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How to Explain the Price of Bitcoin?

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

JEL Classification: E42, G11, G12, G15.

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

1. Introduction

Bitcoin is the main virtual currency[3] in circulation. In December 2020, the coinmarketcap.com website listed 8,507 virtual currencies for a total capitalization of approximately 671 billion dollars. Bitcoin's capitalization is close to 441 billion dollars, or 66% of the market.[4] Created in 2008 by Satoshi Nakamoto (2008),[5] bitcoin has been exchanged since 2009 on a peer-to-peer basis through Blockchain, a distributed accounting register (for more details, see for example, Blundell-Wignall 2014; Böhme *et al.* 2015; Gans and Catalini 2017). The cryptographic protocol, known to all users, implies that only 21 million bitcoins will be created by 2140[6]. The main characteristic of bitcoin is that it lies outside the traditional financial system. Unlike a legal currency issued by a central bank, bitcoin is completely decentralized and is not the counterpart of any monetary base. However, the mining process avoids the double expenditure issue. It has no legal tender and no legal guarantee of repayment.

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 subject to several 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 interests or dividends. Gains derive solely from price fluctuations, the foundations of which we are trying to understand.

How does the literature explain the evolution of the price of bitcoin? Buchholz *et al.* (2012) analyze daily data specific to bitcoin, 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 price on the Mt. Gox and Tradehill platforms, the volume of bitcoin's transactions on Mt. Gox (before it closed, Mt. Gox dealt with 72% of bitcoin's trading volumes), Google searches, posts on Twitter, etc. This study, conducted from July 2010 to March 2012, concludes that bitcoin price developments are mainly explained by interactions between supply and demand. Demand is primarily determined by the volume of bitcoin transactions (which is strongly impacted by Google searches and bitcoin price volatility). Supply is determined by the number of bitcoins available on the market. However, these interactions between supply and demand have a negligible impact on bitcoin price in the absence of a positive price shock. Conversely, their effect is significant following a positive price shock when bitcoin is increasingly in demand by investors.

Van Wijk (2013) analyzes the impact of economic performance on the evolution of bitcoin price. He 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, oil prices and the Dow Jones index all have an impact on bitcoin price in the long run, while in the short run only the Dow Jones index has an impact. This analysis is interesting because the explanatory power of the results is greater than in the vast majority of models in the literature. However, there may be a bias, because the period of the analysis is around the beginnings of bitcoin.

Kristoufek (2014) combines the ideas of Buchholz *et al.* (2012) with those of Van Wijk (2013) by performing a regression that includes elements specific to bitcoin, such as total bitcoins in circulation, number of transactions, estimated volume output, trade volume vs. transaction volume ratio, hash rate, bitcoin / US dollar exchange rate, bitcoin / Chinese Renminbi exchange rate, Wikipedia and Google searches and some macroeconomic variables (Financial Stress Index, gold price). Bitcoin price is explained by searches on Wikipedia and Google, technical components such as hash rate and mining difficulty, bitcoin use in trade and the supply of bitcoin. The author finds no significant relationships between bitcoin price and macroeconomic components. However, the Wavelet Coherence technique used by

Kristoufek (2014) studies interconnections between the variables taken two by two. It can lead to neglect some relationships which can have a different effect on bitcoin price.

Bouoiyour and Selmi (2014; 2015) suggest that bitcoin price can be explained by hash rate, bitcoin circulation speed (velocity), Google searches and values of the Shanghai Stock Exchange. This Stock Exchange is used to analyze the effect of the Chinese market. 81%[7] of mining co-ops are concentrated in China and in 2015 60% of bitcoin transactions[8] took place in China (Woo, 2017). Stock market and regulatory developments could impact bitcoin issuance.[9]

Ciaian *et al.* (2015) identify 3 sets of potentially relevant variables: the determinants of bitcoin supply and demand, macroeconomic determinants, and the attractiveness of bitcoin as an asset for investors. Then they build 3 regressions using a VECM on daily data for the period 2009-2014. They conclude that the attractiveness of bitcoin is 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 price. Ciaian *et al.* (2016)[10] use time series over the period 2009 to 2015 and formulate testable hypotheses based on Barro's model (1979). They show that the determinants of supply and demand (number of bitcoins in circulation, hash rate, velocity, etc.) have a significant impact on bitcoin price and this impact tends to increase over time. The attractiveness of bitcoin has an impact in the short run, but this effect fades in the long run. 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 used by the authors.

