BIT, BTC and ETC are insignificant, while the rest are positive and significant.

Estimation of the diagonal elements of the D matrix, in BEKK model denote the asymmetry of one market over the covariance between the two markets. For example, in Table 5, negative shocks in the solar energy index market positively affects the covolatility with the XRP, XLM, BIT, ETH and LTC markets, with a 10% significance.

The coefficients for MIOTA, BTC and ETC are insignificant and for ADA is significant but negative, thus shocks in ADA market lowers the covolatility between the two markets. In contrast, the asymmetry between solar energy index market on the covariance with ADA index is significant and positive, same for XRP, BIT, ETH and BTC are both positive and significant. Coefficients of D(2,2) elements of Solar Energy Index and MIOTA and ETH Cash are insignificant.

In case of Wind Energy Index, all D(1,1) coefficients are significant and positive, except for ADA, and ETH Cash, which are insignificant and BIT and LTC, which are significant, but negative. The asymmetry effect of the wind energy index on the covolatility with ADA, MIOTA, ETH , BTC, ETH Cash and LTC are both positive and significant, while for XRP and XLM are insignificant and for BIT is significant but negative.

The asymmetry effects of most of the cryptocurrency markets over the nuclear energy index are both positive and significant, except for XRP and ETH, which are insignificant, and for BTC are significant but negative. The coefficients for the D(2,2) elements are both positive and significant except for XRP, XLM and LTC, which are insignificant, and for MIOTA, which is significant, but negative.

The D(1,1) coefficients for the asymmetry effects of the cryptocurrency indexes on the covolatility with the CRB index are positive and significant, with except for ADA and ETH Classic, which are insignificant.

The D(2,2) elements for the asymmetry effect of the CRB Index market on the ADA, MIOTA, BIT and ETH Cash are positive and significant, while the rest of the coefficients are insignificant.

The D(1,1) coefficients for the diagonal elements of the D matrix, in case of Baltic Dry index are mostly positive and significant. The asymmetry effect of ETH Classic, XLM and MIOTA over the covolatility with Baltic dry index is insignificant, while for the XRP and LTC, the coefficients are significant but negative.

The D(2,2) elements are mostly insignificant, for the asymmetry effects of Baltic dry index, except over the covolatility with ADA (negative), XRP, MIOTA and LTC (all positive).

Table 3

Estimation of Diagonal Elements of A in the Diagonal BEKK Model. Weights that Each Asset has on the Covolatility Spillover Effect

Type		Clean				Dirty				
Variable		**ADA/USD**	**XRP/USD**	**MIOTA/USD**	**XLM/USD**	**BTC/USD**	**ETH/USD**	**BCH/USD**	**ETC/USD**	**LTC/USD**
Solar Energy Index	A(1,1)	0.2856***	-0.2117***	0.3117***	0.1985***	-0.2309***	0.2433***	0.3438***	0.2960***	0.1808***
	A(2,2)	0.2006***	0.7115***	0.3659***	0.3057***	0.2583***	0.2142***	-0.2349***	0.3322***	0.3314***
Wind Energy Index	A(1,1)	0.3024***	0.0385	0.0035	0.0484	0.2435***	-0.0085	0.3523***	0.3009***	-0.0057
	A(2,2)	0.01387	0.7570***	0.3164***	0.3051***	-0.0409	0.2668***	0.0210	0.0269	0.3578***
Nuclear Energy Index	A(1,1)	0.3109***	-0.1214**	0.1749***	-0.0725	-0.2698***	0.1972***	0.3501***	0.2932***	-0.0899
	A(2,2)	-0.1352**	0.761***	0.3154***	0.3011***	0.1918***	-0.2729***	0.0786	0.1379**	0.3568***
CRB Index	A(1,1)	0.3095***	0.0000	0.0089***	0.0199	-0.2265***	-0.2561***	-0.3548***	0.3031***	-0.0065
	A(2,2)	0.0078	0.7380***	0.3141	0.3103***	-0.0084	-0.0088	-0.0296	0.0147	0.3534***
Baltic Dry Index	A(1,1)	0.2364*	0.8288***	0.8446***	0.8874***	-0.0036	0.1105**	0.2888***	0.2989***	0.8468***
	A(2,2)	0.8532*	0.3596***	0.2281***	0.2624***	0.8774***	0.8650***	0.8697***	0.865***	0.2368***

