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An Explanatory Model for the price of Bitcoin and the public interest in the topic

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Abstract

The volume of cryptocurrency transactions is gaining momentum in the market and attracting attention to better understand the evaluation processes, procedures, and pricing. This study describes a model that contains a set of basic pricing factors for cryptocurrency. The approach considers the monetary survey in the American financial market and statistically describes some basic properties of these prices, examines the relationship between the money market and the main factors specific to cryptocurrencies and investigates potential drivers and predictors of quotations. The results based on the exploratory analysis and time series regression suggest that the term "bitcoin price" BTC_PRICE in Google Trends® searches presents a significant impact on fluctuations in the price of Bitcoin.

Keywords

Bitcoin, cryptocurrency valuation, pricing, cryptocurrency, money market.

1. Introduction

Cryptocurrency is a topic that receives significant attention. On the one hand, it is based on a fundamentally new technology that is not entirely what we understand. On the other hand, at least in its current form, it fulfills functions similar to those of other traditional assets. Broad academic attention focuses on the development of theoretical models of cryptocurrencies. The theoretical literature on cryptocurrencies suggests a number of factors that are potentially important in the valuation of cryptocurrencies. The first group of papers builds models emphasizing the network effect of cryptocurrency adoption (Pagnotta and Buraschi 2018; Biais et al. 2018; Cong, Li and Wang 2019) and emphasizes the price dynamics induced by the positive externality of the network effect. The second group of studies focuses on the production side of coins - the problem of miners (Cong, Ele and Li 2018; Sockin and Xiong

2019) - and shows that the evolution of cryptocurrency prices is linked to the marginal cost of production. The third group links cryptocurrency price movements to those of traditional asset classes such as fiat money (Schilling and Uhlig 2019; Jermann 2018). The fourth grouping encompasses themes about the empirical patterns of cryptocurrencies. Borri (2019) shows that individual cryptocurrencies are exposed to tail-market risks from the cryptomarket. Makarov and Schoar (2020) think that cryptocurrency markets exhibit periods of potential arbitrage opportunity between exchanges. Griffin and Shams (2020) study Bitcoin price manipulation. Given this context, the theoretical models that exist of cryptocurrencies seek the predictability of the prices of these assets. Among the economic and financial factors, the present study aims to investigate whether there is a model that describes the price of Bitcoin in relation to the monetary aggregate. Thus, the objective is to describe a model that relates the price of Bitcoin, the level of searches on Google Trends® for keywords on the subject and the monetary aggregate M2.

The justification is in line with the fact that cryptocurrency pricing seems to follow the general law of supply and demand. Given its demand, the price reaches significant swings. Although previous publications are classified into four fields of research, an empirical model on their price still needs to be studied.

The work is organized into three sections, in addition to this introduction and the conclusion. The first discusses the theoretical framework, the second the methodology employed, while the third consists of the analysis of the results with their respective discussions.

2. Theoretical Reference

Some authors argue that the evolution of cryptocurrency prices does not follow a pattern, and therefore their returns are not predictable (SCHILLING AND UHLIG 2019). While other articles point out that in dynamic valuation models, these returns can potentially be predicted by some factors (CONG, LI AND WANG 2019; SOCKIN AND XIONG 2019). This study assumes that returns can be predicted. It makes a brief history of the concepts that relate to the currency, its basic functions and the essential themes of the research that exists regarding the returns and risks of cryptocurrencies.

For each cryptocurrency its price is calculated which takes the volume weighted average of all prices reported in each market. A cryptocurrency needs to meet a list of criteria, such as being traded on a public exchange with an application programming interface (API) that tells you the last price traded and the last 24 hours trading volume, and have a non-zero trading volume on at least one supported exchange so that a price can be determined.

2.1. Network and production factors

The theoretical literature on cryptocurrencies emphasizes the importance of network factors in the valuation of cryptocurrencies (CONG, LI AND WANG 2019; SOCKIN AND XIONG 2019; PAGNOTTA AND BURASCHI 2018; BIAIS ET AL. 2018). In particular, the network effect of user adoption can potentially play a central role in the valuation of cryptocurrencies. As the adoption of cryptocurrencies by users generates a positive externality of the network, prices respond to the adoptions of these users. Thus, variations in user adoptions can contribute to movements in cryptocurrency prices.

Network factors, in a non-exhaustive list, include wallet user growth, asset growth in the ecosystem, and transaction count growth.

In a dynamic model of cryptocurrencies with the network effect, prices not only reflect the current adoption of cryptocurrencies, but also contain information about the expected future growth of the network, a key mechanism of Cong, Li and Wang (2019).

Regarding factors of production, studies argue that mining costs are essential to the infrastructure and security of cryptocurrencies (SOCKIN AND XIONG 2019; ABADI AND BRUNNERMEIER 2018; CONG, LI 2018). Sockin and Xiong (2019) show that in a general equilibrium model with production, prices are closely linked to the marginal cost of mining, evaluating utility tokens.
Utility tokens are a special type of token that helps capitalize on or fund projects for startups, companies, or project development groups (LUX, TOBIAS AND MATHYS, VINZENZ).