Given the inability of traditional factors to explain bitcoin price, recent works consider the existence of price manipulations in the crypto-assets market. Price manipulation is defined by Kyle and Viswanathan (2008) as an *"intent [is] to pursue a scheme that undermines economic efficiency both by making prices less accurate as signals for efficient resource allocation and by making markets less liquid for risk transfer"*. The bitcoin market is a favourable space for price manipulation due to its concentration. Banque de France statistics (2018) confirm these speculative phenomena, since 96% of bitcoins are held by only 2.5% of users. Moreover, Selmi *et al.* (2018) and Urquhart (2018) have discovered that bitcoin is inefficient as bitcoin price does not reflect the real state of the market.

Gandal *et al.* (2018) analyze transaction flows on the Mt. Gox platform. They identify suspicious trading activities that coincide with sharp increases in bitcoin price, including the price peak of 2013. The authors point out the lack of regulation on bitcoin transactions which, in essence, are OTC. This idea is echoed by Chen *et al.* (2019), who conclude from the same Mt. Gox data that activities carried out by so-called "abnormal" accounts have a significant impact on bitcoin 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 manipulations.

Following the price spike of December 2017, Griffin and Shams (2018) study the technique used to artificially influence bitcoin price. They identify tether as being involved in many arbitrage operations with bitcoin. This crypto-asset, held mainly by its issuers, appears to be used to initiate pump and dump operations. Typically, tether holders buy bitcoin when its price drops, which results in an increase in the tether price. This price level is maintained for several days in order to define an equilibrium price that attracts unsuspecting investors. The insider investors sell their positions brutally at the end of the month to recover the tethers, which leads to a drop in bitcoin price (as shown in Figure 1).

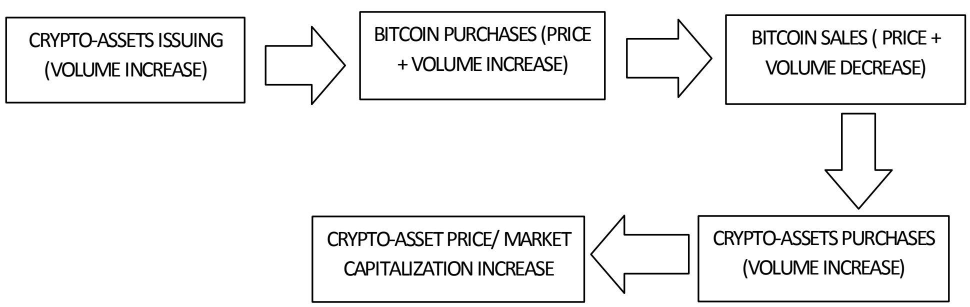

Figure 1: Bitcoin price manipulation scheme

We built a VECM covering the period 2015-2019. We first confirmed that the traditional macroeconomic determinants (gold, oil, SSE, etc.) had no impact on bitcoin price. We found that the volumes of ripple and tether, Google searches, and mining difficulty have short-run and long-run effects on bitcoin price. The volume of ether and of bitcoin have a long-run effect on bitcoin price.

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

2. Empirical Specification

2.1. Econometric Approach

The econometric model contains interdependent variables (bitcoin 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 produce spurious results. In order to avoid this, we start by testing the properties of the series.

First, the stationarity of time series is analyzed using two unit root tests: Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP). If the variables have a unit root, we could consider a long-run relationship between them. We perform the Phillips-Ouliaris cointegration test and use the Johansen test to verify the number of co-integration relationships. If two individual time series are non-stationary, their combination may be stationary (Engle and Granger 1987). 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) based on a VAR, is estimated for the co-integrated series. An error correction term indicates the speed of adjustment of any imbalance to a long-run equilibrium state. The VECM type is shown by the equation below. We chose the third type, with no trend but with a constant.

$\Delta y_t = \gamma(y_{t-1} - \theta X_{t-1} + C_0) + C_2 + \Sigma_i \delta_i \Delta y_{t-i} + \Sigma_j \rho_j \Delta X_{t-j} + \varepsilon_t$ with $i = 1, ..., p-1$ and $j = 1, ..., p-1$.

