What explains Bitcoin's price?

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Abstract

Bitcoin's price is still a puzzle despite the highly evolving literature. This paper tries to identify some variables that explain its evolution.We show that macroeconomic variables and Google searches tend not to explain bitcoin's price anymore. We are therefore interested in variables specific to the crypto-assets ecosystem: volumes of ether, ripple and tether. The negative relationship that emerges from the results shows that these crypto-assets are used for price manipulation or pump and dump activities on bitcoin market.

JEL Classification: E42, G11, G12, G15.

Keywords: bitcoin, ether, ripple, tether, crypto-asset,asset pricing, price manipulation.

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1 Introduction

Bitcoin is the main virtual currency in circulation[1]. In February 2019, the site coinmarketcap.com lists 2104 virtual currencies for a total capitalization of approximately 113 billion dollars. Bitcoin's capitalization is close to 60 billion dollars, or 53% of the market[2] . Created in 2008 by the Satoshi Nakamoto collective (2008)[3] , bitcoin has been exchanged since 2009 on a peer-to-peer basis through the Blockchain, which is a distributed ledger (for more details, see, for example, Blundell-Wignall 2014; Böhme and *al.* 2015 ; Gans and Catalini 2017). The cryptographic protocol, known to all users, implies that only 21 million bitcoins will be created by 2140 [4]. The characteristic of bitcoin is: it is out of the traditional financial system. Unlike a legal currency issued by a central bank, bitcoin is completely decentralized. It is not the counterpart of any monetary base. However, the mining process avoids the problem of double expenditure. It has no legal tender and has no legal guarantee of repayment.

The economic analysis concludes that bitcoin cannot be considered as a conventional currency (Lo and Wang 2014; Yermack, 2015; Ammous, 2018). Its acceptability as a means of payment is low. It is rarely used as a unit of account. Its volatility is high compared to traditional currencies and its exchange rate is the subject of many flashes. Bitcoin can therefore be considered as a crypto-asset rather than a currency. Its emergence has attracted the attention of investors who have sometimes considered it as digital gold (Popper, 2015). Bitcoin does not pay interest or dividends. The gains come only from price fluctuations, the foundations of which we are trying to understand.

The purpose of this article is to identify the main drivers of bitcoin price movements. This question has certainly been the subject of contributions in the literature (Buchholz and*al.* 2012, Van Wijk (2013) and Kristoufek 2014). However, traditionally used factors such as macroeconomic variables or the number of searches for the word "bitcoin" on search engines tend to weakly explain the observed changes in bitcoin's price (Ciaian and *al.*, 2016). We introduce in econometric analysis other crypto-assets such as ether, tether and ripple. Indeed, since the peak of bitcoin's price in December 2017, we can wonder about the existence of price manipulation of bitcoin's price by the different exchange platforms and other crypto-assets (Gandal and *al.*, 2018; Griffin and Shams, 2018; Chen and *al.*, 2019). These price manipulations or pump and dump would artificially cause significant price variations of bitcoin.

To analyze the relationships between crypto-assets, we build a VAR and a VECM, over the period: 2015-2018. We first confirm that the traditional macroeconomic determinants (gold, oil, FSI, etc.) have no impact on bitcoin's price. We then show that Google searches have a short-term but no long-term

[1]We also talk about e-money or crypto-money.

[2]For more details, see: `https://coinmarketcap.com/fr/`

[3]"A purely peer-to-peer version of electronic cash would allow online payments to be sent directly from one party to another without going through a financial institution." (Nakamoto, 2008, p. 1).

[4]In February 2019, 17,563,863 bitcoins were issued. See `https://www.blockchain.com/fr/charts/total-bitcoins`

effects. Ripple and ether volumes have a short-term effect on the evolution of bitcoin's price. The difficulty in mining bitcoins, the cost per transaction and the number of tethers in circulation are explanatory factors for bitcoin price evolution in the short and long terms.

The paper is organized as follow. In section 2, the main results of the literature are displayed. In Section 3, we present the econometric approach and the data and then the results obtained are interpreted and discussed. In Section 4, we conclude and suggest avenues for future research.

2 Literature review

How does the literature explain the evolution of bitcoin's price? Buchholz and *al.* (2012) analyze daily bitcoin-specific data such as: the total number of bitcoins in circulation, the total number of daily transactions, the value of transactions, the average price of a bitcoin, bitcoin's price on MtGox and Tradehill platforms, the volume of bitcoins transactions on the MtGox platform (which before 72% closed trading volumes), searches on Google posts on Twitter ... This study, conducted from July 2010 to March 2012, concludes that bitcoin price developments are mainly explained by the interactions between supply and demand. Demand is determined primarily by bitcoin transaction volume (which is heavily impacted by Google searches and bitcoin price volatility) and supply by the number of bitcoins available on the market. However, these interactions between supply and demand have a small effect on bitcoin's price in the absence of a positive price shock. Their effect is significant following a positive price shock because bitcoin is increasingly demanded by investors. .

Van Wijk (2013) analyzes the impact of economic performance on the evolution of bitcoin price. It uses global macroeconomic and financial variables from July 2010 to June 2013: oil prices, Dow Jones Index, FTSE 100 Index, Nikkei 225 Index, Euro-Dollar and Yen-Dollar exchange rate). He concludes that the euro-dollar exchange rate, the oil price and the Dow Jones index have an impact on bitcoin's price in the long run. In the short term only the Dow Jones index has an impact on bitcoin's price. This analysis is interesting because it gives results that have an explanatory power of more important than the majority of the models built in the literature. Nevertheless, there may have a bias, because the period of analysis concerns the beginnings of bitcoin.

