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The Bitcoin's Network Effects Paradox—A Time Series Analysis

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Abstract

Bitcoin faces a network effects problem: although its widespread adoption is related to an increase in the number of users, its price volatility lowers consumption. Given the low consumption, a low number of merchants accepting bitcoins would also be expected. However, an increasing number of venues (*i.e.* merchants) are observed. This paper aims to investigate that paradox. An econometric procedure is followed examining the linkages among Bitcoin's price volatility, market capitalization, and the number of venues, by using weekly time series data for a five-year time period (February 2013-February 2018). The results indicate that the number of merchants is unaffected by a shock of the market capitalization, while it is only initially affected by a shock of the price and then stabilizes. Our study contributes to a better understanding of the network effects' phenomena appearing in the Bitcoin's market and has significant implications for e-commerce practitioners concerning their decision-making process about Bitcoin adoption.

Keywords

Bitcoin, Network Effects and Network Externalities, Market Capitalization, Price Volatility, Bitcoin Venues

1. Introduction

Bitcoin is the first decentralized peer-to-peer electronic payment network [1] and the leading cryptocurrency in terms of market capitalization [2]. However, Bitcoin's price volatility is considered as one of its main barriers to its widespread adoption and constitutes a critical issue for both academics and practitioners [3] [4] [5] [6].

Bitcoin, as a peer-to-peer electronic payment network, exhibits network effects [7] [8], which means that the value of the system grows for each user, as more users join the network [9] [10]. Bitcoin's widespread adoption is based on the mutual acceptance between merchants and consumers, which is a cross-side positive network effect, while the price volatility is a negative network effect. Bitcoin's adoption faces a network effects problem as the benefit in exchange of bitcoins is positively correlated with the number of users [11] [12]. More specifically, in order for Bitcoin to achieve widespread adoption, people have to use it in exchange for goods and services. But the problem is that people who own bitcoins prefer to hold them as an investment because they expect a higher value, due to its price volatility, instead of using them for consumption [13] [14]. Since the interest for consumption is low, it would be expected that few merchants will be interested in accepting bitcoins as a means of transaction. However, it was observed that the number of venues that accept bitcoins continuously increases [15] despite the small consumer base. These two contradictory facts constitute a paradox inside the Bitcoin network effect and this was the motive for this study. To the best of our knowledge, no other studies exist in the literature referring to this contradiction.

This paper aims to investigate the aforementioned paradox, by examining the relations among Bitcoin's price volatility, market capitalization, and the number of venues that accept bitcoins, using weekly time series data for a five-year period (February 2013-February 2018). This paradox, as previously described, is probably explained by that the negative network effect of Bitcoin's price volatility is not yet internalized; thus, the existing negative network externalities (*i.e.* speculative and investment trends) hinder Bitcoin's widespread adoption.

The distinction between network effects and network externalities is not clear in the literature [16] [17]. Our study attempts to bridge this theoretical gap by indicating the close relationship of the two terms, as well as highlighting the differences between them. It also attempts to fill the practical gap that exists since there is not so far a full understanding of the network effects' phenomena and the network externalities that appear in the Bitcoin's market, which conduce to the delay of its widespread adoption.

The remainder of the paper is organized as follows: the theoretical background about network effects, externalities, and their relation to Bitcoin, as well as the variables of the study are presented in the next section. After that, the data and the descriptive statistics results are given, followed by the methodology of our study. The empirical results are given in the following section and then, conclusions and implications are summarized. The limitations of the study and future research directions are also outlined in the last section.

2. Theoretical Background

2.1. Network Effects, Externalities, and Bitcoin

Network effects have been defined as the circumstances in which the net value of an action (e.g. consuming goods, subscribing to telephone services) is affected by the number of agents (*i.e.* participants in the network) taking equivalent actions [17]. Network effects appeared as a concept in early of 20th century by Theodore Vail, the President of Bell Telephone and were popularized in early 1980s by Robert Metcalfe in the homonymous law [18]. According to Metcalfe's law, the value of a network is proportional to the square of the number of nodes, *i.e.* the number of network users [10]. Moreover, Liebowitz and Margolis [9] coined the term of "synchronization value", which is the additional value derived from the fact that the users of the network are able to interact with other users and this value is the essence of network effects. For example, Bitcoin's value is limited if it is composed of only two users, while Bitcoin's value raises for each user as more and more users join the system and interact with each other. Network effects are believed to be endemic in the digital economy. Digital economy experiences problems that are different in character from the problems that have been solved by markets for more ordinary commodities in the traditional economy [9] [19] [20]. In the traditional economy, the rarer a product is, the more value it has (e.g. diamonds, oil). On the contrary, in the digital economy, a digital product in abundance has greater value: the more something is demanded and the more is expected to be demanded then the more valuable it becomes (e.g. mobile phones, social media).

This feature of digital products is known as "network externalities", which are the economic concept of the external consequences derived by the network effects and are considered the drivers of the networked economy [21]. The term was coined by Jeff Rohlfs [22]. A network externality is the effect of a transaction between two parties on a third party which is not involved in the execution of that transaction [23] and depends upon the number of other users who are in the same network [19]. Network externalities are the side effects or consequences on the user of a good/service that the existence of other users utilizing the same or similar goods/services has. The enchantment of network externalities is that they often come out as surprise and as a byproduct that was not calculated or foreseen in any way [23]. Network externalities are exhibited wherever a user enjoys benefits or suffers costs from changes in the size of an associated network [17]; thus, they can be positive and negative. Positive network externalities are the main reason for building networks. However, the same phenomenon can be both positive and negative, depending on the role of the observer [23]. For example, in Bitcoin, as more users join the network, positive network externalities arise for exchange services since the increase in transactions will grow their profits, but these increased transactions cause congestion in the network, resulting in the augmentation of transaction fees, *i.e.* a negative network externality for the users.