2.2. Prediction of cryptocurrency factors

Existing theoretical models of cryptocurrencies suggest several predictions about their returns. On the one hand, Schilling and Uhlig (2019) explain that the evolution of cryptocurrency prices does not follow a pattern, and therefore cryptocurrency returns are not predictable. Other articles predict that in dynamic cryptocurrency valuation models, returns can potentially be predicted by the momentum, investor attention, and cryptocurrency valuation rates (CONG, LI, AND WANG 2019; SOCKIN AND XIONG 2019). Motivated by the theoretical development that exists and empirical discoveries in financial markets, Liu, Yukun and Tsyvinski, Aleh (2018) verify that cryptocurrency returns are predictable by the momentum, by the attention of investors' and by the proxies for cryptocurrency valuation rates.

2.2.1 Cryptocurrency Moment

One of the most studied asset pricing regularities is momentum (JEGADEESH AND TITMAN 1993; MOSKOWITZ AND GRINBLATT 1999). As discussed in Cong, Li, and Wang (2019), the network effect of user adoption generates a positive externality that is not immediately incorporated into cryptocurrency prices. This channel could potentially lead to a boost effect on cryptocurrency returns. In their model, Sockin and Xiong (2019) generate momentum in the cryptocurrency market through investor attention, a mechanism similar to De Long et al. (1990).
The momentum effect of the time series is linked to the externalities of the network, as I suggested in Cong, Li, and Wang (2019). In its dynamic cryptocurrency valuation model, the boost effect is generated by the positive externality of the network effect that is not incorporated into cryptocurrency prices immediately. That is, their model implies that control for the growth of cryptocurrency adoption takes on the momentum effect of the time series.

2.2.2 Attention of the investor in cryptocurrencies

Sockin and Xiong (2019) suggest that investors' attention is potentially tied to future cryptocurrency returns.
The study by Liu, Yukun and Tsyvinski, Aleh (2018) suggests that the word "Bitcoin" relates to the most visible cryptocurrency in the market and uses the diversion of Google searches to "Bitcoin" in proxy, with the capture of investors' attention in a given week to compare with the average of the previous four weeks. With this measure they standardize the research to have a mean of zero and a standard deviation of one. An increase of one standard deviation in the surveys leads to increases in weekly returns of about 3.00% for the accumulated returns of the one-week currency market and about 5.00% for the accumulated returns of the two-week currency market.
Investors' attention and returns from one to four weeks and one to five weeks are positively correlated, with only one to four being statistically significant. On the other hand, the returns with six, seven and eight weeks in advance present a negative correlation, but without statistical

significance.
Liu, Yukun and Tsyvinski, Aleh (2018) conclude that there is a positive effect of investor attention on cryptocurrency returns. The average return studied is higher than 6.12% and lower than 0.70%, generating a difference of 5.42%, which is economically large and slightly lower than the initial study sample estimate of 6.09%.

2.2.3 Negative investor attention

According to Sockin and Xiong (2019) investor attention positively predicts cryptocurrency returns, however, they claim that not all investor attention is positive and differentiate positive from negative attention by showing that negative attention is followed by depreciation of cryptocurrency prices in the future.
The study by Liu, Yukun and Tsyvinski, Aleh (2018) suggests that when changing the search for "Bitcoin" to the phrase "Bitcoin Hack" added to the search for the word "Bitcoin" in proxy, investors' attention becomes negative compared to the same previous search patterns.
The study of this relationship predicts a significant negative of cumulative currency market returns from one to six weeks. With an increase of one standard deviation in the proportion, it leads to a reduction of 2.00% next week. The regression results found show negative predictability of return of investors' attention.
Positive investor sentiment is followed by cryptocurrency price appreciation, and negative sentiment is followed by depreciation (LIU, YUKUN AND TSYVINSKI, ALEH 2018).

2.2.4 Interaction between moment and attention

There are effects of time series momentum and investors' attention on the cryptocurrency market. Stock market research (Hong, Lim and Stein 2000; Hou, Xiong and Peng 2009) shows that there is a strong relationship between momentum and investor attention. It's possible that these two factors capture the same underlying phenomenon. Sockin and Xiong (2019) propose a potential channel to generate momentum. In their model, the boost arises because users have incorrect expectations about future prices. It suggests that the timing of the cryptocurrency and the attention of investors' could potentially arise from the same underlying mechanism of information asymmetry and the results could also interact with each other. They conclude that investors' attention is high after the outperformance of the cryptocurrency market.

