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NFTs and Cryptocurrencies—The Metamorphosis of the Economy under the Sign of Blockchain: A Time Series Approach

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Abstract: Although NFTs (non-fungible tokens) and cryptocurrencies are active on the same market, their prices are not so closely related over time. The objective of this paper is to identify the relationship between the two types of assets (NFTs and the cryptocurrencies Ethereum, Crypto Coin, and Bitcoin), using data for the period between September 2020 until February 2022. The conclusions of the study are useful for cryptocurrency and NFT issuers, but also for investors on the financial market who are reconfiguring their portfolios with increasing frequency, and use these new assets for speculative or hedging purposes based on blockchain technology. The results highlighted relationships between NFTs and Ethereum, between Ethereum and Crypto Coin, and between Bitcoin and Ethereum, Ethereum being a bridge between all four. Therefore, NFTs present a relationship with Ethereum, the NFTs price had a causal effect on the price of Ethereum.

Keywords: NFT; Bitcoin; Ethereum; Crypto Coin; digitalization; VAR; granger causality

MSC: 62N02

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1. Introduction

The pandemic crisis generated by COVID-19 has demonstrated the importance of digital technologies in continuing economic activity, given the physical distancing measures imposed by the authorities. Consumer and business adaptation has been rapid, the digital technologies providing a high degree of resilience with positive effects on national economies [1–11]. Digitization is present in citizens lives and in companies' activities, the new information technologies being gradually used at different levels, both personal and corporate [12–17].

Technological innovation has led to the emergence of new payment, investment, and exchange forms, such as cryptocurrencies, assets through which digital content creators can capitalize on their work (non-fungible tokens, or NFTs), and financial products and services offered through FinTech [18–23]. Cryptocurrency represents a digital system of payment, based on blockchain technologies, the transactions not being verified by bank institutions [24]. Blockchain technology has revolutionized the business environment, by "transforming economical, environmental, and organisational performance" [25]. The main advantages of this technology are security, transparency, decentralization, peer to peer data synchronization, pseudo-anonymity or total anonymity, and the validity of the data [26]. There are also voices that emphasize only the negative aspects of this new technology, "categorized as a combination of a soap bubble, a Ponzi scheme, and an ecological disaster" [26]. Non-fungible tokens (NFT) are the latest digital phenomenon that uses blockchain technology in order to certify the ownership of specific assets, such as music, images, videos, and parts of virtual worlds [27]. NFTs transform digital works of art and other collectibles into one-of-a-kind and verifiable assets: "NFTs are unique units of data recorded on a permanent ledger or blockchain. NFTs are used to record ownership of both physical and digital goods" [28]. Using NFTs, the digital information can be produced, organized, consumed, and stored in an innovative way which welcomes consumers. The main characteristic of NFTs is the introduction of the scarcity concept in the digital world [29]. In addition, these digital tokens offer new possibilities for innovators to reshape the landscape of entrepreneurship through blockchain technology [30,31].

NFTs are used in different fields, such as sport, broadcasting, art, content creation, and the tech-crypto business [32], and the innovation has been embraced in other entities, such as museums or wildlife conservation organizations. Wildlife conservation is a growing concern given the negative externalities generated by human activity and the accelerated extinction of some animal and plant species. A solution for financing this constitutive process that must be carried out in the unfulfilled term is the launch of non-fungible crypto wildlife tokens. In this way, the nature, but also the tourism industry may benefit from the blockchain technology [33]. Another possibility to extend the use of NFTs is in the intellectual property field. In this sector, the patent ownership changes can be traced using blockchain technology. In addition, NFTs would provide liquidity to this market, and additional opportunities to capitalize the inventions for different entities, such as R&D companies or universities [34].

In this context, the main aim of this paper is to establish if there is a relationship between cryptocurrencies and the NFT price over the time, the conclusions of the study being useful for cryptocurrency and NFT issuers, but also for investors on the financial market who reconfigure their portfolios with growing frequency and use these new assets for speculative or hedging purposes based on blockchain technology. Therefore, the research question deriving from this is: Is there a causal relationship between the NFT price and cryptocurrencies' prices?

In order to respond to the research question, the paper is organized as follows: the next section reviews the findings of the recent literature on NFTs and cryptocurrencies, the third part of the paper presents the data and methods applied in order to verify the research hypotheses, the fourth section describes the results of the empirical analysis, while the last parts of the paper present the final discussions and conclusions.