Kristoufek (2014) will couple the ideas of Buchholz and *al.* (2012) to those of Van Wijk (2013), by performing a regression including elements specific to bitcoin (total bitcoin in circulation, number of transactions, estimated volume output, trade volume vs. transaction volume ratio, hash rate, US dollar, between bitcoin and Chinese Renminbi, searches on Wikipedia & Google) as well as macroeconomic variables (Financial Stress Index, gold price). Bitcoin's price is explained by searches on Wikipedia and Google, the technical components namely the hash rate and difficulty, bitcoin's price use in trade and the supply of bitcoin. It does not find significant relationships with the macroeconomic components. The analysis technique (Wavelet Coherene) used by Kristoufek (2014) has a limit, because it studies the interconnections between elements taken two by two, which can lead to neglecting relations that combined can have a different effect on bitcoin's price.

Bouoiyour and Selmi (2014) and Bouoiyour and Selmi (2015) estimate that bitcoin's price would be explained by the hash rate, bitcoin circulation speed (velocity), Google searches and values of the Shanghai Stock Exchange.

Ciaian and *al.* (2015) identify 3 sets of potentially relevant variables: the determinants of bitcoin supply and demand, the macroeconomic determinants, and the attractiveness of bitcoin as an asset for investors. They then build 3 regressions using a VECM on daily data for the period 2009-2014. They conclude that the attractiveness of bitcoins the most important factor in the evolution of the price followed by market forces. However, these assumptions must be tested simultaneously to measure the impact of each of them on the evolution of bitcoin's price. Ciaian and *al.* (2016) then use time series over the period 2009 to 2015 and from the model of Barro (1979) formulate testable hypotheses. They show that the determinants of supply and demand (number of bitcoins in circulation, the hash rate, velocity, etc.) have a significant impact on bitcoin's price and this impact tends to increase over the time. The attractiveness of bitcoin has an impact in the short term, but this effect fades in the long term. There is no significant impact of macroeconomic and financial determinants. However, these results seem insufficient, because so-called "general" models have very unstable results depending on the combinations of variables made by the authors.

Given the inability of traditional factors to explain bitcoin's price, recent works consider the existence of price manipulation in the crypto-assets market. Gandal and *al.* (2018) analyze transaction flows on the MtGox platform. They identify suspicious trading activities that coincide with sharp increases in bitcoin's price, including the peak price observed in 2013. The authors point out the lack of regulation on bitcoin transactions which, in essence, are OTC. The statistics of the Banque de France (2018) confirm these speculative phenomena, since 96% of bitcoins are held by only 2.5% of users. This concentration would make bitcoin susceptible to possible price manipulation. This idea is echoed by Chen and *al.* (2019), who from the same MtGox data, conclude that activities carried out by so-called "abnormal" accounts have a significant impact on bitcoin's price. These activities are carried out according to specific exchange schemes: self-loop, unidirection, bi-direction, triangle, polygon and star. These "abnormal accounts" are controlled by a small number of holders, which would tend to confirm the hypothesis of price manipulation.

Following the price spike of December 2017, Griffin and Shams (2018) study the technique used to artificially vary bitcoin's price. They identify the tether as being involved in many arbitrage operations with bitcoin. This crypto-asset, held mainly by its issuers, would be used to initiate pump and dump operations. Typically, tether holders buy bitcoin when its price drops, which implies an increase in its price. This price level is maintained for several days seeming to define a price of equilibrium that attracts unsuspecting investors. The insider investors sell their positions brutally at the end of the month to recover the tethers, which translates into a fall in bitcoin's price.

The implementation of a VAR / VECM allows us to confirm that the macroeconomic variables are no longer significant. But, on the other hand, bitcoin price changes can be explained by the variables of the ecosystem.

3 Empirical Specification

3.1 Econometrical Approach

The econometric model contains interdependent variables (bitcoin's price and its explanatory variables). We analyze causality between endogenous time series and specify a multivariate autoregressive vector -VAR- (Lütkepohl and Krätzig, 2004).According to Engle and Granger (1987), interdependent and non-stationary time series regressions can give erroneous results. In order to avoid these cases, we start by testing the properties of the series concerned.

First, the stationarity of time series is analyzed using two unit root tests: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP). A VAR is then built. The number of variable delays is determined by the Akaike Information Criterion (AIC), FPE (Final Prediction Error), SC (Schwarz Information Criterion) and Hannan-Quinn Information criterion (HQ). The impact of the variables used on the bitcoin price is analyzed using response and variance decomposition functions. In a second step, the Johansen test is used to verify the existence of co-integration relationships. If two individual time series are non-stationary, their combination may be stationary (Engle and Granger 1987). In this particular case, the series are considered as co-integrated. There is a long-term equilibrium relationship between them. The number of co-integrating vectors is determined by the maximum eigenvalue test and the trace test. In a third step, an error correction model (VECM) is estimated for the co-integrated series. An error correction term indicates the rate of adjustment of any imbalance to a long-term equilibrium state.

3.2 Data and Descriptive statistics

The daily variations in the bitcoin's price denominated in dollars are studied over the period from 08/07/2015 to 09/30/2018.