2.2.5 Cryptocurrency valuation index

In the stock market, intrinsic and market value relationships are commonly referred to through indicators and are measured as the ratio of book value to market value. Another measure of value used in the literature that is correlated with intrinsic market value is the measure of long-term accumulated returns (DE BONDT AND THALER 1985; AND MOSKOWITZ 2015). It's more difficult to define a similar measure of intrinsic value for cryptocurrency, as it's still difficult to measure the future economic benefit.
In their dynamic cryptocurrency asset pricing model, Cong, Li, and Wang (2019) argue that the relationship of cryptocurrency's intrinsic value can be defined as market capitalization over the number of users. They conclude that none of the five indices predicts future currency market returns with statistical significance over any horizon. Overall, there is a very weak relationship between the future returns of the coin market and the current ratio of cryptocurrency fundamentalist index and market price.
Both the literature and the market have debated the nature of cryptocurrencies. Schilling and Uhlig (2019) show that in an economy where fiat money and cryptocurrency coexist and

compete with each other, the evolution of their prices is linked to fiat money.
There is a hypothesis that proposes that cryptocurrencies are the "digital gold" and serve the purpose of precious metal ballast. Schilling and Uhlig (2019) argue that returns may have exposure to macroeconomic risks such as monetary policies. These arguments examine the relationships between returns from cryptocurrencies and from traditional assets such as currency, commodity, and net worth. If cryptocurrency investors' prove this hypothesis, returns are expected to get the same attention as traditional precious metals commodities. On the other hand, Liu, Yukun and Tsyvinski, Aleh (2018) state that the results of individual currency returns have no statistically significant correlation with currency factors and thus, there is no evidence for the exchange between fiat currencies and cryptocurrencies to be consistent.

2.2.6 Macroeconomic factors

To relate the exposure of macroeconomic factors to cryptocurrency returns, one considers the growth of durable, non-durable consumption, industrial production, and personal income growth.
For the top three cryptocurrencies, market returns are not statistically significant when related to macroeconomic factors. Individually for Bitcoin and Ripple, all exposures are not statistically significant, while for Ethereum, the growth factor of durable consumption is significant.

2.2.7 Rules

A potentially important determinant for cryptocurrency valuation is regulations and to test this importance Auer and Claessens (2018) and Shanaev et al. (2019) use their method in order to find out if the current returns of cryptocurrencies are lower during the days of regulatory events. They conclude that cryptocurrency returns respond to negative regulatory events, but not to positive regulatory events.

2.2.8 Speculative interest

Liu, Yukun and Tsyvinski, Aleh (2018) affirm that cryptocurrency returns respond to present and future speculative expectations of growth. Network growth rates are used to examine whether outcomes are driven by variations in speculative interests and whether the currency market returns positively to predict future growth. An adverse hypothesis is that current correlations between the size of network activity and currency market returns may happen mechanically and not truly capture the value of network externalities.

3. Methodology

3.1 Search strategy

This study has as its strategy the exploratory descriptive research. First, it reviews the mechanisms and predictions of existing theoretical models and subsequently establishes a set of basic asset pricing factors for this class.
Uses standard empirical asset pricing tools and methods. Eventual findings about the moment are related to the articles Jegadeesh and Titman (1993), Moskowitz and Grinblatt (1999), Moskowitz, Ooi and Pedersen (2012), Asness, Moskowitz and Pedersen (2013), and Daniel and Moskowitz (2016). Da, Engelberg, and Gao (2011) use Google searches as a proxy to get investors' attention.
The proposed econometric model is expressed through equation 1.

$$\hat{y}_{i,t} = \hat{\beta}_0 + \sum_1^n \hat{\beta}_n * X_{k,t} + \hat{\gamma}_n * D_{i,t} \quad (1)$$

Where:

$\hat{y}_{i,t}$: Asset price XBT_USD i at the moment t;
$\hat{\beta}_n$: Estimated parameters of the quantitative variables of the model;
$X_{1,t}$: BTC variable representing the search for the term "bitcoin";
$X_{2,t}$: BTC_ PRICE variable which represents the search for the terms "bitcoin" and "price" concurrently;
$X_{3,t}$: BTC_ AÇÃO variable which represents the search for the terms "bitcoin" and "action" concurrently;
$\hat{\gamma}_n$: Estimated parameters of the qualitative variable of the model;
$D_{i,t}$: *Dummies* of period;

Equation 1 is used as the basis for the study of bitcoin pricing. Due to the heterogeneity of prices over periods, the time series is divided. The form of this division is through statistical clustering and empirical analysis.
For both longitudinal slices, descriptive statistics and regression of the time series model are made to estimate the parameters. Ordinary least squares regression is performed and the stepwise procedure is applied with a significance of 5.00%.
Time lags (LAGS) are studied, observing the models through the general significance (F) and the coefficient of determination (R^2), where 0 is considered in phase, that is, equivalent to the present week studied and subsequent LAGS from 1 to 7, in lag.