2. Literature Review

NFTs are the new stars of the digital world because of the possibility of monetizing digital content of different assets and introducing scarcity into this complex world. Digital assets are marketed and monetized by NFTs [35]. NFTs are a recent technological phenomenon similar to the most well-known ones, including blockchain (2009) and smart contracts (2015). Their popularity has grown considerably after the great success of Crypto Kitties, from late 2017 [36]. Crypto Kitties is a game through which users can buy, sell, or collect digital cats. In 2021, the NFTs market exploded, and an increasing number of consumers are interested in this market in the context of the intensification of cryptocurrency transactions. The markets of NFTs and cryptocurrencies are seen as alternatives to traditional financial markets, taking into account the fall in securities prices under the impact of the COVID-19 crisis.

In addition, as in the case of any new technology, there is a certain reluctance from the companies interested in promoting these assets, but also from consumers, for which the specialized literature offers complex explanations according to specific theories or models, such as the Technology Acceptance Model [37], Unified Theory of Acceptance and Use of Technology Model [38], Diffusion of Innovations theory [39].

The demand for NFTs is emerging but volatile due to the uncertainty and distant benefits. The main aspects that must be observed by the managers and entrepreneurs interested in NFTs are security, storage, and environmental sustainability (taking into account the energy that must be consumed for blockchain mining). Because of the mining aspects, scholars have drawn attention to the negative externalities generated by cryptocurrencies and NFTs on the environment [40–42].

NFT's popularity is due to the fact that some of them incorporate smart contracts that generate revenue to the original creators based on future transactions. NFTs find applications in various fields of activity. In the field of sports, the applicability of NFT extends from digital collectibles, tickets, monetizing the image of athletes, transferable membership, or ownership stakes. As NFT transactions have intensified, companies have become increasingly interested in these digital assets that can be used to develop sales channels and business models. Gradually, the market has gained consistency and specialists are even talking about an ecosystem that includes several types of stakeholders with specific functions, such as individual content creators, content owners, intermediaries (technical entities that oversee the development, security, and maintenance of the NFT infrastructure; fintech marketplace companies) consumers, collectors, investors, and speculators [32].

Most of the identified studies consider how to use NFTs in different fields, highlighting the potential of these digital assets for business reconfiguration, and the modalities of the sale of products and services by sports clubs and museums. A study by Baker et al. [28] was focused on the use of NFTs in the U.S. sports market, considering the efforts made by different entities to explore future innovation opportunities. The main advantage offered by NFTs is the possibility to track and verify the authenticity or ownership of digital assets. By promoting NFTs, managers and entrepreneurs in this field can manage the sports market in a new way, including the inclination of young generations to use digital products. So, blockchain technology is seen as a new method to reshape entrepreneurship, financial markets, and innovation, and to set up new ecosystems [30], but there are also voices highlighting the use of cryptocurrencies and NFTs by showbusiness celebrities and businessmen for money laundering and tax evasion [20,43–45].

The literature on cryptocurrencies is not so extensive, comprising 2965 studies on the Web of Science platform since 2014. However, an increased interest in the field can be observed since 2017. In case of non-fungible tokens, we can say that the literature in this field is actually quite sparse, with only 32 articles published since 2017, most of them appearing in 2021 (Figure 1). This can be explained by the fact that the cryptocurrency market is very young, established only in 2008 when the blockchain mechanism was introduced by Bitcoin. Another significant year is 2014, when second generation of blockchain, Ethereum, was introduced, using smart contracts to run different applications, such as decentralized finance (DeFi), crowdfunding, decentralized exchanges, data records keeping.