Network effects and network externalities have been used interchangeably in the literature [16]; however, network effects are not always network externalities [17]. The difference between them lies in whether the impact of an additional user on other users is somehow internalized [9]. Internalizing an effect means that it is no more directed towards a third party. Any network effect is an externality only if not internalized [9] [16]. When network effects are internalized, they are no longer externalities [9]. The usual ways to achieve internalization is via fines & taxes or subsidies. For example, network externalities that derive by joining a network can be internalized by subsidizing early adopters, who would not otherwise join this network if they had to face the full marginal cost of their participation in the network.

Network effects [7] [8] and externalities [24] [25] appear in the case of Bitcoin as more participants join the network. Bitcoin's network has multiple participants, which can be grouped in two basic categories: enablers (miners, exchanges, and developers) and users (merchants, consumers, investors, and speculators) [26]. In the case of the Bitcoin's adoption, the network effects mean the more merchants accept bitcoins, the more consumers are likely to pay with bitcoins and vice versa. However, Bitcoin faces a network effects problem, since the benefit in using bitcoins is positively correlated with the number of users: if few merchants accept bitcoins, the benefits for consumers to use products paid with bitcoins are low; if few consumers use bitcoins, merchants have little incentive to accept bitcoins [11] [12]. This benefit in using cryptocurrencies is based on their value, which is linked to the usage to buy goods and services paid with them. Because of this value, most owners of cryptocurrencies want to hold them instead using them to consume; therefore, cryptocurrencies are not widely used in commerce [14]. The utility of a cryptocurrency is based on the mutual concepts of "acceptance" and "usage" between merchants and consumers and the biggest challenge is convincing both parts to use it in exchange for goods and services [12]. In order for Bitcoin to achieve widespread adoption, people have to use it, but the problem is that people who own bitcoins prefer to hold them as an investment instead of using them for consumption because they expect a higher value [13].

Since the number of Bitcoin consumers is small, it would be expected that few merchants will accept bitcoins as a means of transaction. However, as it can be seen in **Figure 1**, which depicts the volatility of the Bitcoin's closing price in USD [27] [28] and the number of venues that accept bitcoins [15], during a five-year time period, there is a steady increase of the venues, despite the lack of interest for consumption, which is due to investment and speculative trends that are triggered by the Bitcoin's price volatility, as aforementioned. More specifically, there are two opposite facts, which constitute a paradox in the Bitcoin network effect: the small consumer base and the increasing number of merchants.

The essence of the paradox lies in the management of expectations, which is a feature of the networked economy. In traditional markets, equilibrium is explained by the balance between costs and demand, between marginal costs and marginal utility. In networked markets, there is also equilibrium to be achieved between actual demand and expectations of total demand [21]. Any investor or

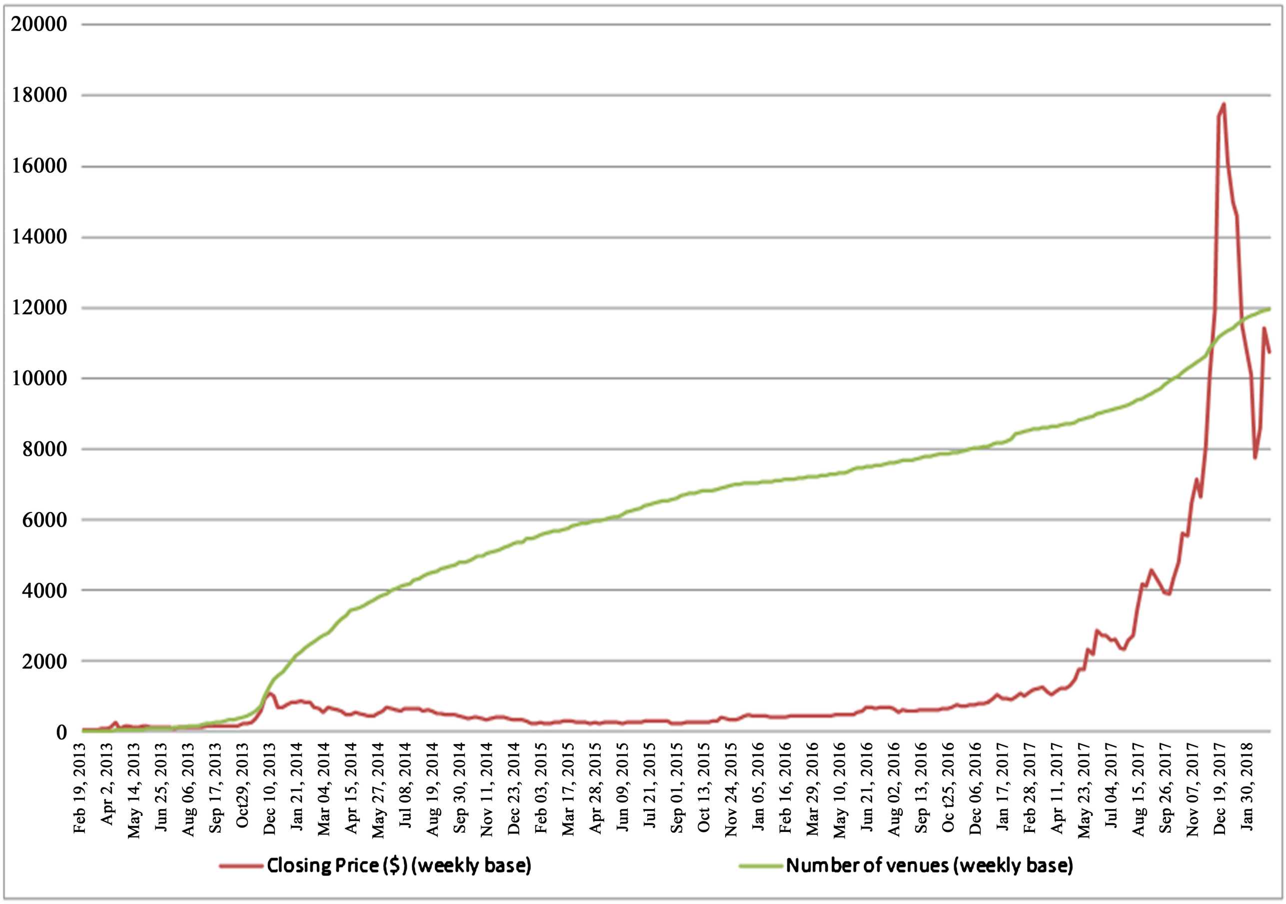

Figure 1. Bitcoin's closing price in USD and venues that accept bitcoins.