*Notes: * denotes significance at the 1% level, ** denotes significance at the 5% level, *** denotes significance at the 10% level.*

Table 4

Estimation of Diagonal Elements of B in the Diagonal BEKK Model - Persistence from one Market over the Covolatility of the Two Markets

Type		Clean				Dirty				
Variable		**ADA/USD**	**XRP/USD**	**MIOTA/USD**	**XLM/USD**	**BTC/USD**	**ETH/USD**	**BCH/USD**	**ETC/USD**	**LTC/USD**
Solar Energy Index	B(1,1)	0.9236***	0.9524***	0.9548***	0.9523***	0.8992***	0.3058***	0.9280***	0.9469***	0.9528***
	B(2,2)	0.9523***	0.7615***	0.9157***	0.9296***	0.9520***	-0.3870***	0.9519***	0.9516***	0.9142***
Wind Energy Index	B(1,1)	0.9219***	0.5350***	1.0295***	0.5340***	0.9026***	0.5300***	0.9247	0.9452***	0.5342***
	B(2,2)	0.5347***	0.7515***	0.2952***	0.9327***	0.5288***	0.9115***	0.5345***	0.5345***	0.9204***
Nuclear Energy Index	B(1,1)	0.9188***	0.9081***	0.9032***	0.9106***	0.8994***	0.9019***	0.9256	0.9469***	0.9092***
	B(2,2)	0.9045***	0.7518***	0.9100***	0.9347***	0.9029***	0.9132***	0.9115***	0.9115***	0.9206***
CRB Index	B(1,1)	0.9168***	-0.9859***	-0.1129	-0.1312*	0.8997***	0.9063***	0.9234***	0.9427***	0.1285*
	B(2,2)	-0.1128	0.7586***	0.9073***	0.9305***	0.1197	0.1166***	-0.9860***	-0.1223*	0.9171***
Baltic Dry Index	B(1,1)	0.9336*	0.0342	-0.0110	0.0217	0.8950***	0.8871***	0.9357***	0.9456***	0.0441
	B(2,2)	0.0415	0.9254***	0.9203***	0.9484***	-0.0049	0.0151***	0.0625	0.1137	0.9108***

*Notes: * denotes significance at the 1% level, ** denotes significance at the 5% level, *** denotes significance at the 10% level.*

Table 5

Estimation of Diagonal Elements of D in the Diagonal BEKK Model - the Asymmetry of one Market Over the Covariance between the 2 Markets

Type		Clean				Dirty				
Variable		**ADA/USD**	**XRP/USD**	**MIOTA/USD**	**XLM/USD**	**BTC/USD**	**ETH/USD**	**BCH/USD**	**ETC/USD**	**LTC/USD**
Solar Energy Index	D(1,1)	-0.1237**	0.3446***	0.0010	0.3620***	0.3515***	0.9520***	-0.0292	0.0010	0.3707***
	D(2,2)	0.3600***	0.2853**	0.0010	-0.0776***	0.2836***	0.8993***	0.3256***	0.0010	-0.1955***
Wind Energy Index	D(1,1)	0.0001	1.0194***	0.5331***	1.0194***	-0.3359***	1.0284***	0.0347***	0.0253	-1.0249***
	D(2,2)	1.0219***	0.1792	0.9079***	0.0271	-1.0210***	0.3331***	1.0219***	1.0219***	0.0093
Nuclear Energy Index	D(1,1)	0.0318	0.4693***	0.4558***	0.4742***	0.3029***	0.4326***	-0.0076***	-0.0755	0.4775***
	D(2,2)	0.4670***	0.0346	-0.2844***	-0.0387	0.4292***	0.2992***	0.4685***	0.4551***	-0.0224
CRB Index	D(1,1)	0.0448	0.2625***	1.0934***	1.0908***	0.3613***	0.3545***	0.0088***	-0.0639	1.0889***
	D(2,2)	1.0904***	0.1916	0.2990***	-0.0056	-1.0960***	-1.1005	0.2591	1.0865***	-0.1147
Baltic Dry Index	D(1,1)	0.2035*	-0.3937**	-0.3261	0.1763	0.4122***	0.4626***	0.1734***	0.0010	-0.3566*
	D(2,2)	-0.3327***	0.1863***	0.3543***	-0.0760	-0.1881	-0.2825	-0.2572	0.0010	0.3244***