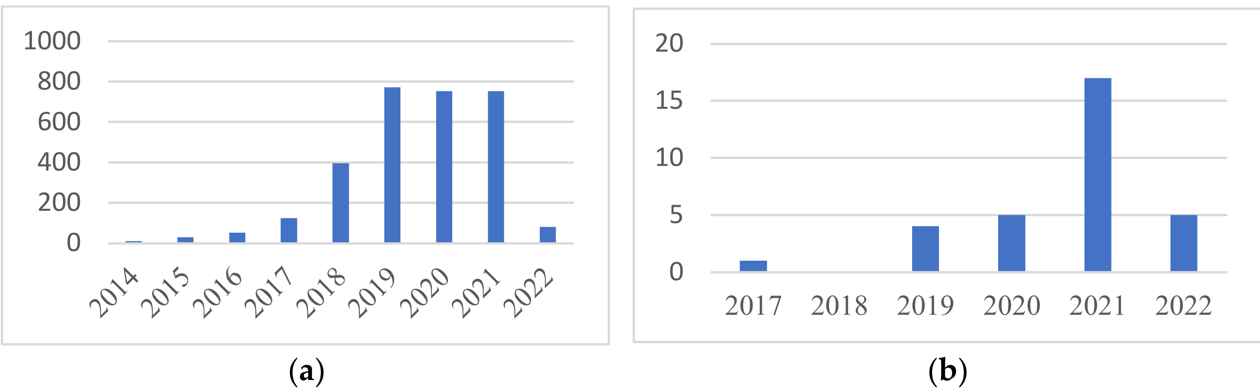

Figure 1. Number of articles related to cryptocurrency (**a**) and non-fungible tokens (**b**), 2014–2022 (February), Web of Science. Source: authors elaboration.

Blockchain is actually a distributed ledger technology (DLT) that generates rethinking the way companies do business, because traditional organizations such as banks (which centralize customer transaction information) are being replaced by decentralized group of resources and actors [34]. These new markets are constantly expanding, which is why researchers are studying the components, trying to identify the behavior of investors and the factors influencing the price, given the intense volatility that characterizes these markets. Despite the differences from traditional financial asset markets, herding behaviors are present in the cryptocurrency markets [46].

Using daily data for the period between January 2018 and April 2021, Ante (2021) [47] studied the relationship between Bitcoin and Ether price and NFT sales. Based on the VAR framework, the conclusions of the study are that (1) NFT sales are Granger-caused by the BTC price, (2) NFT wallets are Granger-caused by the ETH price, and (3) NFT markets are influenced by cryptocurrency prices. The main explanation for these results is that cryptocurrencies are the main currency used for NFT transactions. Ante [47] focused his study on the NFTs market, using data from the Ethereum blockchain between June 2017 and May 2021. In fact, he analyzed the 14 largest submarkets through the prism of the interactions and causal relationships between them. Using vector autoregression *(VAR)* model, the scholar demonstrated that there are strong interconnections between NFT markets, in the short and long run. In addition, the researcher concluded that the market is immature, but that it is developing at a rapid pace.

The study by Ko et al. [48] used the data regarding transactions recorded by Larva Labs over the period from June 2017 to March 2022. The performance of NFTs was compared with the return of other assets, such as stocks, bonds, gold, and cryptocurrencies. The conclusion was that "NFTs provide superior investment returns than all the other asset classes". Unfortunately, these tokens also have a very high volatility, which is why investors need to be careful in building the portfolios that include these assets. The researchers also studied the applicability of conventional asset-pricing models, such as the CAPM, for cryptocurrencies and NFTs, and demonstrated that there are some similarities between these digital assets and traditional financial assets. This fact intensifies the preoccupation in the field for the creation of new models to explain the evolution of prices and the profitability for these digital assets. The evaluation of the price of NFTs is realized in a less traditional, conventional way, the researchers trying to identify the specific factors influencing the course for these tokens.

Similar results were obtained by Borri et al. [49], stating that there are intense connections between the returns of NFTs and cryptocurrencies, but in many cases, the return variations of NFTs remain unexplained. Using data from 2018 to the end of 2021 for the most important exchanges (Crypto kitties, Gods Unchained, Decentral, Open Sea, and Atomic), the scholars focused on the examination of the exposure of the NFTs market to the cryptocurrency market and also to traditional assets, such as equity, commodity, and currency. The conclusions regarding the relationship with the traditional assets market was that there is little correlation between these markets, similar to the findings of Chen [30] and Ko et al. [48]. Taking into account these conclusions, Ko et al. [48] suggested the inclusion of NFTs in the portfolios of investors. In this way, due to the low correlation with the traditional asset class, NFTs can be successfully used in order to construct a well-diversified portfolio. Similar conclusions are supported by a study by Schaar and Kampakis [50] based on regression (HR), used to investigate the performance of a specific NFT collection (CryptoPunks) for the 2017–2021 period.

The study by Umar et al. [51] focused on NFTs and five major asset classes, namely, bitcoin, bonds, stocks, gold, and crude oil. The scholars applied SWC methodology and concluded that NFTs absorbed "risk during the outbreak of COVID-19" (p. 5). The NFTs–bitcoin movements observed were explained by the technology-driven effect considering that the two assets are based on the same technology.