Google searches for the word "bitcoin" are used to test the hypothesis that the searches would express investor interest in bitcoin (Kristoufek, 2015). The frequency of research on a virtual currency would be "a good measure of the potential interest of that currency for investors" (Ciaian and *al.*, 2015, p. 16). As bitcoin is an asset with no economic basis and no value from its exploitation, it depends entirely on investors' confidence in its sustainability. To this end, the communication made around bitcoin will make it possible to reduce the costs of access to information and increase its attractiveness[5] . Ciaian and *al.* (2015) therefore believe that "bad news" such as the many attacks on bitcoin trading platforms could discourage investment and reduce demand for bitcoin, and therefore price. Symmetrically, good news would contribute to the increase in investment demand and therefore in price. "Thus, investment's behavior leads by media can affect the bitcoin's price in a positive or negative way, depending on the type of information dominant in the media at a given time" Ciaian and *al.* (2015). Kristoufek (2013) finds a "bidirectional" causal relationship between bitcoin's price and Google searches. Google searches are pro-cyclical: when the bitcoin's price is rising, they further increase the price. While in a downward phase, they push the price even lower. However, for Glaser and *al.* (2014), the bad news, and in particular the news about the decline in bitcoin's price, has no (or almost no) impact on the price because bitcoin is either used for purely speculative purposes or hoarded in order to benefit from the promise of a price increasing when the 21 million monetary units will be reach[6] . Good news has a significant impact on price because they keep current investors and attracts others.

The cost per transaction or price level expressed in dollars is used in our analysis in accordance with this idea that: "*the price level is an important factor because goods and services are expected to be available at the same prices, everywhere, and imbalances controlled by the exchange rate. When the price level of one currency declines relative to the price level of the other currency, the first currency should appreciate and its exchange rate should increase. Expected causality ranges from the price level to the bitcoin exchange rate. The price level in our case is constructed as the average price of a commercial transaction for a given day* "Kristoufek (2015). An increase in the cost per transaction should therefore lower bitcoin's price.

The difficulty in mining bitcoins represents the issue of the mathematical operation to be solved in order to validate an operation on bitcoin's Blockchain. Transaction's validation leads to the creation of new bitcoins. The difficulty is therefore calculated according to an algorithm: it increases with the number of bitcoins in the system. To prove its credibility, the validation of bitcoin transactions is based on the Proof of Work (PoW[7]). This validation technique considers accurate the results obtained following the largest investment in computing power (CPU). This requires substantial investments in IT equipment and

[5]Investment demand depends on the costs associated with seeking information on potential investment opportunities available in the market" Ciaian and *al.* (2015), p.17.

[6]Baur and *al.* (2018), p.3.

[7]

> "A Proof-of-Work system is sort of like a puzzle, requiring the miners to go through a lot of computational work in order to prove that a transaction is legitimate. Once the initial computational work is performed and the puzzle is solved, it is much easier to verify that the answer is the correct answer." Lee (2014), p.32.

electricity. Combined with the increasing difficulty imposed by the logarithm[8] , investment in mining bitcoins can be very expensive and loss-making. However, Kristoufek (2015) believes that bitcoin price growth may encourage investment in computer hardware for mining, which would lead to indirect bitcoin detentions and increase the difficulty. This increase in difficulty implies the exit of the system from the least efficient miners. If these miners use mining as an alternative to direct investment, they will become mere buyers of bitcoins and thus increase demand and price[9] .

The Financial Stress Index (FSI) expresses risk aversion. It is characterized by: "*its global scope, daily frequency, dynamic weighting scheme, transparency and methodical construction, and its ability to be decomposed into indicator categories and regions*" (Office of Financial Research, 2017). The FSI is composed of several elements: spreads on loans, the valuation of shares in several markets, the measurement of the refinancing by financial institutions of their activities, an aggregate indicator of the valuation of assets considered as safe havens, an aggregate indicator of volatility in equities, credit, money and commodities, and finally, volatility in the US, emerging markets and other advanced economies. This variable is used to test the "safe haven" quality of bitcoin. This feature questions the benefits of having bitcoins in your wallet. Azzi and *al.* (2016, p.10) use the VIX S&P500 and conclude that bitcoin has asymmetric volatility. Bitcoin's price tends to rise in periods of high volatility in the financial market, conveying a message of uncertainty that pushes investors to invest more. While in the case of a fall in prices, investors interpret it as a drop in uncertainty on the markets and abandon bitcoin for traditional assets. This characteristic therefore makes it possible to hedge the risk present in traditional markets. This characteristic of bitcoin seems to have disappeared following the price crash of 2013. The use of the FSI rather than the VIX makes it possible to ensure the disappearance of the quality of refuge asset of bitcoin.

The price of oil, the gold price, the Shanghai Stock Exchange and the Federal Funds Rate help analyze the relationship between bitcoin and macroeconomic variables (Van Wijk 2013, Ciaian and *al.*, 2015). According to Van Wijk (2013), stock market indices reflect the general state of the global economy. A favorable macroeconomic and financial environment could encourage investments in bitcoin and increase its price. The decline in the price of a traditional asset may encourage investors to divert their funds to other alternative investments such as bitcoin (Dimitrova, 2005). The price of oil (in dollars) is considered as a leading indicator of inflation (Krugman and Obstfeld, 2003). A price change indicates a change in the general level of prices that could affect bitcoin's price either upwards or downwards (Ciaian and *al.*, 2015).

The presence of gold (in Swiss francs) in the analysis also makes it possible to test the quality of safe haven of bitcoin. Bitcoin is thus compared to digital gold (Popper, 2015). A positive and significant relationship of bitcoin with the gold price would mean that bitcoin is a safe haven asset.

[8]Number of bitcoin transactions Kristoufek (2015), p.9.

[9]Kristoufek (2015), p.9.

The Shanghai Stock Exchange price is used to analyze the effect of the Chinese market. China concentrates 81%[10] of mining co-ops and in 2015 60% of bitcoin transactions took place in China (Woo, 2017). Stock market and regulatory developments could impact the issuance of bitcoins[11] . The Federal Funds Rate measures the effect of the dollar on bitcoin. Federal Funds Rate impacts the value of the dollar. Their increase involves the appreciation of the dollar and a shift of capital to US assets. In the opposite case, the capital is invested in speculative assets such as bitcoin (Dyhberg, 2015 and Zhu and *al.*, 2017).