3.2 Methodological procedures

To survey the sample of this study, the Google Trends® tool is used, which returns the most popular terms searched by the user in a given period. For the control variable, the Bloomberg® Terminal is used and the survey of the Bitcoin-USD quote, the American monetary expansion (M2) and the quotation of two other cryptocurrencies, selected by the volume of transactions.
For the division of the periods we used two techniques. One of an essentially quantitative nature and the other of an economic-financial nature.
In the first, for the creation of groups, or clusters, of the collected data, the analysis of clusters is made through SPSS®. In the second, the groups are selected through the classification of relevant events from the economic-financial perspective, using Microsoft Excel® for data manipulation.
From the groupings obtained, descriptive statistics and regressions are performed using Stata®. For the time series, the data are considered in phase and with LAGS for the analysis.
The Google Trends® tool presents graphs with the frequency in which a chosen term is searched in various regions of the world and in several languages, which also bring topics of the most searched subjects that are related to the subject and selected period.
The term "Bitcoin" is inserted in the search bar, with the default of the search area limited to the United States and database of the last five years, with start date on 09/03/2017 and end date 08/21/2022, in which the tool returns a graph specifying the amount of searches of the chosen term and dates that have relevance of numbers of this search.
The numbers obtained represent the research interest relative to the highest point on the chart of a given region in a given period. A value of 100 represents the peak popularity of the term, while a value of 50 means it has gained half the popularity. A score of 0 means that there is not enough data about the term on that particular date. Based on the results of

this tool are selected two other subjects related to the searched term, being them "Bitcoin-Price" and "Bitcoin-Action", we conducted a search with the same standards of the first.
The three search results are tabulated in a Microsoft Excel® spreadsheet with the addition of the Bitcoin quote in US Dollar (XBT-USD), from the same periods collected. The quotation information is captured by the Bloomberg® Terminal tool, using the same five years of information for relation.
The interest in studying how the return quotes of cryptocurrencies behave in relation to the market are represented, by a metric variable, or quantitative, and, therefore, can be studied through the estimation of regression models, which according to Favero (2017), have as their main purpose to analyze how the relationships between a set of explanatory variables behave, metrics or dummies.
Concomitantly to the discussion of each of the concepts and the resolution of the proposed example in an analytical way, the first solution is presented through the Microsoft Excel® Regression tool and for the result, the data are executed in the SPSS® and Stata® software, respectively.