speculator who expects Bitcoin returns is a potential consumer, while merchants expect to increase their sales turnover. When the equilibrium between those expectations will be achieved, the size of the network will be optimal for both parts, meaning that the Bitcoin's widespread adoption as a means of transaction is achieved. At this point, it is worth clarifying the existence of the Bitcoin's network effects paradox in the short and long term. Bitcoin price is highly volatile; however, as it is shown in **Figure 1**, the sudden increase or decrease (shock) in the Bitcoin price in the short term is accompanied by a long-term trend of increase or decrease in Bitcoin price. If the long-term trend of the Bitcoin price is increasing or it is expected to increase, despite the short-term shocks during this trend, the demand for bitcoins is increased, thus the number of the Bitcoin users (*i.e.* potential consumers) rises; therefore, an increasing number of venues are expected and the paradox is eliminated. On the other hand, if the long-term trend of the Bitcoin price is decreasing or it is expected to decrease, the demand for bitcoins is also decreased, thus the number of the Bitcoin users is reduced; therefore, an increase in the number of venues is contradictory and this constitutes a paradox.

The existence of this paradox can be explained possibly by the fact that the negative network effect of Bitcoin's price volatility is not yet internalized. Consequently, negative network externalities exist (e.g. speculative and investment trends) and the equilibrium network size is smaller than optimal. This is the reason for which Bitcoin's price volatility remains one of its main barriers to mass adoption [3] [4] [5] [6]. Nevertheless, Bitcoin has shown its ability to internalize network effects so far. For example, until today internalization in Bitcoin has been applied in two cases: 1) the case of early miners, who were subsidized (rewarded) to join Bitcoin by receiving greater reward for each mined bitcoin according to the Bitcoin protocol. Since the proof-of-work mining system of Bitcoin requires a great amount of computational power, miners should be financially sustainable in order to face expenses for hardware investments and electricity power, as they are the basic enablers of the Bitcoin network [29] and are dependent on the user participants, and 2) the case of early users of Bitcoin, who were also motivated to join the network, since the transaction fees were minimal compared to the transaction fees of other payment networks (e.g. credit cards, PayPal). However, as more and more users were joining the network and transactions increasing, negative network externalities derived from the fact that the network was overloaded. The transactions' verification was delayed for a long period of time, because the size of the blocks was not enough to support the increased amount of transactions. This fact conduced to a significant increase of the transaction fees, in order miners to be motivated to accelerate the verification of the transactions, by using more computational power. These negative network externalities for users were internalized by the Bitcoin forks, which were all attempts to increase the transaction capacity of the network, thus resulting to incentivize more users to adopt Bitcoin.

The above examples show that the Bitcoin's ability to internalize the network effects eliminates the derived network externalities and conduces to an increase of the users. When more people use Bitcoin in exchange for goods and services, the speculative trends will decrease and the volatile cryptocurrency should start to stabilize [30].

2.2. Variables of the Study

The aforementioned paradox is related with the concepts of price volatility, users' (merchants and consumers) adoption, and network effects. For the investigation of the paradox, the following three variables were taken into consideration.

One variable is the closing prices of Bitcoin, whose variances indicate the Bitcoin's price volatility and represents the negative network effect that affects the observed paradox. Price volatility is a negative network effect, whereby too many investors and speculators can cause the network to be useless for payments, thus reducing the benefit in using bitcoins in exchange for goods and services for the other users of the network. Bitcoin's price volatility is internally driven, meaning that the Bitcoin's market returns are driven by its market participants and this feature indicates that Bitcoin's is still in an early life-cycle stage [31]. An internal and structural reason underlying Bitcoin's price volatility is its perfectly inelastic supply (due to its fixed supply, as it is defined by the system's protocol), which results in small changes in demand to cause large price movements [32]. These large price movements in turn conduce to expectation for returns. Therefore, speculative demand is considered to be the primary driver of Bitcoin's price volatility [31] [32], which hinders consumption and should also be expected to hinder the interest for merchants to accept bitcoins, while an increase in the number of venues is observed, as aforementioned.

Another variable is the number of venues that accept bitcoins, whose upward trend indicates the merchants' adoption and represents a positive same-side network effect [33]. This network effect in conjunction with consumers' adoption forms a positive cross-side network effect. However, this network effect can be actually evaluated only by the side of merchants, since there are recorded data only about the venues that accept bitcoins, while the number of Bitcoin consumers is not officially recorded. According to Suomi [23], measuring networks is difficult and overall measures that might allow for comparing different types of networks are rare, if any. This study is akin to other empirical studies [34] but it was considered not to use, as variables, the number of unique transactions or addresses [7] [34] nor the number of digital wallets and nodes. Because, since one user can have more than one digital wallet, which in turn may consist of many unique addresses, and conduct many transactions of low value, but the user is still only one with a given total amount of bitcoins, these variables are perhaps a way to measure the size of the network in the absence of other recorded data but may lead to misconceptions about the actual size of the network. Also, the number of unique transactions, unique addresses, and the number of digital wallets refer to all types of "users" (merchants, consumers, investors, and speculators) without distinction. Therefore, these variables are not suitable to evaluate the observed paradox of this study. Finally, in the literature the number of network nodes is considered the only actual comparable figure [23]. However, in the case of Bitcoin, since the number of nodes only refers to mining bitcoins, transactions' verification and even transactions between them (e.g. for remittances or just for sending bitcoins from one wallet to another of the same node), it does not reflect the interaction between merchants and consumers.