The volumes of ether, tether and ripple in circulation are introduced into the econometric analysis to determine the nature of their relationship with bitcoin. The common point of these 3 crypto-assets is to be mainly held by their issuers (Ethereum for ether, Tether Limited for tether and Ripple Company for ripple). This feature may offer holders the opportunity to perform pump and dump operations. The tether for example is issued on a discretionary basis. It is first sold on Bitfinex before spreading on other crypto-assets exchange platforms that are very tied to Bitfinex such as Poliniex and Bittrex. It is on these platforms that Griffin and Shams (2018) will see correlations between the printing of tether and the evolution of bitcoin's price. Typically, the tether issuers arbitrate between the conversion of the tether in dollars and the conversion of another, better-known crypto-asset, which valuation is higher in dollars: bitcoin. They print tether that supports bitcoin's price in phases of lower prices below a "floor price" (cf. Appendices, Graph 2 and 3). The support provided by the issuers of the tether prevents the loss of confidence of other investors in bitcoin. Thus bitcoin's price is artificially high. However, according to their policy of transparency, the issuers of the tether are obliged to communicate the statements of bank accounts on their site each end of month to justify that the number of tethers in circulation is well guaranteed by the same number of monetary units in dollar. They sell the bitcoins in their possession which allows them to build their reserve of dollars and increase the company's capitalization. In the case of the existence of price manipulation on the crypto-assets market, the expected relationship between the bitcoin price and the volume of these crypto-assets is negative.

The data on bitcoin's price, the difficulty of the mining, the cost per transaction are extracted on quandl.com. The data on tether, ripple and ether come from coinmarketcap. Data on FSI from the Office of Financial Research, Google from Google Trend, oil data from U.S. Oil. Energy Information Administration, the data on Shanghai Stock Exchange from Datastream, the gold data from `https://www.gold.org/research`. The data on the Federal Funds Rate are extracted from the database of the Federal Reserve of St Louis. The description of the variables are displayed in Table 1 and Table 2 displays the correlations.

[10] `https://www.buybitcoinworldwide.com/fr/minage/pools/`

[11] Between August 2016 and August 2017 China was responsible for more than two thirds of the bitcoin issue. See "The rise of virtual currencies in China: authorities between mistrust and support" Treasury General Directorate, Beijing, October 26, 2017.