*Notes: * denotes significance at the 1% level, ** denotes significance at the 5% level, *** denotes significance at the 10% level.*

Table 6

Covolatility Spillover Effect

Type		Clean				Dirty				
Variable		**ADA/USD**	**XRP/USD**	**MIOTA/USD**	**XLM/USD**	**BTC/USD**	**ETH/USD**	**BCH/USD**	**ETC/USD**	**LTC/USD**
Solar Energy Index	(1,1)	0.0352	-0.0112	0.0083	0.0041	-0.0367	0.0031	-0.0497	0.0605	0.0039
	(2,2)	0.0039	-0.0926	0.0702	0.0374	-0.0027	0.0321	-0.0054	0.0074	0.0369
Wind Energy Index	(1,1)	0.0045	0.0021	0.0001	0.0010	-0.0109	-0.0001	0.0081	0.0089	-0.0001
	(2,2)	0.0002	0.0319	0.0012	0.0162	-0.0005	-0.0025	0.0005	0.0006	-0.0023
Nuclear Energy Index	(1,1)	-0.0005	-0.0068	0.0040	-0.0015	-0.0007	-0.0032	0.0004	0.0005	-0.0021
	(2,2)	-0.0029	-0.0012	0.0007	-0.0003	-0.0024	-0.0007	0.0019	0.0031	-0.0004
CRB Index	(1,1)	0.0029	0.0000	0.0002	0.0004	0.0024	0.0028	0.0128	0.0055	-0.0001
	(2,2)	0.0001	0.0000	0.0035	0.0076	0.0001	0.0001	0.0007	0.0003	-0.0028
Baltic Dry Index	(1,1)	0.0074	0.0222	0.0141	0.0157	-0.0001	0.0035	0.0093	0.0095	0.0130
	(2,2)	0.0140	0.0109	0.0071	0.0086	-0.0001	0.0057	0.0169	0.0196	0.0074

Following the methodology in (Chang *et al.*, 2018) and (Hsu, Sheu, & Yoon, 2021), the covolatility spillover effect was estimated, in order to observe the impact of the return shock of one market on the co-volatility between the two markets. Thus, if the two coefficients between two markets are positive, then the assets are considered to be diversifiers, so that the positive performance of one market could neutralize the negative performance of the other market.

For example, the diversifiers, from the next table (Table 6.) are the following pairs: Solar Energy Index – ADA, MIOTA, XLM, ETH , ETH Cash and LTC; Wind Energy Index - ADA, XRP, MIOTA, XLM, XLM, BTC and ETH Cash; Nuclear Energy Index – MIOTA, BTC and ETH Cash, CRB Index – ADA, XRP, MIOTA, XLM, BIT, ETH , BIT Classic and ETH Cash, Baltic Dry Index - ADA, XRP, MIOTA, XLM, ETH , BIT Classic, ETH Cash and LTC.

In contrast, if both the coefficients among the two assets are negative, then the two assets can be considered hedging instruments, because losses in one asset can be diminished by the positive returns in another asset. For example, hedges are the next pairs: Solar Energy Index – XRP, BIT and BTC; Wind Energy Index – BIT, ETH and LTC; Nuclear Energy Index – ADA, XRP, XLM, BIT, ETH and LTC; CRB Index – LTC; Baltic Dry Index – BIT.

Discussions and Policy Implications

When analyzing the estimation of the coefficients, it can be seen, from Table 3, that the clean cryptocurrencies possess both positive and negative significant effects of their news on the green finance and economical indexes, except for Wind Energy Index and CRB Index, that have A(1,1) insignificant coefficients. In contrast, almost all of the dirty cryptocurrencies present positive and significant impact of their news on the covolatility with the green finance indexes and economical indexes.