The last variable is market capitalization, which is related to the first aforementioned variable as it is calculated by multiplying the closing price by the circulating supply of bitcoins [27]. Therefore, Bitcoin's market capitalization follows its price volatility and it is expected to affect the observed paradox similarly. Market capitalization is the economic result that derives from the trading interaction of Bitcoin's users. Thus, market capitalization represents the additional value of interaction among the users of the Bitcoin network, *i.e.* the "synchronization value", which derives by the existence of network effects, according to Liebowitz and Margolis [9], as mentioned above. Market capitalization determines the total value of the Bitcoin network [35] and is used to rank its relative size compared to other cryptocurrencies or traditional forms of payments (e.g.

credit cards, fiat currencies); thus, network externalities derive, e.g. more digital wallets, exchange services appear for a cryptocurrency with bigger market capitalization than others. The examination of the relations among the above three variables will help to elucidate the observed network effects' paradox of this study.

3. Data and Descriptive Statistics

Historical data were collected for a time period of five years (February 19, 2013-February 27, 2018) by the databases of three websites. This is the first five-year time period in which venues that accept bitcoins appear.

Closing prices were extracted by a combination of two websites: 1) Coinmarketcap [27], which has daily historical data since April 28, 2013 and 2) Coindesk [28], which has daily historical data since July 18, 2010. Coinmarketcap was preferred for the collection of the majority of the large amount of data, as the processing of the extracted data was more user friendly than that of Coindesk; however, the latter covered an earlier time period.

The numbers of venues that accept bitcoins were recorded by the website Coinmap.org [15], which has weekly historical data since February 19, 2013, while the first non-zero value appears on February 26, 2013 and is 3 venues. The website belongs to SatoshiLabs s.r.o. company and all entries are crowdsourced: they are added voluntarily either by users who are interested in publishing a venue in the map or by bitcoin merchants themselves. Consequently, the data analyzed in this paper were recorded on a weekly basis, because the only available historical data about Bitcoin's venues are given on a weekly basis.

Similarly to the closing prices, the market capitalization prices were extracted by the combination of the two websites: Coinmarketcap [27] and Data.bitcoinity.org [36].

In **Table 1**, the descriptive statistics of the examined variables are depicted.

Table 1. Descriptive statistics.

	LMARKET	LNPRICE	LNVENUES
Mean	23.57250	6.338397	8.084566
Median	22.61651	6.144379	8.800034
Maximum	38.00527	9.785605	9.387398
Minimum	19.48800	3.381675	1.098612
St. Deviation	3.841811	1.234070	1.765193
Skewness	3.019497	0.748604	-2.335614
Kyrtosis	11.14081	3.663765	7.965144
Jarque-Bera	1125.884	29.39262	507.3304
Probability	0.00000	0.00000	0.00000

a. L, LN = Logarithms, where: LMARKET is the Bitcoin's market capitalization; LNPRICE is the Bitcoin's closing price; LNVENUES is the number of venues that accept bitcoins.

In Table 1, we can see that all variables present positive asymmetry (except for LNVENUES), they are leptokurtic, and do not follow normal distribution.

4. Methodology

Based on the study of Shin and Pesaran [37], a multi-variable unstructured VAR model of order p can be written as:

$$y_t = \sum_{i=1}^{p} A_i y_{t-i} + Bx_t + e_t,\quad t = 1,2,\cdots,T \tag{1}$$

where:

$y_t = \left(y_{1t}, y_{2t}, \cdots, y_{nt}\right)'$ is an $n \times 1$ vector of jointly determined dependent variables.

A_i $\quad i = 1,2,\cdots,p$

B $\quad$ are $n \times n$ and $n \times d$ coefficient matrices.

x_t $\quad$ is a $d \times 1$ vector of deterministic or exogenous variables.

p $\quad$ is order of lags.

According to Shin and Pesaran [37], we make the following assumptions in the above model:

- $E\left(e_t\right) = 0$, $E\left(e_t e_t'\right) = \Sigma$ for all t, where $\Sigma = \left(\sigma_{ij}, i, j = 1,2,\cdots,n\right)$ is an $n \times n$ positive definite matrix, $E\left(e_t e_{t'}'\right) = 0$ for all $t = t'$, and $E\left(e_t / x_t\right) = 0$.
- All the roots fall outside the unit circle.
- There is not full collinearity among $y_{t-1}, y_{t-2}, \cdots, y_{t-p}, x_t \quad t = 1,2,\cdots,T$.

4.1. Unit Root Tests

For the integration test of the series of the examined model, we use the Dickey-Fuller [38] [39] tests, as well as Phillips-Perron [40] test. Dickey-Fuller [38], through Monte-Carlo simulation, found a suitable asymmetric distribution that used in unit root test. This distribution can be used to separate an AR (1) model from an integrated series. In the case that a time series follows an autoregressive model of higher order, AR (p) then we use the Augmented Dickey-Fuller (ADF) [39] test, which comprises the lags of dependent variable that corrects the autocorrelation of the residuals. Phillips [41] and Phillips-Perron [40] suggest a non-parametric test for the estimation of coefficients' model making some changes to t-statistic. Phillips-Perron test (PP) differs from the ADF test mainly on the examination of autocorrelation and heteroscedasticity of errors. In other words, Phillips-Perron methodology deals with a non-randomness of the residuals, modifying t distribution using non parametric methods [42].