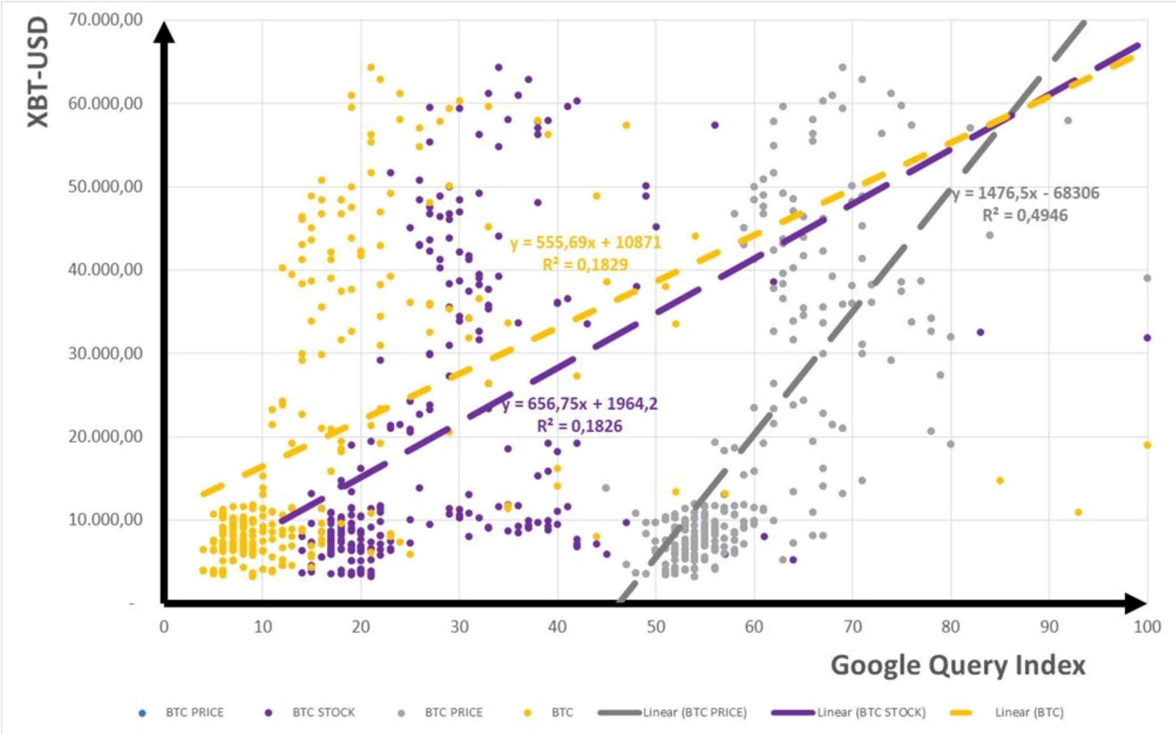
4. Analysis of results

4.1. Clustering

The clustering in its application does not present a predictive character for other observations of the sample, and the inclusion of new observations or data in the database is necessary the reapplication of the modeling, and new groupings or a complete rearrangement of the observations in the groups can be generated.
It consists of a set of exploratory techniques with the intention of verifying the existence of similar behaviors between the relation of certain variables.
The groupings must represent the joint behavior of the observations from certain variables, that is, the observations of a given group must be relatively similar to each other, in relation to the variables inserted in the analysis, and considerably different from the observations of other groups.
Bussab et al. (1990), state that the different criteria of agglomeration schemes can lead to different formations of clusters, and the homogeneity that the researcher desires depends fundamentally on the objectives stipulated in the research.
When starting the calculation of the research results, the SPSS® software is used for clustering with three, five and ten periods as planned by the methodology, however, there is no statistical significance in any sample.
The test performed by means of stepwise with the variable in phase and the lags, result in an adjustment coefficient (R^2) of low variance extracted, lead to shallow conclusions and without content for the basis of more elaborate studies, there is also no conclusive data that would answer the pricing of the XBT-USD.

In turn, the results in Figure 1 present the groups of outputs that are generated: regression statistics, analysis of variance (ANOVA), table of regression coefficients and residue table.

Figure 1 - Scatterplot of queries in Google Trends® allied to the price of Bitcoin.

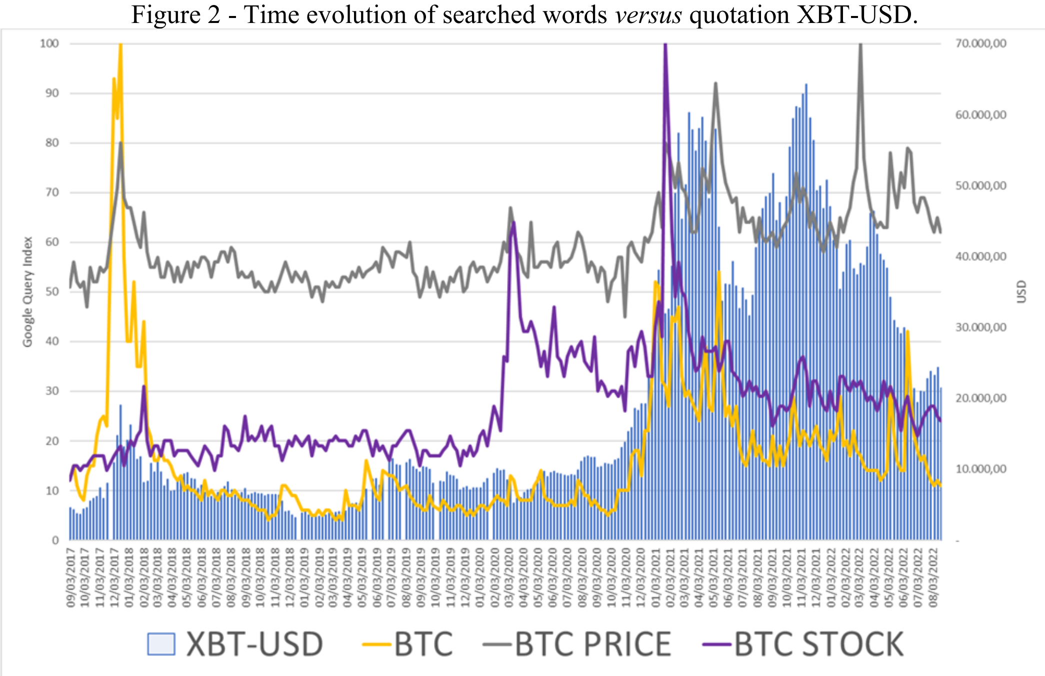


Source: Google Trends® and Bloomberg®.

From the identification and formation of the clusters in Figure 1, BTC_PRICE stands out, in which its R^2 is in 49.46%. In each group generated, the existing variability within the clusters and between them is analyzed, in order to be able to support the decision regarding the statistical significance of the periods of 1 to 5 weeks and 6 to 7 weeks.

The cluster analysis of this research is static, where the data from the last five years is used for research (start date on the day 09/03/2017 and end date 08/21/2022), without new value additions, as shown in Figure 2.

Figure 2 - Time evolution of searched words *versus* quotation XBT-USD.



Source: Google Trends® and Bloomberg®.

In the clustering by Microsoft Excel®, the division into three periods is performed based on events that observe a difference in variance, as shown in Figure 2, generating the periods that are used for modeling in SPSS® and Stata® software.
The 0-0 period, which precedes the Covid-19 pandemic, is marked by the significant increase in the search for the term BITCOIN in Google® searches, between 09/03/2017 and 05/13/2018.

Figure 3 - Quotation.

Source: Bloomberg®.