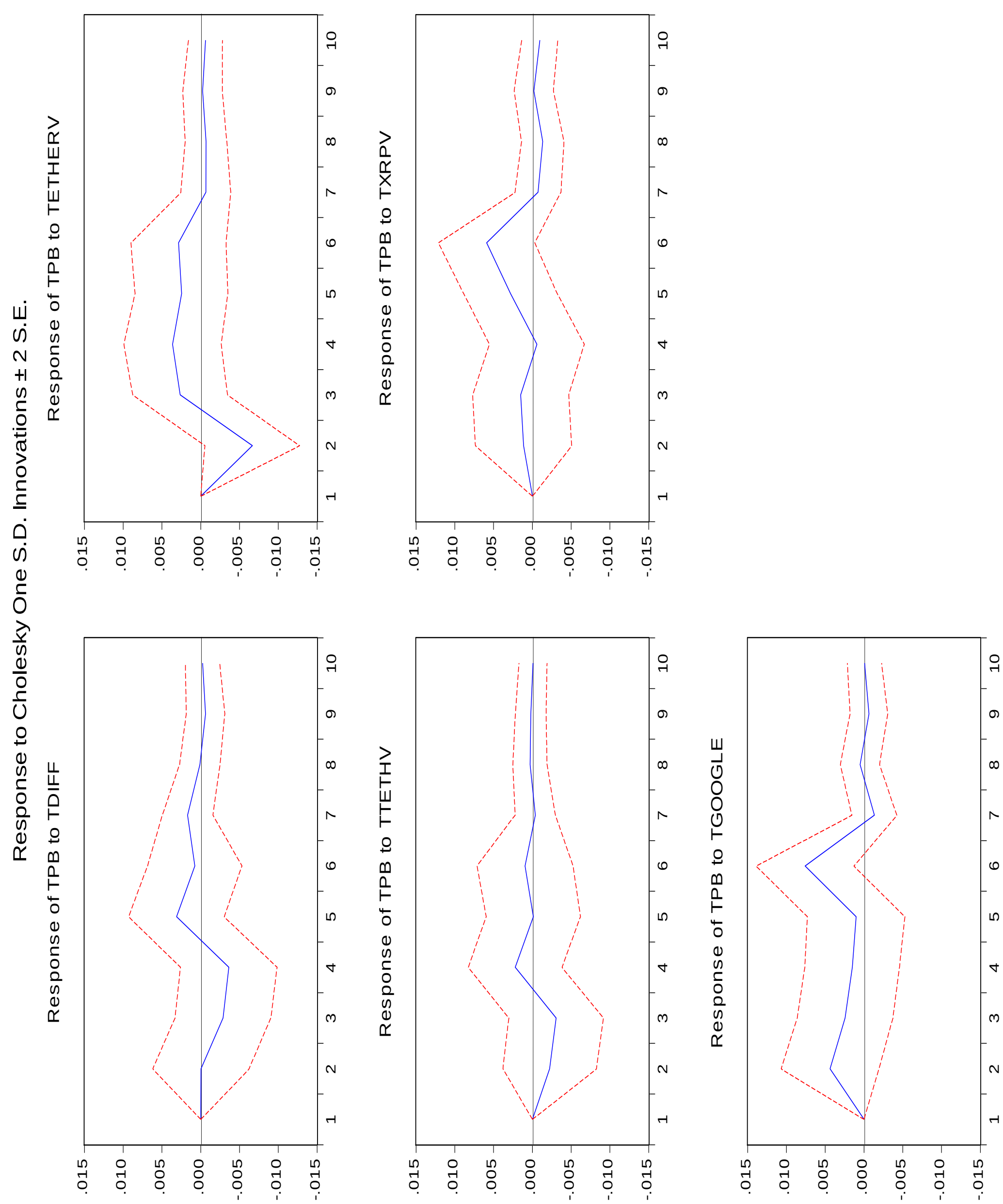
Table 1: Descriptive statistics

BTC_PRICE	CPTRA	DIFFICULTY	ETHERV	FFR	FSI	GOLD	GOOGLE	OIL	SSE	TETHV	XRPV
3455.96	32.22	1.38E+12	8.11E+08	0.87	-1.74	1218.98	1.87	53.25	3138.88	7.65E+08	3.03E+08
1079.55	10.03	4.46E+11	58385100	0.66	-2.03	1235.76	1.29	51.78	3140.32	10607500	4241970
19498.68	161.69	7.15E+12	9.21E+09	1.95	3.71	1344.04	14.29	81.60	3993.67	6.25E+09	9.11E+09
213.24	3.44	5.23E+10	102128	0.07	-4.18	1044.89	0.29	22.48	2644.30	112	24819
3993.56	35.57	1.89E+12	1.26E+09	0.58	1.61	65.96	2.15	13.40	232.36	1.27E+09	8.65E+08
1.38	1.31	1.63	2.46	0.44	0.68	-0.79	3.48	0.13	0.21	1.49	5.78
4.35	3.68	4.50	11.58	1.87	2.85	2.86	16.80	2.37	3.37	4.08	43.42
445.70	352.96	617.74	4691.57	97.77	89.01	121.85	11456.22	21.95	14.81	482.20	84750.23
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3977810	37084.13	1.59E+15	9.33E+11	997.65	-2005.61	1403044	2150.55	61289.02	3612852	8.81E+11	3.49E+11
1.83E+10	1454716	4.10E+27	1.82E+21	385.53	2966.55	5003509	5323.38	206324	62087850	1.86E+21	8.60E+20
1151	1151	1151	1151	1151	1151	1151	1151	1151	1151	1151	1151

Table 2: Correlations between variables

	BTC_PRICE	CPTRA	DIFFICULTY	ETHERV	FFR	FSI	GOLD	GOOGLE	OIL	SSE	TETHV	XRPV
BTC_PRICE	1.00	0.96	0.65	0.85	0.79	-0.63	0.38	0.78	0.76	0.08	0.80	0.62
CPTRA	0.96	1.00	0.68	0.84	0.79	-0.56	0.36	0.68	0.75	0.07	0.83	0.59
DIFFICULTY	0.65	0.68	1.00	0.58	0.89	-0.43	0.19	0.17	0.83	-0.37	0.86	0.26
ETHERV	0.85	0.84	0.58	1.00	0.70	-0.55	0.32	0.61	0.66	0.07	0.83	0.74
FFR	0.79	0.79	0.89	0.70	1.00	-0.70	0.41	0.37	0.88	-0.19	0.81	0.36
FSI	-0.63	-0.56	-0.43	-0.55	-0.70	1.00	-0.38	-0.45	-0.71	-0.34	-0.43	-0.35
GOLD	0.38	0.36	0.19	0.32	0.41	-0.38	1.00	0.22	0.44	-0.17	0.28	0.20
GOOGLE	0.78	0.68	0.17	0.61	0.37	-0.45	0.22	1.00	0.34	0.27	0.41	0.57
OIL	0.76	0.75	0.83	0.66	0.88	-0.71	0.44	0.34	1.00	-0.10	0.80	0.37
SSE	0.08	0.07	-0.37	0.07	-0.19	-0.34	-0.17	0.27	-0.10	1.00	-0.18	0.14
TETHV	0.80	0.83	0.86	0.83	0.81	-0.43	0.28	0.41	0.80	-0.18	1.00	0.54
XRPV	0.62	0.59	0.26	0.74	0.36	-0.35	0.20	0.57	0.37	0.14	0.54	1.00

Figure 1: Bitcoin impulse responses



3.3 Methodology and Empirical Results

We test the existence of unit root with Augmented Dickey-Fuller and Phillips Perron tests. All variables are order 1 integrated with trend and constant at the 1% threshold except FSI variables, Google, the volume of circulating ethers and the volume of ripples in circulation (XRP) that are stationary at level with trend and constant at the threshold of 5%. The variables are put in growth rate in order to make them stationary and of the same scale.

3.3.1 Traditional Variables from the bitcoin Literature: Model 1

We build a VAR from a few variables used in the literature to explain bitcoin's price. This VAR has as endogenous variables: bitcoin price growth rate (TPB), bitcoin cost per transaction growth rate (TCPTRA), growth rate of bitcoin mining difficulty (TDIFF) and Google searches growth rate (TGOOGLE). The exogenous variables are: the FSI growth rate (TFSI), the oil price growth rate (TOIL), the gold price growth rate (TGOLD), the growth rate of the Shanghai Stock Exchange (TSSE) and the growth rate of the Federal Funds Rate (TFFR).

The stability of the VAR is verified thanks to the unit circle. All data contains in the circle, so the VAR is stable. The criteria of information (AIC and HQ) make us retain six delays . The growth rates of searches on Google (TGOOGLE) cause in the sense of Granger the growth rate of bitcoin (TPB). We can therefore assume the existence of short-term and long-term relationships between bitcoin and its explanatory variables.The Johansen test is performed and indicates that there are at least 3 co-integration relationships between the variables at the 5% threshold.