4.2. Johansen Cointegration Test

Johansen [43] and later on, Johansen and Juselius [44] [45] proposed a technique using VAR models (Vector Autoregression), where the maximum number of cointegrating vectors among a group of variables can be defined. This technique is known as Johansen maximum likelihood cointegration test. Maximizing likelihood function with the constraint that there are r cointegrating relationships among variables, we can proceed to cointegration tests applying the criterion of maximum likelihood with the following assumptions:

H_0: r cointegrating vectors

H_1: $r+1$ cointegrating vectors

Johansen and Juselius [44] for the above test created two statistical criteria, namely trace statistic and maximum eigenvalue. The asymptotic critical values for these tests can be found in MacKinnon, Haug, and Michelis [46] tables.

4.3. Granger Causality/Block Exogeneity Test

If there exists a cointegration vector between the variables under consideration, there is causality among these variables at least in one direction [47]. Granger [48] proposed a time-series data based approach in order to determine causality.

4.4. Impulse Response Function

A disadvantage of VAR models is that parameters' estimators of the system cannot be explained from economic point of view. This problem can be solved transforming a VAR model in a moving average one (Vector Moving Average—VMA). So, the responses can be calculated deriving from a random shock of errors of the values in endogenous variables.

To calculate these variations, impulse response functions are used. This function determines the responses of endogenous variables in shocks coming from certain variables. Thus, the response from a sudden shock of one or more standard deviations on current and future values in endogenous variables is calculated.

The explanation of impulse response functions is done with errors' orthogonalization where variance-covariance matrix is transformed to a lower triangular matrix. This transformation is called Cholesky decomposition. We have to point out that Cholesky decomposition depends on the sequence of the functions written on VAR model. Changing the sequence, we have different impulse response functions.

4.5. Variance Decomposition

Variance decomposition indicates the proportion of the variance of disturbance terms of a series in comparison to the proportion of the disturbance terms of other series. If the disturbance term does not explain any of the forecast error variance, then this series is the exogenous variable.

5. Empirical Results

5.1. Unit Root Analysis

In **Table 2**, the results from the two unit root tests used, namely ADF test and PP test, are depicted.

Given that the variables are integrated order I (1), we may proceed to determine whether there exists a long-run relationship using the Johansen cointegration test. The first step involves determining the optimal number of lags k to apply the VAR model. Two information criteria were used to determine the optimal number of lags that is the Schwarz Information Criterion (SBC) and Hannan-Quinn Criterion (HQ). The optimal length of time lags in each variable is two. Thus, a VAR second order model—VAR (2) arises.

5.2. Johansen Cointegration Test

Cointegration test, using Johansen methodology, is applied examining the long-run relationship among the variables. The Johansen technique examines the number of cointegrating vectors. In Table 3, the results of Johansen cointegration test are depicted.

In Table 3, we can see that both trace statistic and maximum eigenvalue present a cointegrating vector. Thus, it is concluded that there is a long-run relationship among the variables of the examined model. The cointegrating vector is

Table 2. Unit root analysis.

Variable	ADF		PP	
	C	C, T	C	C, T
LMARKET	0.838 (0)	−0.189 (0)	0.510 [3]	−0.508 [3]
ΔLMARKET	−13.99 (0)*	−14.89 (0)*	−13.982 [2]*	−14.091 [1]*
LNPRICE	−0.925 (1)	−1.553 (1)	−1.087 [5]	−1.816 [5]
ΔLNPRICE	−17.313 (0)*	−17.280 (0)*	−17.288 [5]*	−17.258 [5]*
LNVENUES	−1.880 (3)	−1.084 (3)	−0.310 [10]	−1.460 [10]
ΔLNVENUES	−6.828 (2)*	−7.870 (2)*	−10.354 [4]*	−11.162 [1]*

a. *indicates 10% level of significance. b. The numbers within parentheses followed by ADF statistics represent the lag length of the dependent variable used to obtain white noise residuals. c. The lag lengths for ADF equation were selected using Schwarz Information Criterion (SIC). d. MacKinnon [49] critical value for rejection of hypothesis of unit root applied. e. The numbers within brackets followed by PP statistics represent the bandwidth selected based on Newey-West [50] method using Bartlett Kernel. f. C = Constant, T = Trend, L, LN = Logarithms, Δ = First Differences.

Table 3. Johansen cointegration tests—VAR (2).

Cointegration rank tests	Hypothesis	Trace statistics	Critical values	p-values	Cointegrating equations
λ trace tests					
0.160	H_0:r = 0, H_1:r > 0	56.074	29.797	0.000	1
0.039	H_0:r = 1, H_1:r > 1	10.657	15.494	0.233	0
0.001	H_0:r = 2, H_1:r > 2	0.288	3.8414	0.591	0
λ_{max} tests					
0.160	H_0:r = 0, H_1:r = 1	45.416	21.131	0.000	1
0.039	H_0:r = 1, H_1:r = 2	10.368	14.264	0.188	0
0.001	H_0:r = 2, H_1:r = 3	0.591	3.841	0.591	0

a. Trace and max-eigenvalue tests indicate one cointegrating equation at 5% level. b. MacKinnon, Haug, and Michelis [46] p-values.

the following:

$$\ln \text{Market}_t = 13.563 \ln \text{Price}_{t-1} - 42.454 \ln \text{Venues}_{t-1}$$
$$(8.374) \qquad\qquad (6.773)$$

5.3. Granger Causality/Block Exogeneity Results

For the causal relationship between time series, the VAR Granger causality/block exogeneity Wald tests, developed by Enders [51], are applied. According to Enders, in VAR systems an endogenous variable can be used as exogenous with time lags. For this causality test, we use chi-square (Wald) statistics, which examines the joint significance of each variable with the lagged endogenous variables in every equation of VAR model [52].

In Table 4, in the first part where LMARKET is the dependent variable, we can see that the probabilities of the variables LNPRICE and LNVENUES (0.0062 and 0.0605 respectively) are less than 5% and 6% level of significance. Therefore, we can reject the null hypothesis meaning that LMARKET is endogenous and there is a causal relationship from LNPRICE and LNVENUES to LMARKET.