Using data for period from March 2013 to March 2019, Dowling [16,27] analyzed the links between the NFTs market and the cryptocurrency market, considering that both assets are based on blockchain technology. The scholar concluded that "NFT pricing seems quite distinct to cryptocurrency pricing in terms of volatility transmission" (p. 5), but there are common factors driving both markets, such as sentiment and uncertainty [52]. Unlike traditional financial asset markets or cryptocurrency markets where the links between the sub-markets are quite strong, in the case of the NFT market, little spillover was detected between component submarkets.

In a study focused on the largest blockchain market, Decentral, NFTs termed *LAND* are traded based on parcels of virtual real estate [27]. Inefficiency in pricing and a rapid rise in value were demonstrated, the possible explanations for this inefficiency being the immaturity of the market, manipulation, and even fraud. Fraud is also a reality in the cryptocurrency market, but although incidents are less frequent, the impact is greater [53].

Using weekly data between 2017 and 2021, based on the vector autoregressive (VAR) model, Pinto-Gutiérrez et al. [54] found that "the previous week's Bitcoin returns are significant attention drivers to NFTs" (p. 11). The scholars also used a wavelet coherence analysis, to demonstrate that the interest of investors in NFTs increased after a rise in both Bitcoin and Ether returns was recorded. The growing interest of investors in NFTs was thus explained by the explosion in the cryptocurrencies' price since 2021.

Based on the studies in the field, if most NFTs are created and registered as individual assets on the Ethereum blockchain, there would certainly be a strong relationship with cryptos, and mostly with Ethereum. In this context, the following hypotheses were formulated:

H1: *NFT price is significantly influenced by the cryptocurrency prices.*

H2: *NFT price and cryptocurrency prices present a causal relationship.*

3. Data and Methodology

In order to respond to the research questions, we analyzed the data related to NFTs, Ethereum, Crypto Coin, and Bitcoin, i.e., their prices. The monthly data are provided by Yahoo Finance, from September 2020 until February 2022. The data description is presented in detail in Table 1 [55–58].

Table 1. Variables description.

Variables	Description	Studies in the Literature
NFT	NFT open price	Ante, 2021 [47], Dowling, 2022 [16]. Dowling, 2022 [27], Nadini et al., 2021 [59], Kong and Lin 2021 [60], Umar et al. [51]
Bitcoin	Bitcoin USD open price	Sharma et al. [12], Ante, 2021 [61], Dowling, 2022 [27], Umar et al., 2022 [51]
Crypto Coin USD	Crypto Coin USD open price	Ante, 2021 [47], Dowling, 2022 [16]
Ethereum	Ethereum open price	Ante, 2021 [47], Kong and Lin, 2021 [61] Dowling, 2022 [16], King and Koutmos Kong, 2021 [47], Truby et al., 2022 [42]

As it can be observed in Figure 2, the four variables registered a similar trend, increasing until 2021, and oscillating thereafter, but still presenting a slightly similar trend.

In order to examine the characteristics of the variables included in the analysis, the descriptive statistics of the data were conducted (Table 2). The average price of NFTs for the analyzed period is 0.154, varying from 0 to 0.475, with standard deviation 5.120, skewness 0.707, and kurtosis 3.989. The mean for the Bitcoin price is 39,668.56, minimum value is 13,780.99, maximum is 61,320.45, standard deviation is 13,713.11, skewness −0.155, and kurtosis 2.251. In case of Crypto Coin USD, it registered an average of 0.217, and a standard deviation of 0.175, the values varying between 0.058 and 0.690, skewness is 1.518, and kurtosis is 4.2570. The medium price in the case of Ethereum is 2200.30, with standard deviation of 1325.39, skewness is 0.086, and kurtosis is 1.999.