The 0-1 period begins on 05/20/2018 and closes on 09/06/2020, where it's possible to identify a possible stabilization in the period, with less variance. This period is marked by the enactment of the Covid-19 pandemic where it inaugurates the expansion of M2, as can be seen in Figure 3. Until then the price of "Bitcoin" that does not exceed the value of USD 20,000.00 (twenty thousand dollars) at any time.
In the period 1-0 (09/13/2020 to 08/21/2022), it's observed the increase in the value of Bitcoin and reaching the maximum price of USD 64,336.55 on 11/14/2021. In this period coincides the discovery of the Covid-19 vaccine, where at the end of August 2020 Russia becomes the first country in the world to approve the Sputnik V® vaccine, which inaugurates a period of approval of new vaccines around the world.
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Based on the periods presented, it's observed that certain events and actions of the market may be related to the price of "Bitcoin". In tests of this study, it's observed that the explanatory power of the variation of the quotation is reduced as the weeks go by. The periods mentioned serve as a study basis for the analysis of lags between weeks.

4.2. Time series regression

After performing the modeling in the Stata®, it's possible to capture the results of the dependent variable XBT-USD in phase (LAG_0) and lagged from 1 to 7 weeks (LAGS) based on three variables, which are: BTC, BTC_PRICE e BTC_STOCK, synthesized between figures 5 and 12.
Through the results obtained it's possible to identify that the parameters of the equations adjust to each period differently, as presented below. The 0-0 period is the one with the highest results

of R² with all kinds of lags (from the LAG_0 to the LAG_7). It's also possible to verify the prevalence of the variable BTC_PRICE for the LAGS from 0 to 3.
The period of 0-1 is considered a transitional phase, given its low value of R². The only independent variable that presents statistical significance in this period is the BTC_PRICE in LAGS 1 to 3;
From the LAG_3, the variable BTC_STOCK appears with the parameter that has significance in the LAG_4 and LAG_5;
The constant presents significance only in the periods 0-0, but from the LAG _5 does not show significance in any period. This finding corroborates the need to consider different periods, which could be operationalized by different intercept adjustments.
The three-week lag shows that the search for the term is presented as a price antecedent of USD 477 to 762 for each point.
The term BTC_STOCK has no economic meaning and can be inferred as the search made by people with low knowledge about the currency, since Bitcoin and Stock are different class assets.
From the LAG_3, all periods 0-0 present significance in variable BTC_STOCK, but without economic explanation.
Note that the term that most frequently presents significance in all LAGS is the BTC_PRICE, being present in all periods 1-0 and in general, there is no sufficiently explanatory study basis that justifies the lag of this variable after 3 weeks.

LAG_0: The period 0-1 does not present a variable with statistical significance, having the lowest R² of LAG.

Figure 4 - Summary analysis LAG_0.

Model	R^2	Period	btc	btc_price	btc_stock	_constant
Lag_0	72,66%	0-0		519,7479		-20331,72
				0,0000		*0,0010*
	15,28%	0-1				
	20,40%	1-0	487,3243	388,564		
			0,0050	*0,0470*		

Source: Prepared by the authors.

LAG_1: The period 0-1 is the one with the lowest R^2. Only one variable is statistically significant.

Figure 5 - Summary analysis LAG_1.

Model	R^2	Period	btc	btc_price	btc_stock	_constant
Lag_1	60,35%	0-0		549,32		-23991,48
				0,0010		*0,0010*
	15,98%	0-1		227,2501		
				0,0120		
	21,60%	1-0	488,7785	441,0318		
			0,0050	*0,0250*		

Source: Prepared by the authors.

LAG_2: The period 1-0 is the one that presents intermediate R^2, having only the BTC_PRICE with statistical significance. The 1-0 period is the one that contains the highest XBT-USD quotes of the sample.
It comprises the nine months after the decree of the pandemic, in which the volume of M2 in the American economy is at an all-time high (22.68%) presented so far. From this LAG, a descending R² is noted in the period 0-1.

Figure 6 - Summary analysis LAG_2.

Model	R^2	Period	btc	btc_price	btc_stock	_constant
Lag_2	55,52%	0-0	-137,4221	694,9281		-31199,39
			0,0050	0,0000		0,0000
	15,71%	0-1		224,9515		
				0,0120		
	18,76%	1-0	356,4666	537,6093		
			0,0450	0,0080		

Source: Prepared by the authors.

LAG_3: The period 0-0 is the one that presents the greatest explanatory power of the study, in which all the variables of the model present statistical significance. The R^2 is not the largest among the lags, extracting only 50.67% of the variance.

Figure 7 - Summary analysis LAG_3.

Model	R^2	Period	btc	btc_price	btc_stock	_constant
Lag_3	50,67%	0-0	-117,1472	529,4575	477,3317	-27023,26
			0,0240	0,0050	0,0150	0,0020
	13,78%	0-1		187,4368		
				0,0350		
	19,30%	1-0		655,6121		
				0,0020		

Source: Prepared by the authors.