In the second part, where LNPRICE is the dependent variable, the probability of LMARKET (0.6083) is larger than 5% level of significance whereas the probability of LNVENUES (0.000) is less than 5% level of significance. So, there is causality of LNVENUES on LNPRICE.

Finally, in the third part where LNVENUES is the dependent variable, the probability of LMARKET (0.6930) is larger than 5% level of significance, while probability of LNPRICE (0.0033) is less than 5% level of significance, concluding causality of LNPRICE on LNVENUES.

In Figure 2, we can see that there is unidirectional causality from LNPRICE

Table 4. VAR Granger causality/block exogeneity Wald.

Dependent variable: LMARKET			
Excluded	X^2	D.F.	Probability
LNPRICE	10.16624	2	0.0062
LNVENUES	5.611255	2	0.0605
All	11.52954	4	0.0212
Dependent variable: LNPRICE			
Excluded	X^2	D.F.	Probability
LMARKET	0.994223	2	0.6083
LNVENUES	58.26527	2	0.0000
All	60.19397	4	0.0000
Dependent variable: LNVENUES			
LMARKET	0.733576	2	0.6930
LNPRICE	11.40486	2	0.0033
All	12.88240	4	0.0119

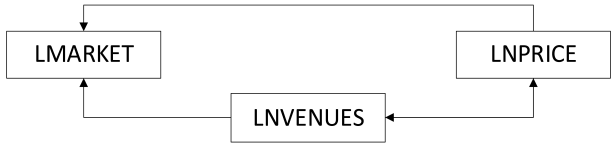

Figure 2. Direction of causalities according to the Granger causality/block exogeneity Wald test.

on LMARKET and from LNVENUES on LNMARKET. Also, there is a bidirectional causality between LNPRICE and LNVENUES.

The absence of causality from LMARKET on LNPRICE and LNVENUES means that there is no causal relationship with direction from LMARKET to LNPRICE and LNVENUES. These findings are reasonable because 1) Bitcoin's market capitalization does not cause its price, since the market capitalization is calculated by multiplying the price by the circulating supply of bitcoins [27], thus Bitcoin's price causes its market capitalization, but the contrary cannot occur and 2) venues cannot cause Bitcoin's market capitalization, since merchants are only one type of Bitcoin's users [26], while other types of users (*i.e.* investors, speculators) conduct the majority of the transactions, thus forming the majority of the market capitalization [53].

Granger causality/block exogeneity Wald test shows the existence and direction of causal relationship but it doesn't show the sign of this relationship, if it is positive or negative, as well as the time period which is required in order this interaction to occur.

5.4. Impulse Response Plots

The impulse response function describes the effects on endogenous variables for future periods. In other words, through this technique we examine the response of a variable to a shock which occurs in another variable. A sudden shock influences directly not only the variable itself but also the rest of the endogenous variables of the system via the dynamic structure of a VAR model. Dynamic model reflects the intertemporal evolution of a dependent variable in relation to its lagged values. **Figure 3** plots the impulse responses of LMARKET, LNPRICE, and LNVENUES over a horizon of 10 weeks. Standard errors are calculated by the Monte Carlo method, with 100 repetitions (of ±2 standard deviations). The curves in the nine graphs indicate the forecasting of how each endogenous variable (LMARKET, LNPRICE, and LNVENUES in the first, second, and third row respectively) will respond to a shock which occurs in another variable. A flat curve shows that there is a stable effect on the endogenous variable, when there is a shock on the other variables. Also, a curve that is not significantly different from the X-axis shows that there is not significant effect on the endogenous variable, when there is a shock on the other variables.

Thus, in the first graph (row 1 column 1) causing a shock to endogenous variable LMARKET, LMARKET will have a slight increase in the first weeks and afterwards a slight decrease until the next 10 weeks. The curve in row 1 column