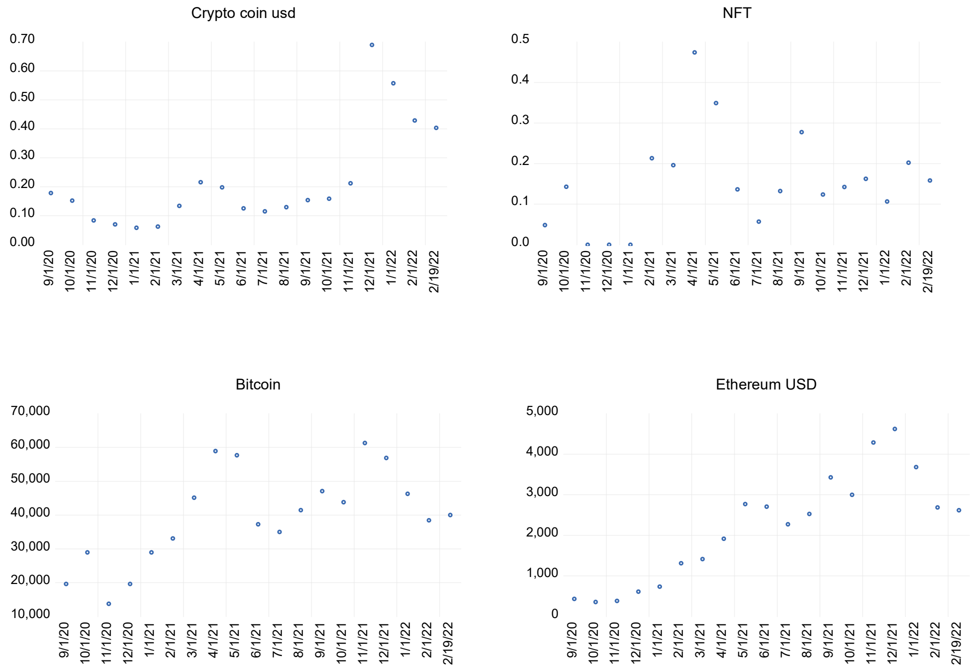

Figure 2. Variables trend.

Table 2. Summary Statistics of Dependent and Explanatory Variables.

Variables	Mean	Standard Deviation	Min	Max	Skewness	Kurtosis
NFT-USD	0.154	0.120	0.000	0.475	0.971	3.989
Bitcoin USD	39,668.58	13,713.11	13,780.99	61,320.45	−0.155	2.251
Crypto Coin USD	0.217	0.175	0.059	0.690	1.518	4.257
Ethereum	2200.30	1325.39	360.31	4623.68	0.086	1.999

In order to analyze the relationship between the two variables we used the VAR methodology, the model being the vector autoregressive model (VAR) or vector error correction model (VEC).

The VAR model was introduced into the economic field and its widespread application in dynamic analysis of economic systems was promoted by Sims [62]. In the case of the VAR model, each endogenous variable is considered as the lagged value of all endogenous variables in the system [63]. Johansen cointegration is used to identify the long-run relationship among variables, using the trace test and the max-eigenvalue test [62]. As Johansen cointegration can be applied in case the variables are of order I(1), the stationarity was tested using the Augmented Dickey–Fuller test. Engle and Granger [64] combined cointegration and error correction models are applied in order to establish the trace error correction model. In case of a cointegration relationship between variables, the error correction is derived from the autoregressive distributed lag model. Thus, each equation in the VAR model is an autoregressive distributed lag model; the VEC model is a VAR model with cointegration constraints [65].

The Vector Correction Model (VECM) has been applied to establish if the model is divergent or convergent, and thus the variables are close to the equilibrium from long-run to short-run. The VEC model presents a cointegration relationship, with a wide range of short-term dynamic fluctuation, restricting long-term behavior of the endogenous variables and converging to their cointegration relationship. VECM derives from the unrestricted vector autoregressive (VAR), in order to estimate non-stationary time series that were identified to be cointegrated [66]. Each variable represents a linear function of past lags of itself and past lags of the other variables [67]. The VECM model can be expressed as:

$$\Delta Y_t = \sum_{i=1}^{p} \phi Y_{t-1} + \mu_t \tag{1}$$

where: Y_t is the vector of endogenous variables; p is the order of lag; Y_{t-1} is the lagged variable; ϕ is the coefficient to be estimated; and μ_t is a stochastic error term, which also known as impulse or innovation [68].

A current trend in the Fintech literature is represented by a belief that endogeneity occurs as a consequence of explaining how a choice variable affects a desired outcome. In our case, NFT represents the endogenous variable, Bitcoin USD, Crypto Coin USD, and Ethereum representing the exogenous variables.

The analysis was performed using EViews Student version.

4. Empirical Results

Using time series variables, NFT price, Crypto Coin price, and Bitcoin price, we first checked the stationarity of variables using Augmented Dickey-Fuller test. The results and findings are presented in Table 3. The results indicate that all variables are stationary at 1st difference.

Table 3. Unit root test—ADF.