However, dirty cryptocurrencies exhibit both positive and negative effects: on one hand, they can serve as effective instruments for risk hedging and diversification, but on the other hand, their negative environmental impact, caused by the high energy consumption required for mining, is a major concern (Aibai, Julaiti & Gou, 2024). These effects vary significantly depending on the region: in areas with access to renewable energy sources, the environmental impact can be mitigated, whereas in regions dependent on fossil fuels, dirty cryptocurrencies can exacerbate environmental issues and increase energy costs (Aleksandrov, 2021).

When analyzing the effects of the volatility persistence of cryptocurrencies on the covolatility with the green finance indexes and economical indexes, it can be observed, from Table 4 that most of the coefficients are positive and significant, at a level of significance of 10%, even if the cryptocurrencies are in the clean or dirty category.

The persistence of volatility is a measure of how long the effects of a shock to a financial system last. In the context of cryptocurrencies, volatility persistence refers to the amount of time it takes for a shock (like a sudden price change) to dissipate and for the cryptocurrency's price to stabilize (Long *et al.*, 2023). This is chiefly due to aspects like their relatively recent introduction, the ambiguity surrounding regulatory frameworks, and their acute responsiveness to market sentiment.

Here's why the volatility persistence of cryptocurrencies it can be observed to have positive and significant effects on the covolatility with the green finance indexes and economic indexes, irrespective of whether they are in the clean or dirty category: first, cryptocurrencies are subject to high levels of speculation and sentiment-driven trading (Letho, Chelwa, & Alhassan, 2022).

Any significant news or developments (such as changes in regulatory outlook, technological advancements, or major events affecting liquidity) can lead to increased volatility. This can create a wavelet effect, influencing the green finance and economic indexes (Bouri, Shahzad, Roubaud, Kristoufek, & Lucey, 2020). Moreover, Financial markets are interconnected, with movements in one often influencing others. Cryptocurrencies, while relatively new, have gained substantial market size and influence.

In times of significant volatility, cryptocurrencies might be used for hedging purposes. As investors turn to these digital assets during periods of market turbulence, the relationship between these markets and the crypto markets may become stronger (Letho *et al.*, 2022). Additionally, cryptocurrencies are traded 24/7 worldwide, which leads to continuous adjustments and reactions to new information. This can lead to greater responsiveness to global market changes and hence explain the positive correlation with various indexes.

When analyzing the asymmetry on the covolatility between the cryptocurrency markets and the green finance indexes and economical indexes, the results are heterogenous, thus we suggest the reader to analyze the specific results section.

Following the methodology in (Chang *et al.*, 2018) and (Hsu *et al.*, 2021), the impact of the return shock of one market on the covolatility between the two markets was estimated.

The results show that ETC could be considered a diversifier for all of the indexes, thus the positive performance of ETC could neutralize the negative performance of the green finance indexes, BRC Index and Baltic Dry Index. An explanation consists in non-synchronous Trading Hours - cryptocurrencies are traded 24/7 worldwide, while the green finance and economic indices have specific trading hours. This can lead to non-synchronous price movements. Moreover, cryptocurrencies function on independent networks and are subject to distinctive regulatory landscapes compared to the conventional financial markets.

These factors can provide them with a buffer against economic disruptions that affect traditional assets and industries, thus positioning them as a beneficial instrument for portfolio diversification.

In our study, ETC shows positive performance, so, it could help offset or "neutralize" the negative performance of the other indices in the portfolio. The rationale here is that, even when the green finance indexes, the CRB Index, and the Baltic Dry Index are performing poorly, ETC might still perform well due to the unique factors influencing its price (the price of ETC, like other cryptocurrencies, is influenced by factors unique to the crypto markets such as technology updates, regulatory news, investor sentiment, and trading volumes). Thus, it could potentially counterbalance the negative performances and stabilize the overall portfolio.

Also, in almost all of the cases, LTC and BIT can be considered hedging instruments, thus losses obtained from their variability can be diminished by the positive returns green finance indexes, CRB Index and Baltic Dry Index.