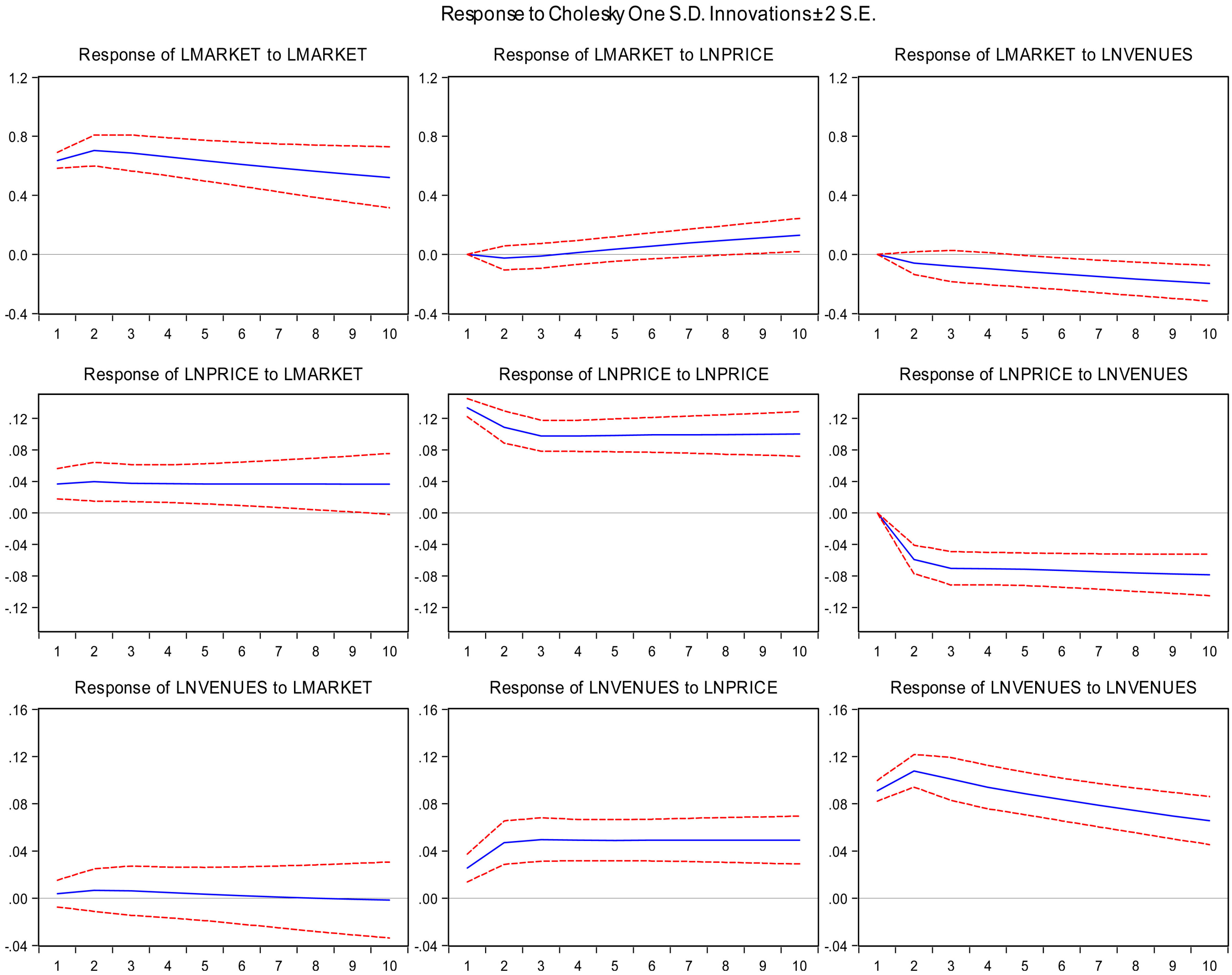

Figure 3. Impulse responses.

2 shows that a shock of LNPRICE has a positive effect on LNMARKET and the graph in row 1 column 3 shows that a shock to LNVENUES has a negative effect on LMARKET.

In the first graph of the second row, the flat curve indicates that a shock to LMARKET will have a stable effect on the endogenous variable LNPRICE. The graph in row 2 column 2 shows that a shock to LNPRICE has a positive permanent effect on LNPRICE, and the graph in row 2 column 3 shows that a shock to LNVENUES has a decrease on LNPRICE for two weeks and for the rest period LNPRICE remains steadily decreased.

Finally, the graph in row 3, column 1, where the curve is not significantly different from the X-axis, indicates that a shock to LMARKET has no significant variation on the endogenous variable LNVENUES. The graph in row 3 column 2 shows that a shock of LNPRICE has a positive effect in the first two weeks and then becomes stable on LNVENUES for the rest of the period. The last graph in row 3 column 3 shows that a shock of LNVENUES has a decreasing effect on LNVENUES.

5.5. Variance Decompositions Results

In Table 5, Table 6, and Table 7, the forecast error variance decompositions between the examined variables, across the 10-week forecast period for each of the variables set, are presented. Shocks are defined with Cholesky methodology. Standard errors are generated through Monte Carlo simulations (100 repetitions).

So, in Table 5 we can see that in the fifth and tenth week period, LNPRICE accounts for 0.09% and 1.25% respectively of the variation in LMARKET and the variable LNVENUES accounts for 1.45% and 4.26% respectively of the variation in LNMARKET.

In Table 6, we notice that for the same time period, LNMARKET accounts for 8.41% and 8.16% respectively of the variation of LNPRICE, whereas LNVENUES accounts for 22.12% and 28.03% of the variation of LNPRICE.

In Table 7, we can see that LMARKET accounts for 0.23% and 0.14% in the fifth and tenth week period of the variation of LNVENUES and LNPRICE accounts for 17.77% and 22.91% for the same time period of the variation of LNVENUES.

6. Conclusions

In this study, we examined empirically the linkages among the Bitcoin's price volatility, market capitalization, and the number of venues that accept bitcoins,

Table 5. Forecast error variance decomposition (LMARKET).

Variance Decomposition of LMARKET				
Period	S.E	LMARKET	LNPRICE	LNVENUES
1	0.636712	100.000 (0.000)	0.000 (0.000)	0.000 (0.000)
2	0.950968	99.542 (0.601)	0.069 (0.291)	0.387 (0.464)
3	1.175901	99.226 (0.974)	0.054 (0.345)	0.718 (0.867)
4	1.352321	98.892 (1.226)	0.050 (0.340)	1.057 (1.185)
5	1.498528	98.452 (1.457)	0.097 (0.394)	1.450 (1.462)
6	1.624017	97.890 (1.733)	0.204 (0.549)	1.904 (1.731)
7	1.734433	97.208 (2.086)	0.374 (0.786)	2.417 (2.010)
8	1.833470	96.409 (2.529)	0.606 (1.080)	2.983 (2.307)
9	1.923699	95.500 (3.056)	0.899 (1.416)	3.599 (2.623)
10	2.006996	94.488 (3.656)	1.250 (1.784)	4.261 (2.959)

Table 6. Forecast error variance decomposition (LNPRICE).

Variance Decomposition of LNPRICE				
Period	S.E	LMARKET	LNPRICE	LNVENUES
1	0.138553	7.113 (2.902)	92.886 (2.902)	0.000 (0.000)
2	0.189979	8.123 (3.701)	82.199 (4.597)	9.676 (2.762)
3	0.228211	8.359 (4.321)	75.364 (5.831)	16.276 (4.148)
4	0.260798	8.421 (4.692)	71.736 (6.516)	19.842 (4.863)
5	0.290216	8.419 (4.954)	69.459 (6.975)	22.120 (5.334
6	0.317380	8.386 (5.175)	67.808 (7.310)	23.804 (5.684)
7	0.342801	8.338 (5.385)	66.518 (7.573)	25.143 (5.962)
8	0.366833	8.281 (5.597)	65.464 (7.796)	26.253 (6.195)
9	0.389729	8.221 (5.816)	64.573 (7.993)	27.204 (6.398)
10	0.411676	8.160 (6.043)	63.800 (8.175)	28.038 (6.583)

Table 7. Forecast error variance decomposition (LNVENUES).