Variables	Level		First Difference	
	t-Statistic	Prob.	t-Statistic	Prob.
NFT-USD	−2.599	0.111	−4.579	0.003
Bitcoin USD	−1.891	0.328	−3.726	0.014
Crypto Coin USD	−1.386	0.566	−4.026	0.008
Ethereum	−1.405	0.556	−3.495	0.022

As the four variables are integrated of order I, the Johansen cointegration technique can be applied to identify if there is a long-run relationship among variables. The trace test indicates that there is a long-run relationship between variables (Table 4) as the trace statistic is greater than the critical value, thus rejecting the null hypothesis that there is no cointegration and accepting the alternative that there is at most 3-integration relationship, considering a probability of 90%. Instead, the trace test rejects the null hypothesis at most 1 (Prob = 0.1787) and at most 2 (Prob = 0.1973). Therefore, the trace test indicates that there exist three cointegration relationships among the three variables.

Table 4. Unrestricted Cointegration Rank Test (Trace).

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob. **
None	0.770	49.500	47.856	0.035
At most 1	0.543	24.537	29.797	0.179
At most 2	0.375	11.237	15.495	0.197
At most 3	0.174	3.241	3.842	0.072

Trace test indicates cointegrating at the 0.05 level ** denotes rejection of the hypothesis at the 0.05 level.

The conclusion is also confirmed by the max-eigen value test (Table 5), and thus three cointegration relationships among the three variables.

Table 5. Unrestricted Cointegration Rank Test (Maximum Eigenvalue).

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob. **
None	0.7697	24.9629	27.5843	0.1004
At most 1	0.5426	13.2992	21.1316	0.4251
At most 2	0.3752	7.9968	14.2646	0.3790
At most 3	0.1736	3.2407	3.8415	0.0718

Max-eigenvalue test indicates cointegrating at the 0.1 level. ** denotes rejection of the hypothesis at the 0.05 level.

The presence of cointegration between variables suggests a long-term relationship among the variables under consideration, VECM being suitable to be applied.

The long run model (Table 6) can be written as follows:

$$\begin{array}{c} \text{NFT} = 6.25 \times 10^{-5}\ \text{Ethereum} - 0.1339\ \text{Crypto Coin} - 1.27 \times 10^{-5}\ \text{Bitcoin} \\ (1.3 \times 10^{-5}) \qquad (0.0921) \qquad (1.2 \times 10^{-6}) \end{array} \tag{2}$$

Table 6. VECM results.

Error Correction:	D(NFT)	D(Crypto Coin)	D(Ethereum)	D(Bitcoin)
CointEq1	−0.6046 (0.6352) [−0.9518]	−0.7421 (0.6014) [−1.2339]	4929.719 (2828.57) [1.7428]	82,207.85 (58,010.9) [1.4171]
D(NFT(−1))	−0.2127 (0.4155) [−0.5120]	0.0060 (0.3934) [0.0153]	−3751.910 (1850.31) [−2.0277]	−47626.48 (37,947.8) [−1.2551]
D(Bitcoin(−1))	6.16×10^{-6} 5.9×10^{-6} 1.0364	2×10^{-6} 5.6×10^{-6} 0.3554	−0.4492 (0.3201) [−1.4031]	−10.6571 (0.5427) [1.6334]
D(Crypto coin(−1))	−0.0836 (0.3097) [−0.2700]	−0.4775 (0.2932) [−1.6286]	504.2578 (1378.99) [0.3657]	19,493.50 (28,281.5) [0.6893]
D(Ethereum(−1))	−0.0001 (7.2×10^{-5}) [1.4162]	0.0001 (6.8×10^{-5}) [1.8618]	−0.4492 (0.3201) [−1.4031]	−10.6571 (6.5653) [−1.6233]
C	0.0107 (0.0294) [0.3649]	0.0027 (0.0279) [0.0984]	131.4039 (130.998) [1.0031]	1222.143 (2686.63) [0.4549]

According to this equation, NFT has a negative and significant relationship with Ethereum, whereby a one unit increase in Ethereum price results in a 6.25×10^{-5} decrease in NFT price. Meanwhile, Bitcoin and Crypto Coin register a negative and significant relationship with NFT, so that when the Bitcoin price increases by 1 unit, the NFT price decreases by 1.27×10^{-5} units, and when the Crypto Coin price increases by 1 unit, the NFT price decreases by 0.1339 units, thus confirming hypothesis 1.

The results from VECM (Table 6) show that the model is 60.46% divergent monthly. The cointegration between the three variables does not indicate the direction of a causal relationship between them. In order to verify the direction of causality between NFT, Bitcoin, Ethereum, and Crypto Coin, Granger causality between the three variables was estimated (Table 7).