LAG_4: From LAG_4 it's noted that the period 0-1 of all lags, BTC does not present any statistical significance. The 0-0 period is what encompasses the lowest XBT-USD quotes in the sample.

Figure 8 - Summary analysis LAG_4.

Model	R^2	Period	btc	btc_price	btc_stock	_constant
Lag_4	48,45%	0-0			762,6156	-1807,7
					0,0010	0,0400
	12,23%	0-1				
	22,33%	1-0		676,7813	-373,1928	
				0,0010	0,0100	

Source: Prepared by the authors.

LAG_5: The variable _constante does not present significance from the LAG _5 in any period. The period 0-0 is the one that presents the greatest explanatory power, having a R^2 of 39.52%.

Figure 9 - Summary analysis LAG_5.

Model	R^2	Period	btc	btc_price	btc_stock	_constant
Lag_5	39,52%	0-0			719,6767	
					0,0030	
	9,77%	0-1				
	26,33%	1-0	402,6302	673,7744	-504,66	
			0,0210	0,0010	0,0000	

Source: Prepared by the authors.

LAG_6: The period 1-0 is the one that presents intermediate explanatory power, presenting significance in 3 variables.

Figure 10 - Summary analysis LAG_6.

Model	R^2	Period	btc	btc_price	btc_stock	_constant
Lag_6	30,08%	0-0			713,0718	
					0,0070	
	8,67%	0-1				
	28,04%	1-0	374,9464	715,073	-578,8713	
			0,0310	*0,0000*	*0,0000*	

Source: Prepared by the authors.

LAG_7: Although the period 0-0 does not have the highest R^2 of the samples, it's the one that presents greater significance in variable BTC_STOCK, also encompassing the period 1-0 in variable BTC_PRICE. In this LAG the lowest R^2 is obtained, being it in the period 0-1, with 7.55%.

Figure 11 - Summary analysis LAG_7.

Model	R^2	Period	btc	btc_price	btc_stock	_constant
Lag_7	52,00%	0-0			920,7041	
					0,0000	
	7,55%	0-1				
	31,00%	1-0		869,1068	-605,2312	
				0,0000	*0,0000*	

Source: Prepared by the authors.

5. Conclusions

The pricing of cryptoassets is a theme that is present in society.
Among the variations in the price of the virtual currencies currently available, emphasis is given to the understanding of Bitcoin given its dissemination.

The attention of investors' is perceived when there is growth in the search curve given by Google Trends® of the terms BTC, BTC_PRICE and BTC_STOCK. This high coincides, is in phase, with price increase. When the investor's attention is negative, the opposite effect is observed. Even if such an observation has no causal relationship with the price of the currency, this is a movement that presents significance in the study.

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Conflict of Interest Declaration

The authors have no conflicts of interest to declare. All co-authors have seen and agree with the contents of the manuscript and there is no financial interest to report.

References

1. Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2012). Value and Momentum Everywhere. Chicago Booth Research Paper No. 12-53. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2174501. Accessed on March 3, 2022.
2. Auer, R. A., & Claessens, S. (2018). Regulating Cryptocurrencies: Assessing Market Reactions. BIS Quarterly Review Special Features Series. Retrieved from https://www.semanticscholar.org/paper/Regulating-Cryptocurrencies%3A-Assessing-Market-Auer-Claessens/4af3cd01857cecbdf49cadb4fe592c3a2ab86ae5. Accessed on May 18, 2022.
3. Biais, B., Bisiere, C., Bouvard, M., & Casamatta, C. (2018). The Blockchain Folk Theorem. Swiss Finance Institute Research Paper No. 17-75. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3108601. Accessed on March 24, 2022.
4. Bondt, W. F. M. D., & Thaler, R. (1985). Does the Stock Market Overreact? The Journal of Finance, 40(3). Retrieved from https://www.jstor.org/stable/2327804. Accessed on May 18, 2022.
5. Borri, N., & Shakhnov, K. (2018). The Cross-Section of Cryptocurrency Returns. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3241485. Accessed on March 24, 2022.
6. Borri, N., & Shakhnov, K. (2018). Cryptomarket Discounts. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3124394. Accessed on March 24, 2022.
7. Bussab, W., et al. (1990). An Experimental Analysis Of Ecological Dominance In A Rocky Subtidal Macroalgal Community. Retrieved from https://www.sciencedirect.com/science/article/abs/pii/002209819090160E. Accessed on October 10, 2022.
8. Cong, L. W., Li, Y., & Wang, N. (2020). Token-Based Platform Finance. NBER Working Paper No. W27810. Retrieved from https://autopapers.ssrn.com/sol3/papers.cfm?abstract_id=3692166. Accessed on March 3, 2022.
9. Corbet, S., et al. (2019). Cryptocurrencies as a financial asset: a systematic analysis. International Review of Financial Analysis, 62. Retrieved from https://centaur.reading.ac.uk/79186/. Accessed on March 24, 2022.
10. Daniel, K. D., & Moskowitz, T. J. (2013). Momentum Crashes. Swiss Finance Institute Research Paper No. 13-61. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2371227. Accessed on March 10, 2022.
11. Da, Z., Engelberg, J., & Gao, P. (2010). In Search of Fundamentals. AFA 2012 Chicago Meetings Paper. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1589805. Accessed on March 10, 2022.
12. Favero, L. P. (2017). Manual de Análise de Dados - Estatística e Modelagem Multivariada com Excel®, SPSS® e Stata®. Grupo GEN. Retrieved from

https://app.minhabiblioteca.com.br/#/books/9788595155602/. Accessed in September 2022.