In (I U Haq, 2022), where the impact of environmental cryptocurrency index on the green finance indexes was analyzed, findings are consistent with ours. In (Yen & Cheng, 2021), the economic policy uncertainty in China predicts cryptocurrency volatility, while the same index from U.S., Japan, or Korea do not possess the same effect on the cryptocurrency volatility. China stands as one of the world's leading economies, wielding considerable sway over international financial markets.

Any alterations to its economic strategies can trigger substantial repercussions in the worldwide economy, thereby impacting the cryptocurrency markets as well. Relative to many other nations, China sees an elevated level of cryptocurrency adoption. The significant involvement of Chinese investors and traders in global cryptocurrency exchanges results in their contribution to a sizable portion of the worldwide trading volume. Changes in China's economic policy could potentially impact these traders' behavior, affecting market liquidity and leading to price volatility.

The research offers several valuable managerial contributions in the realm of finance and economic strategy, particularly for stakeholders involved in cryptocurrencies, green finance, and regional economies.

The distinction between 'clean' and 'dirty' cryptocurrencies underscores the importance of considering environmental impacts in financial decisions. It can guide companies or countries towards more sustainable investment practices, incentivizing them to support 'clean' cryptocurrencies.

Our findings provide insights for investment managers who deal with portfolio diversification. Specifically, the research identifies ETC as a potential diversifier, meaning that a positive performance from this cryptocurrency could balance out negative performances of other financial assets.

Also, the study provides valuable data for risk management. It reveals that LTC and BIT can serve as hedging instruments, allowing investors to offset potential losses from their variability by garnering positive returns from green finance and economic indices.

The identification of the asymmetry on the covolatility between cryptocurrency markets and the indices can help in designing effective market strategies.

For the cryptocurrency industry, the research offers valuable insights on how different cryptocurrencies interact with green finance and economic indices. This knowledge can influence their technology and market positioning strategy.

Also, our study offers a few *noteworthy implications at the macroeconomic level*: the strong effects of certain cryptocurrencies like ETH on the covariance with Solar and Nuclear Energy Index, CRB Index, and Baltic Dry Index suggest that the growth and volatility of these cryptocurrencies can indirectly influence the broader economy. This could require central banks and policymakers to consider the effects of cryptocurrencies when formulating monetary policies.

Second, the differentiation of cryptocurrencies into 'clean' and 'dirty' categories and their diverse impact on green finance indices highlights the potential role of environmental policy in shaping economic outcomes. Governments might need to consider this in their efforts to promote sustainable economic growth and green technologies.

Third, the study identifies potential effects of cryptocurrencies on the Baltic Dry Index, which is a key indicator of global trade. If cryptocurrencies continue to grow in importance, they could indirectly influence global trade dynamics.

Fourth, the correlations identified between cryptocurrencies and green finance indices suggest that the expansion and adoption of cryptocurrencies could influence the development and performance of green finance initiatives. This could have important implications for efforts to achieve sustainability goals at a macroeconomic level.

Fifth, the potential for certain cryptocurrencies to act as diversifiers or hedging instruments might influence the overall stability of financial systems, particularly during times of economic stress.

The study presents several *implications at the microeconomic level* as well: the identification of certain cryptocurrencies as potential diversifiers or hedging instruments suggests opportunities for firms and individual investors to manage risk more effectively. This can be particularly valuable during times of market uncertainty or volatility.

Also, the differentiation of cryptocurrencies into 'clean' and 'dirty' and their variable impacts on green finance and economic indexes provide insights for portfolio construction.

Investors might adjust their holdings in response to the differing volatilities and potential returns.

Businesses involved in green technologies or sustainability initiatives may want to consider the potential influence of cryptocurrencies on their industry's financial indices. These entities may need to consider this influence when planning their financing strategies.

Also, the correlation between certain cryptocurrencies and economic indicators like the Baltic Dry Index may influence business decisions around resource allocation, particularly for firms involved in shipping or global trade. The volatility and risk associated with cryptocurrencies may have implications for financial reporting and disclosure practices, especially for businesses that hold or transact in these digital assets.

From a *policy perspective*, the analysis of spillover and covolatility effects between cryptocurrencies and green finance indices provides insights into how these markets interact, which is crucial for understanding broader economic stability.