The VECM is used to test the properties of all our variables. We build it with six delays. The endogenous variables are: bitcoin's price (BTC_PRICE), the cost per transaction (CPTRA) and the difficulty of mining bitcoins (DIFFICULTY). The exogenous variables are: FSI, Google search (GOOGLE), oil price growth rate (TOIL), gold price growth rate (TGOLD), Shanghai Stock Exchange growth rate (TSSE) and the rate of growth of the Federal Funds Rate (TFFR). We opt for a co-integration equation and model 3 (presence of a constant in the model).

We identify a short-term relationship between bitcoin price, cost per transaction, difficulty of mining bitcoins, and Google searches.There is a long-term relationship between bitcoin's price, the cost per transaction and the difficulty of mining bitcoins.

No macroeconomic variables are significant. A positive and significant relationship between bitcoin's price and the FSI would have led to asymmetric volatility that would give bitcoin the status of safe haven. However, the absence of a significant relationship between the FSI and bitcoin's price allows us to deduce as Azzi and *al.* (2016) that bitcoin cannot now be considered a safe haven. For other macroeconomic components that have a non-significant relationship with bitcoin's price, Baur and *al.* (2017) explain that bitcoin does not yet play an important role in the financial system. It is not sufficiently used in the traditional financial system because "bitcoins are held speculatively and are therefore hoarded" (Baur and *al.*, 2017; p. 9).

The searches on Google is the main explanation for the bitcoin price variance (1.25%). Google searches have a positive effect on bitcoin's price when it is little known, this effect drops after 2 periods. The difficulty has a negative effect on bitcoin's price. The bitcoin's response to a shock of difficulty is around -0.02 at the 4th period (see Graph 1). Although it has a short and long-term relationship with bitcoin, its explanatory power of the bitcoin price variance is less important than Google searches (about 0.49%). For bitcoin users the potential gains from acquiring bitcoin are greater than the difficulty of issuing new bitcoins. This phenomenon is also illustrated in the sphere of minors who despite the gradual decline in commissions received following the validation of transactions, continue to exercise this activity . In addition, the validation of an operation is done after 2 to 6 resolution's propositions of the mathematical equation. The choice of the solution is made among these proposals for resolution. We therefore have 5 proposals that are not remunerated for their work . Mining activity is therefore increasingly used to keep the bitcoin community active. Finally, an element related to the increasing difficulty of validating transactions in bitcoins is the cost per transaction. This cost has increased significantly from $ 0.10 in July 2016 to $ 35 on December 23, 2017. The possibilities of remuneration being low from the emission of new bitcoins, the miners to support a little more the costs related to the mining require higher transaction fees. However, this cost has fallen sharply since the price peak of December 2017, due to the decrease in the volume of transactions (2.3 transactions that are processed every second in 2019 against 4.8 in December 2017) and the increase in the computing power held by the miners. However, this cost does have a negative and significant relationship in the short and long term with bitcoin.

Table 3: Causality test of Granger

Dependant variable: TPB			
Excluded	Chi-sq	df	Prob.
TCPTRA	7.33	6	0.29
TDIFF	6.55	6	0.36
TETHERV	5.14	6	0.53
TTETHV	5.47	6	0.48
TXRPV	8.18	6	0.22
GOOGLE	14.77	6	0.022
All	45.17	6	0.14

Table 4: Variance decomposition of bitcoin

Period	S.E.	TPB	TCPTRA	TDIFF	TGOOGLE	TETHERV	TTETHV	TXRPV
1	0.0402	100.00	0.00	0.00	0.00	0.00	0.00	0.00
2	0.0403	99.19	0.24	0.02	0.28	0.18	0.07	0.02
3	0.0405	98.19	0.42	0.09	0.74	0.32	0.21	0.02
4	0.0406	97.85	0.43	0.32	0.79	0.33	0.23	0.04
5	0.0407	97.35	0.56	0.34	0.89	0.41	0.22	0.21
6	0.0410	96.57	0.57	0.39	1.22	0.41	0.23	0.60
7	0.0411	96.20	0.57	0.49	1.24	0.44	0.40	0.65
8	0.0411	96.17	0.58	0.49	1.24	0.45	0.40	0.65
9	0.0411	96.14	0.58	0.49	1.25	0.46	0.40	0.66
10	0.0411	96.13	0.59	0.49	1.25	0.46	0.40	0.67

3.3.2 Traditional model with the volume of ethers in circulation: Model 2

We use the VAR of the previous model to which we add to the endogenous variables, the rate of growth of the volume of ethers in circulation (TETHERV). The stability of the VAR is verified thanks to the unit circle. All data contains in the circle, so the VAR is stable. The criteria of information (AIC and HQ) make us retain six delays. The growth rate of searches on Google (TGOOGLE) causes in the sense of Granger the growth rate of bitcoin (TPB). There may be short-term and long-term relationships between bitcoin and its explanatory variables. The Johansen test indicates that there are at least 3 co-integration relationships between the variables at the 5% threshold.

The VECM tests the properties of all variables. It is built to six delays with as endogenous variables: bitcoin's price (BTC_PRICE), the cost per transaction (CPTRA) and the difficulty of mining bitcoins (DIFFICULTY). The exogenous variables are: ETHERV, FSI, GOOGLE searches, oil price growth rate TGOLD), the growth rate of the Shanghai Stock Exchange (TSSE) and the rate of growth of the Federal Funds Rate (TFFR). We opt for a co-integration equation and model 3 (presence of a constant in the model). We identify a short-term relationship between bitcoin price, the volume of ethers in circulation, cost per transaction, difficulty mining bitcoins, and searches on Google and the FSI. There is a long-term relationship between bitcoin's price, the cost per transaction and the difficulty in mining bitcoins. We use the same modeling steps for the following 2 models. The number of lags of each VAR and VECM are not changed. In all the models only the growth rate of searches on Google causes the growth rate of bitcoin price (cf. Table 3, Granger causality test).