Variance Decomposition of LNVENUES				
Period	S.E	LMARKET	LNPRICE	LNVENUES
1	0.094443	0.164 (0.732)	7.283 (3.501)	92.551 (3.653)
2	0.150983	0.259 (0.895)	12.556 (4.606)	87.183 (4.751)
3	0.188337	0.277 (1.076)	14.992 (5.285)	84.729 (5.439)
4	0.216180	0.260 (1.195)	16.529 (5.691)	83.209 (5.838)
5	0.238716	0.233 (1.305)	17.771 (6.024)	81.994 (6.163)
6	0.257651	0.207 (1.432)	18.893 (6.348)	80.899 (6.484)
7	0.273879	0.184 (1.585)	19.950 (6.676)	79.864 (6.817)
8	0.287984	0.167 (1.766)	20.966 (7.008)	78.866 (7.166)
9	0.300378	0.154 (1.977)	21.953 (7.345)	77.891 (7.531)
10	0.311362	0.146 (2.213)	22.918 (7.683)	76.934 (7.910)

using weekly time series data for the five-year time period February 2013-February 2018. Our econometric procedure includes the unit root tests of ADF and PP, Johansen cointegration test, Granger causality/block exogeneity Wald test, impulse response, and variance decomposition, providing a forecasting of how each endogenous variable will respond to a shock which occurs in another variable over a horizon of 10 weeks.

The Johansen cointegration test presents one cointegrating vector; thus, there is a long-run relationship among the variables. The Granger causality/block exogeneity Wald test shows a unidirectional causality from LNPRICE to LMARKET and from LNVENUES to LMARKET. Also, there is a bidirectional causality between LNPRICE and LNVENUES. The impulse response functions and variance decomposition indicate the following key findings: 1) a shock of LNPRICE has a positive effect on LMARKET and a shock of LNVENUES has a negative effect on LMARKET. Consequently, the market capitalization is positively affected by the sudden changes of the Bitcoin's price, but it is not affected by a sudden change in the number of merchants. These results are reasonable and in line with the results of the Granger causality/block exogeneity Wald test because Bitcoin's market capitalization follows the closing prices since it is calculated by multiplying the price by the circulating supply of bitcoins [27], in addition, merchants are only one type of Bitcoin's users [26], while other types of users (*i.e.* investors, speculators) conduct the majority of the transactions, thus forming the majority of the market capitalization [53] and 2) a shock of LMARKET shows no significant effect on LNVENUES and a shock of LNPRICE has a positive effect in the first two weeks and then becomes stable on LNVENUES for the rest of the period. Consequently, the number of merchants is not affected by a sudden change of the market capitalization, while it is affected only initially by a sudden change of the price and then stabilizes. These results verify the existence of the observed paradox, since the number of merchants that accept bitcoins is almost unaffected by the shocks in the Bitcoin market. This finding indicates that merchants are probably motivated by other expectations in their decision to accept bitcoins (e.g. lower transaction fees, no chargebacks, hedge against fiat currencies' financial risks, attract customers) and is in line with the study of McGee and Sammut-Bonnici [21], which stresses that the crux of the paradox in the networked markets lies in the management of expectations. The equilibrium between the expectations of merchants and consumers will conduce to the Bitcoin's widespread adoption as a means of transaction. Moreover, this paper is consistent with prior literature [7] [24] [25] and points out the presence of the strong network effects and externalities that affect Bitcoin's adoption, as well. Internalization of these network effects will absorb the derived network externalities, thus increasing the users. Bitcoin's price stabilization will derive when the speculative investments decrease and more people start using Bitcoin in exchange for goods and services [30].

To conclude, our study provides useful insights on the network effects and externalities for scholars and researchers, since it indicates the close relationship of the two terms, but also highlights the differences between them. Moreover, it has significant implications for electronic commerce practitioners concerning their decision-making process about Bitcoin, by contributing to a better understanding of the networked phenomena that appear in the Bitcoin market and thus reducing their reservedness towards its adoption and use. The number of merchants may show an increasing trend [53], but Bitcoin is still in the early adoption stage [31] and awareness about Bitcoin should expand in order the early majority stage occurs [54]. The understanding of the network effects' phenomena and network externalities that appear in electronic markets conduces to the awareness of the transformational role of Bitcoin and the rest cryptocurrencies, as well. Volatility is expected for a new means of transaction, like Bitcoin. However, it is anticipated to diminish naturally as Bitcoin's worldwide adoption increases [31].

The research interest of this paper focuses on Bitcoin because there are data for the venues that accept bitcoins, which can be processed. The available data for the venues that accept other digital currencies are only in totals per country and not in time series; thus, they cannot be compared with historical price data series. Also, this study examines only the side of merchants, since there are no officially recorded data about the number of Bitcoin consumers and the number of unique transactions, unique addresses, and the number of digital wallets refer to all types of "users" (merchants, consumers, investors, and speculators) without distinction. Another issue in this study is that daily closing prices are missing, because data are recorded on a weekly basis. This may conduce to non-depiction of any potential big daily changes of prices. However, the trend appears even on the weekly recording of data. Future research could be directed towards other digital currencies, given that there will be available databases to retrieve the historical data of the relevant venues or conduct a similar research process with updated data after a couple of years in order to realize the progress in Bitcoin's adoption. Further research could be conducted aiming to investigate the factors that affect the acceptance and use of digital currencies. The emergence of new types of digital currencies makes this topic even more interesting and worthy to be thoroughly studied.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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