13. Griffin, J. M., & Shams, A. (2020). Is Bitcoin Really Untethered?. The Journal of Finance, 75(4). Retrieved from https://onlinelibrary.wiley.com/doi/full/10.1111/jofi.12903. Accessed on March 24, 2022.
14. Hong, H. G., Lim, T., & Stein, J. C. (2020). Bad News Travels Slowly: Size, Analyst Coverage and the Profitability of Momentum Strategies. NBER Working Paper No. w6553. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=226286. Accessed on April 7, 2022.
15. Hou, K., Peng, L., & Xiong, W. (2009). A Tale of Two Anomalies: The Implications of Investor Attention for Price and Earnings Momentum. Retrieved from https://www.princeton.edu/~wxiong/papers/anomaly.pdf. Accessed on March 29, 2022.
16. Hu, A., Parlour, C. A., & Rajan, U. (2018). Cryptocurrencies: Stylized Facts on a New Investible Instrument. Haas School of Business, UC Berkeley. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3182113. Accessed on March 29, 2022.
17. Jagadeesh, N., & Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance, 48(1). Retrieved from https://doi.org/10.1111/j.1540-6261.1993.tb04702.x. Accessed on May 18, 2022.
18. Liu, Y., & Tsyvinski, A. (2018). Risks and Returns of Cryptocurrency. Yale University. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3226952. Accessed on April 7, 2022.
19. Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Positive Feedback Investment Strategies and Destabilizing Rational Speculation. The Journal of Finance, 45(2). Retrieved from https://www.jstor.org/stable/2328662. Accessed on March 14, 2022.
20. Lux, T., & Mathys, V. (2018). FINMA, 18b. Retrieved from https://www.finma.ch/en/news/2018/02/20180216-mm-ico-wegleitung/. Accessed on May 12, 2022.
21. Makarov, I., & Schoar, A. (2018). Trading and Arbitrage in Cryptocurrency Markets. London School of Economics. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3171204. Accessed on March 29, 2022.
22. Moskowitz, T. J., & Grinblatt, M. (1999). Do Industries Explain Momentum? The Journal of Finance, 54(4). Retrieved from https://www.jstor.org/stable/798005. Accessed on April 7, 2022.
23. Moskowitz, T. J., Ooi, Y. H., & Pedersen, L. H. (2012). Time Series Momentum. Chicago Booth Research Paper No. 12-21. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2089463. Accessed on April 7, 2022.
24. Pagnotta, E., & Buraschi, A. (2018). An Equilibrium Valuation of Bitcoin and Decentralized Network Assets. Imperial College London. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3142022. Accessed on March 29, 2022.

25. Schilling, L., & Uhlig, H. (2018). Some Simple Bitcoin Economics. Becker Friedman Institute for Research in Economics Working Paper No. 2018-21. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3155310. Accessed on March 29, 2022.
26. Shanaev, S., et al. (2019). Cryptocurrencies Value and 51% Attacks: Evidence from Event Studies. The Journal of Alternative Investments Winter. Retrieved from https://doi.org./10.3905/jai.2019.1.081. Accessed on May 18, 2022.
27. Sockin, M., & Xiong, W. (2020). A Model of Cryptocurrencies. NBER Working Paper No. w26816. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3550965. Accessed on March 7, 2022.
28. Stoffels, J. (2017). Asset Pricing of Cryptocurrencies and Momentum Based Patterns. Erasmus School of Economics. Retrieved from https://thesis.eur.nl/pub/39587/Stoffels-J-450577-MA-thesis.pdf. Accessed on April 7, 2022.
29. Três motivos para o Bitcoin ter alcançado altas históricas em 2020. Retrieved from https://cointimes.com.br/tres-motivos-para-o-bitcoin-ter-alcancado-altas-historicas-em-2020/. Accessed on November 10, 2022.
30. Yermack, D. (2013). Is Bitcoin a Real Currency? An Economic Appraisal. New York University (NYU) - Stern School of Business. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2361599. Accessed on April 19, 2022.
31. Wooldridge, J. M. (2012). Introductory Econometrics: A Modern Approach. Retrieved from https://economics.ut.ac.ir/documents/3030266/14100645/Jeffrey_M._Wooldridge_Introductory_Econometrics_A_Modern_Approach__2012.pdf. Accessed on September 3, 2022.