3.3.3 Traditional model with the volume of ripples in circulation: Model 3

The endogenous variables of this VECM are: bitcoin's price (BTC_PRICE), the cost per transaction (CPTRA) and the difficulty of mining bitcoins (DIFFICULTY). The exogenous variables are: the volume of ripples in circulation (XRPV), the FSI, Google searches (GOOGLE), the oil price growth rate (TOIL), the gold price growth rate (TGOLD), the growth rate of the Shanghai Stock Exchange (TSSE) and growth rate of the Federal Funds Rate (TFFR). We opt for a co-integration equation and model 3 (presence of a constant in the model).

There is a short-term relationship between bitcoin prices, cost per transaction, the difficulty of mining bitcoins, searches on Google, ripple volume and the FSI. There is a long-term relationship between bitcoin's price, cost per transaction, and the difficulty of mining bitcoins.

3.3.4 Traditional model with the volume of tethers in circulation: Model 4

VECM is used to test the properties of all our variables. We build it with six delays with endogenous variables: bitcoin's price (BTC_PRICE), the cost per transaction (CPTRA), the volume of tether in circulation (TETHV) and the difficulty of mining bitcoins (DIFFICULTY). The exogenous variables are: the volume of tether in circulation (TETHV), the FSI, Google searches (GOOGLE), the oil price growth rate (TOIL), the gold price growth rate (TGOLD), the growth rate of the Shanghai Stock Exchange (TSSE) and the rate of growth of the Federal Funds Rate (TFFR). We opt for a co-integration equation and model 3 (presence of a constant in the model).

We identify a short-term relationship between bitcoin's price, the volume of tethers in circulation, the cost per transaction, the difficulty of mining bitcoins, and searches on Google. There is a long-term relationship between bitcoin's price, the volume of tether in circulation, the cost per transaction and the difficulty of mining bitcoins.

3.3.5 VECM with all the crypto-assets: Model 5

Finally we build a VAR from all variables used in this analysis. The endogenous variables are: bitcoin price growth rate (TPB), bitcoin cost per transaction growth rate (TCPTRA), growth rate of bitcoin mining difficulty (TDIFF) and growth rate. Google research (TGOOGLE), the rate of growth of circulating tethers (TTETHV), the rate of growth of circulating ethers (TETHERV) and the rate of growth of the volume of ripples in circulation (TXRPV) .The stability of the VAR is verified thanks to the unit circle. All data contains in the circle, so the VAR is stable. The criteria of information (AIC and HQ) make us retain six delays. The growth rates of searches on Google (TGOOGLE) cause in the sense of Granger the growth rate of bitcoin (TPB). There is therefore a short-term and long-term relationship between bitcoin and its explanatory variables. The Johansen test indicates that there are at least 3 co-integration relationships between the variables at the 5% threshold.

VECM is used to test the properties of all our variables. We build it with six delays with endogenous variables: the bitcoin price (BTC_PRICE), the cost per transaction (CPTRA), the volume of tether in circulation (TETHV) and the difficulty of mining bitcoins (DIFFICULTY). The exogenous variables are: the volume of circulating tethers (TETHV), the volume of ethers in circulation, the volume of ripples in circulation, the FSI, the searches on Google (GOOGLE), the rate of growth of the oil price (TOIL), the gold price growth rate (TGOLD), the growth rate of the Shanghai Stock Exchange (TSSE) and the rate of growth of the Federal Funds Rate (TFFR). We opt for a co-integration equation and model 3 (presence of a constant in the model). We identify a short-term relationship between bitcoin's price, the volume of circulating tethers, the volume of ripples in circulation, the cost per transaction, the difficulty of mining bitcoins, and Google searches. There is a long-term relationship between bitcoin's price, the volume of tethers in circulation, the cost per transaction and the difficulty of mining bitcoins.Models 2, 3, 4 and 5 (see Table 4) confirm that volumes of crypto-assets (ether, ripple and tether) in circulation have a negative relationship with the price of bitcoin. These crypto-assets would be used in arbitrage operations with bitcoin or at least in price manipulation procedures. By their issuing technique, they are much more likely to be used for price manipulation purposes. The bitcoin price response functions to ether, ripple and tether volumes show that these crypto-assets support the price of bitcoin when it falls (see Graph 1). Griffin and Shams (2018) find in the case of the tether that it is used when the price of bitcoin falls below a certain threshold, but there is no evidence that the tether continues to be used after the bitcoin reached this threshold price. The results of the different VECMs on the relation between bitcoin and these crypto-assets are an aggregation. This aggregation contains the effects of the volumes of ether, ripple and tether on bitcoin's price. In models 2 and 3, we find that the FSI is significant and negative. Bitcoin is not a safe haven. Its volatility and the possible manipulation of prices on the market make it uncertain. At the end, the variance decomposition (see Table 4) shows that we have a lot of work to do to better explain bitcoin's price.