Policymakers can use this knowledge to assess the influence of cryptocurrency market volatility on financial stability and economic resilience, particularly in the context of the green transition.

The evidence that cryptocurrencies, especially "dirty" cryptocurrencies, exert an impact on green finance indices underscores the need for regulatory frameworks that consider the environmental footprint of digital assets. Promoting the adoption of "clean" cryptocurrencies through incentives or regulatory support could help mitigate their negative environmental impact, aligning financial innovation with sustainability goals.

Conclusion

This research aimed to examine the influence of cryptocurrency markets on green finance indices and specific regional economic indices. The research established a distinction between "clean" and "dirty" cryptocurrencies, determined by their environmental footprint. It identified four cryptocurrencies as "clean" and five as "dirty". The study focused on the risk spillover between these cryptocurrencies and three green energy indices (Solar Energy Index, Wind Energy Index, and Nuclear Energy Index) and two economic indices (the Baltic Dry Index and the CRB Index).

The results are mainly derived from diagonal BEKK model estimations, with three matrices (A, B, D) representing different impacts on covariance between markets. The A matrix represents the impact of market news. News from most cryptocurrency markets had a positive effect on covariance with the Solar Energy Index, except for XRP and BIT Classic, where it was negative. However, news from the cryptocurrency markets did not significantly affect covariance with the Wind Energy Index, barring a few exceptions. For the Nuclear Energy Index, the news' impact was predominantly positive, but negative for XRP and BIT Classic and insignificant for XLM and LTC. News from cryptocurrency markets also affected covolatility with the CRB Index and Baltic Dry Index with varied significance and direction.

The B matrix signifies persistence in the market. The effects of volatility persistence of cryptocurrencies on the covolatility with the indices were also analysed. Here, most of the coefficients were positive and significant at a 10% significance level, irrespective of the cryptocurrency being categorized as 'clean' or 'dirty'. For the most part, this persistence had a positive and significant impact on covolatility between the Solar Energy Index and cryptocurrencies, with exceptions for ETH Classic.

Similar patterns were observed for the Wind Energy Index and Nuclear Energy Index. For the CRB Index, the persistence effects were more varied, with both positive and negative impacts. Coefficients relating to the Baltic Dry Index showed positive significance for the most part, with exceptions for ADA, BIT, BTC, and ETC.

The D matrix indicates market asymmetry. The analysis of the asymmetry on the covolatility between the cryptocurrency markets and the indices yielded heterogeneous results. Negative shocks in the Solar Energy Index market positively affected the covolatility with XRP, XLM, BIT, ETH, and LTC markets, with a 10% significance. However, similar shocks lowered the covolatility between Solar Energy and ADA. Similar variations were seen for Wind Energy Index, Nuclear Energy Index, CRB Index, and Baltic Dry Index.

To conclude, the results of the study presented a mixed picture concerning the impact of cryptocurrency news on green finance and economic indices.

The 'clean' cryptocurrencies exerted both positive and negative significant effects, with some exceptions, while the 'dirty' cryptocurrencies generally had a positive, significant impact on the covolatility with the indices. An interesting observation emerged in the case of ETH, which, unlike previous research where it neither caused nor received any effects with other cryptocurrencies, was found to have a strong impact on the covariance with the solar and nuclear energy indices and both economic indices. ETC emerged as a potential diversifier for all indices, indicating that positive performance of this cryptocurrency could offset any negative performance from the green finance and economic indices. On the other hand, LTC and BIT could be considered as hedging instruments, meaning that their variability could be mitigated by positive returns from the green finance and economic indices.

This research is practically considerable for managers, investors, stakeholders, policymakers and academia because contain managerial implications and several implications at the microeconomic level and also microeconomic level.

Main limitation of the present study is the lack of data for a longer period, for three of the cryptocurrencies, (XLM, BTC and ADA), that would allow us to extend out data observations to 2000 for each of the analysed variable.

Future research should explore a broader range of green finance indices and incorporate additional energy-related variables to capture a more comprehensive picture of the interconnections between cryptocurrency volatility and environmental finance. Additionally, investigating the impact of regulatory changes in both cryptocurrency and green finance sectors could enhance the understanding of the policy implications related to volatility spillovers.

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