Table 7. Granger Causality Test.

Null Hypothesis	Chi-Sq	Prob.	Decision
D(Crypto Coin) does not Granger-cause D(NFT)	0.0073	0.7871	Do not reject
D(NFT) does not Granger-cause D(Crypto Coin)	0.0002	0.9878	Do not reject
D(Ethereum) does not Granger-cause D(NFT)	2.0057	0.1567	Do not reject
D(NFT) does not Granger-cause D(Ethereum)	4.1117	0.0426 **	Reject
D(Bitcoin) does not Granger-cause D(NFT)	1.0741	0.3025	Do not reject
D(NFT) does not Granger-cause D(Bitcoin)	1.5752	0.2095	Do not reject
D(Ethereum) does not Granger-cause D(Crypto Coin)	3.4663	0.0626 *	Reject
D(Crypto Coin) does not Granger-cause D(Ethereum)	0.1337	0.7146	Do not reject
D(Bitcoin) does not Granger-cause D(Crypto Coin)	0.1263	0.7223	Do not reject
D(Crypto Coin) does not Granger-cause D(Bitcoin)	0.4751	0.4907	Do not reject
D(Bitcoin) does not Granger-cause D(Ethereum)	8.9107	0.0028 ***	Reject
D(Ethereum) does not Granger-cause D(Bitcoin)	2.6350	0.1045 *	Reject

** denotes rejection of the hypothesis at the 0.05 level; * denotes rejection of the hypothesis at the 0.1 level; *** denotes rejection of the hypothesis at the 0.01 level

Table 7 provides the results of pairwise analyses. Significant probability values denote rejection of the null hypothesis; thus NFT price "Granger-causes" Ethereum price, being a unidirectional causality at the 5% significance level. Ethereum price "Granger-causes" Crypto Coin, being a unidirectional causality at the 10% significance level. The Bitcoin price "Granger-causes" Ethereum price and vice versa, being a bidirectional causality.

As an additional check of the Cointegration test's findings we used the impulse response function. The impulse response functions are shown in Figure 3.

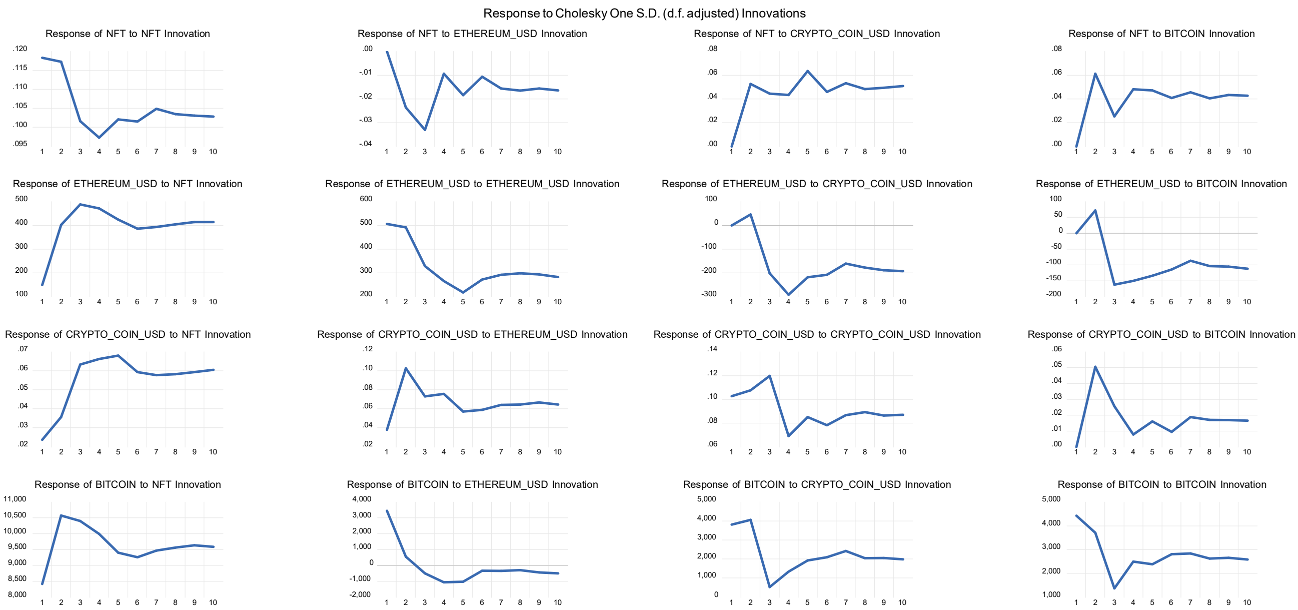

Figure 3. Impulse Response Functions.