Model	1	2	3	4	5
Cointegration	-0.03*	-0.06***	-0.06***	-0.03**	-0.009*
BTC_PRICE (-1)	0.04	0.04	0.04	0.04	0.04
BTC_PRICE (-2)	0.016	0.02	0.03	0.005	-0.02
BTC_PRICE (-3)	0.05*	0.06*	0.06**	0.06**	0.04
BTC_PRICE (-4)	-0.03	-0.02	-0.03	-0.02	-0.05*
BTC_PRICE (-5)	0.21***	0.21***	0.20***	0.20***	0.17***
BTC_PRICE (-6)	-0.08***	-0.08**	-0.08***	-0.06**	-0.09***
DIFFICULTY(-1)	-4.10E-10*	-2.69E-10	-1.52E-11***	-3.21E-10	-1.70E-10
DIFFICULTY(-2)	-4.25E-10*	-3.10E-10	-1.08E-13	-4.54E-10*	-3.51E-10
DIFFICULTY(-3)	-8.01E-10***	-6.89E-10***	-3.63E-12	-8.13E-10***	-6.77E-10**
DIFFICULTY(-4)	-4.06E-10	-2.96E-10	-2.05E-12	-4.11E-10	-2.95E-10
DIFFICULTY(-5)	-3.47E-11	6.42E-11	-1.02E-11**	1.18E-12	7.14E-11
DIFFICULTY(-6)	-2.20E-10	-5.63E-11	1.37E-12	-2.36E-10	-1.05E-10
CPTRA (-1)	1.13	-0.32	-0.44	-0.21	1.40
CPTRA (-2)	-6.67***	-7.71***	-0.59***	-7.56***	-6.37***
CPTRA (-3)	-3.14*	-3.96**	-0.46***	-3.60**	-2.77*
CPTRA (-4)	-3.63**	-4.29***	-0.49***	-3.10*	-2.50
CPTRA (-5)	-0.056	-0.67	-0.48***	0.68	1.12
CPTRA (-6)	-0.45	-0.91	-0.38***	-0.69	-0.61 [-0.42]
TETHV(-1)				-8.30E-08***	-7.02E-08**
TETHV(-2)				5.90E-09	8.91E-09
TETHV(-3)				-6.87E-08**	-6.87E-08**
TETHV(-4)				-1.44E-08	-2.16E-08
TETHV(-5)				3.46E-08	2.64E-08
TETHV(-6)				2.02E-09	-7.03E-09
ETHERV		-3.31E-08***			-5.66E-09
XRPV			-4.86E-08***		-3.57E-08**
GOOGLE	20.87***	52.11***	51.05***	21.08***	29.75***
FSI	-5.70	-5.70	-17.42**	-3.26	-8.83
TGOLD	65.88	64.20	183.57	-268.79	-225.31
TOIL	114.70	267.56	247.77	-14.05	47.93
TSSE	-1094.4	-1009.05	-891.47	-1126.94	-1064.87
TFFR	16.11	8.47	13.71	14.29	14.16
C	-30.35	-101.53***	-93.87***	-26.47*	-40.57**

Notes: Dependent variable: BTC_PRICE. *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

Table 6: VECM results

4 Conclusion

Following the price spike of December 2017, research on the reasons for the evolution of the bitcoin's price, has gradually migrate from traditional variables (searches on Google, macroeconomic environment, variables typical to bitcoin) to variables of the ecosystem of crypto-asset. Our analysis has shown that there is a negative and significant relationship between bitcoin's price and the volumes of ether, ripple and tether. Although the VECM cannot better distinguish the operating phenomenon that is: when exactly the bitcoin is bought and resold, at least for crypto-assets such as ether and ripple. But it already gives us the intuition that there is indeed a link between the volume of these crypto-assets and bitcoin's price. For us, it opens the way to the use of more advanced econometric techniques to better understand these phenomena of pump and dump for crypto-assets other than tether.

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Appendices

Figure 2: Net flow of bitcoins and tethers (Griffin and Shams, 2018)

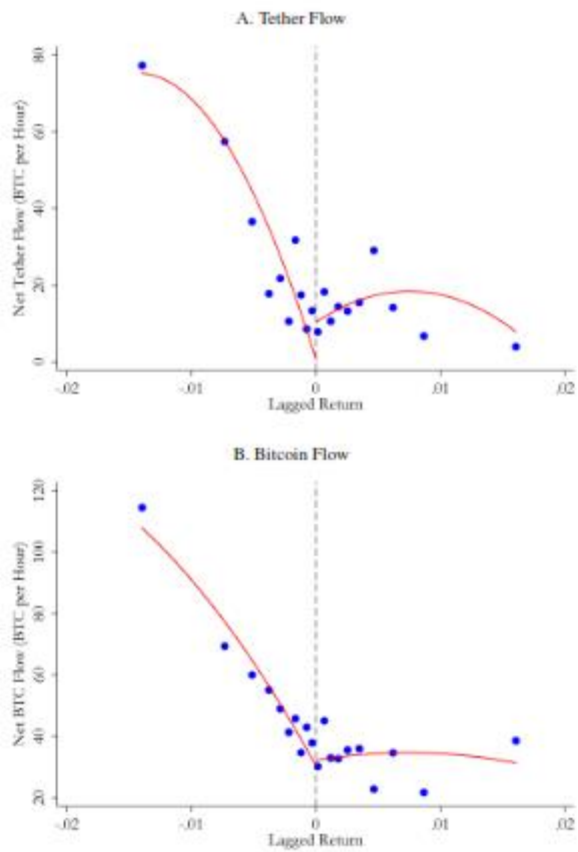

Figure 6. Net flow of Bitcoin and Tether for Quantiles of Lagged Return. This figure shows net hourly flow of Bitcoin and Tether between Bitfinex and two major Tether exchanges, Poloniex and Bittrex, as a function of lagged 3-hour average return. The sample period is from March 1, 2017 to March 31, 2018. The graphs show the average flow per quantiles of lagged return, controlling for 3-hour lagged volatility calculated using five-minute returns. Panel A shows the net outflow of Tether from Bitfinex to Poloniex and Bittrex and Panel B shows the net inflow of Bitcoin from Poloniex and Bittrex to Bitfinex. The red lines show the fitted values of the flow as a second order polynomial function of the lagged return, controlling for lagged volatility.

Figure 3: Prices of bitcoin around high flow of tether (Griffin and Shams, 2018)