The response of NFT to Ethereum is negative and dies out. The responses of NFT to Crypto Coin and Bitcoin are positive and disappear. The response of NFT to the other cryptocurrencies is positive. Thus, hypothesis 2 was confirmed.

In conclusion, although NFTs and the cryptocurrencies are activating on the same market, their prices are not closely related over time. The results highlighted relationships between NFTs and Ethereum, between Ethereum and Crypto Coin, and between Bitcoin and Ethereum, Ethereum being a bridge between all four. Therefore, NFTs present a relationship with Ethereum, the NFT price having a causal effect on the price of Ethereum. Similar results have been obtained by other scholars, such as Dowling [16,27], Chen [30], Ante 2021 [47], Borri et al. [49], Ko et al. [48], Schaar and Kampakis [50], and Umar et al. [51] whose research focused on NFTs and different major asset classes, namely, bitcoin, bonds, stocks, gold, and crude oil.

However, the intensification of the use of these assets by investors is under the sign of contradictory factors. On the one hand, the use of new technologies has certain limits imposed by a certain reluctance on the part of companies interested in promoting these assets, but also consumers, taking into account specific theories or models, such as the Technology Acceptance Model, the Unified Theory of Acceptance and Use of Technology Model, and the Diffusion of Innovations theory [37–39]. As Generation Z will be increasingly present in this market, the barriers generated by the hesitant acceptance of new technologies will be mitigated [68–70]. Even though important differences from traditional financial asset markets are detected, herding behavior is present in cryptocurrency markets [46]. In addition, fraud has been detected in the cryptocurrency market, and although incidents are less frequent, the impact is greater [53]. On the other hand, blockchain technology is a new method for reshaping the world economy through different sectors like entrepreneurship, financial markets, and innovation but cryptocurrencies and NFTs could also be used for money laundering and tax evasion [20,44–46].

5. Conclusions

The blockchain market is characterized by uncertainty and volatility in, with extreme risk being registered among NFTs and other cryptocurrencies. In this context, our paper analyzed the relationship between the cryptocurrency price and the NFT price, contributing to the emerging literature on the latter. In line with Dowling's [16] conjecture, we found that Bitcoin, Crypto Coin, and Ethereum prices affect the NFT price, while the NFT price has a causal effect only on the price of Ethereum. Thus, the NFT price is driven by the cryptocurrency prices. This is plausible, since cryptocurrencies are the common currency for buying and trading NFTs [47,60]. A drop in cryptocurrency value leads to lower purchasing power, depressing the NFT market. In case cryptocurrencies appreciate, investors search for alternative investment opportunities, such as in the context of ETH, the standard denomination of NFTs.

Our results indicate that the NFT market is volatile and sensitive to shocks on account of cryptocurrencies. Although the NFT market is more mature than the other cryptocurrency markets, the NFTs price is caused by the cryptocurrencies' prices, while the NFT price does not have a causal effect on the prices of cryptocurrencies, except the Ethereum price.

These results contribute to the research on spillover effects between blockchain-based markets of different sizes. These results are beneficial not only for investors in the new cryptocurrency and NFTs markets but also for investors in traditional financial markets who can diversify their portfolios, given the weak correlation between the price evolution of NFTs and traditional assets. This study may also help policymakers and regulators to structure and improve their policies toward investing in financial markets, as cryptocurrencies require considerable risk-mitigation avenues for investors and financial markets. Therefore, our results generate useful insights and policy ramifications that highlight the benefits of investing in blockchain markets and suggest ways to remove the risks related to this market.

The authors are aware of the limitations of this research, partly due to the analysis period but also the variables taken into account. A future direction of research could be the analysis of the returns of NFTs and cryptocurrencies for the pre-pandemic period and the pandemic period, in order to identify the importance of economic uncertainty in these segments of the market. In addition, considering the attractiveness of cryptocurrencies for investors, especially during the pandemic period, authors should also consider the analysis of the speculative and hedging possibilities that these assets offer to portfolio investors in different markets (European, American, and Asian markets). The analysis of the correlations of the cryptocurrency market with the markets of traditional assets, such as gold or petroleum, can be another future direction of research.

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