2.2. Data and Descriptive statistics

The daily variations in bitcoin price (BTCPRICE) denominated in dollars are studied over the period 08/07/2015 to 12/31/2019.

Google searches for the word "bitcoin" (GOOGLE) are used to test the hypothesis that searches express investor interest in bitcoin (the demand side).

Mining difficulty (DIFFICULTY) represents the issue of the mathematical operation that must be solved in order to validate an operation on bitcoin's Blockchain.

The volume of bitcoins in circulation (BTCV) to express the supply side.

The Financial Stress Index (FSI) expresses risk aversion.

Oil price (OIL), gold price (GOLD), the Shanghai Stock Exchange (SSE), Dow Jones Index (DJI) and the Federal Funds Rate (FFR) express macroeconomic developments.

The volumes of ethers (ETHERV), tethers (TETHV) and ripples (XRPV) in circulation.

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

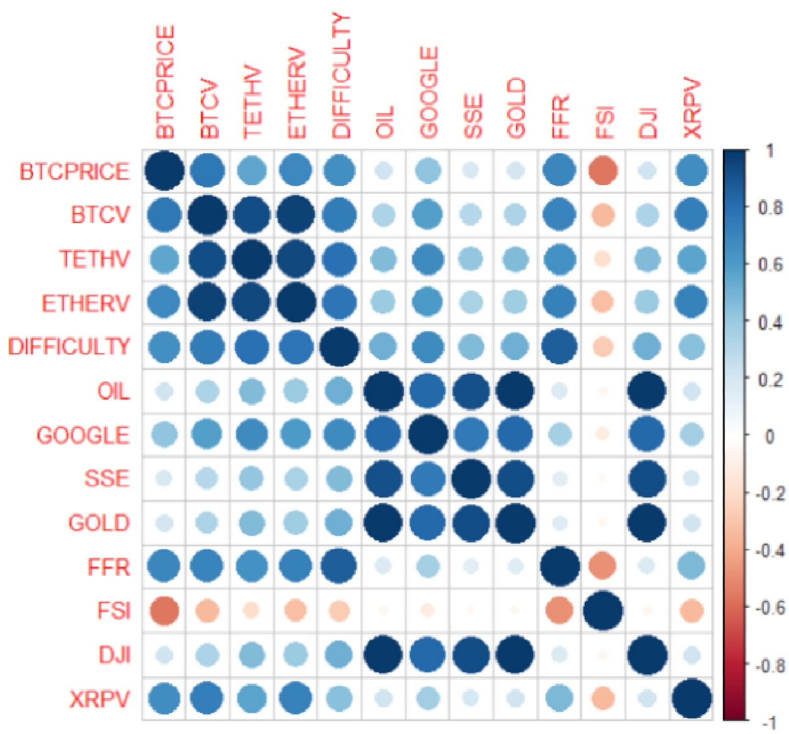

Figure 1: Correlations between variables

2.3. *Methodology and Empirical Results*

We test the existence of a unit root with Augmented Dickey-Fuller and Phillips Perron tests. All the variables have a unit root at the 10% level. We use the Phillips-Ouliaris cointegration test, which shows that our macroeconomic variables are not cointegrated. When we remove these variables, all the remaining series are cointegrated (Table 2). We then carry out the Johansen test, which shows 4 cointegrating equations at 5% level.

To analyze the dynamics between the variables, we build a VAR. The endogenous variables are the cointegrated variables and the exogenous

Table 1
Descriptive statistics

	BTCPRICE	*BTCV*	*DIFFICULTY*	*ETHERV*	*FFR*	*FSI*	*GOLD*	*GOOGLE*	*OIL*	*SSE*	*TETHV*	*XRPV*	*DJI*
Mean	3455.96	2.25E+09	1.38E+12	8.11E+08	0.87	-1.74	1242.92	1.87	53.25	3138.88	6.77E+08	2.91E+08	20510.41
Median	1079.55	2.09E+08	4.46E+11	42613400	0.66	-1.95	1256.8	1.29	51.78	3140.32	3747980	3207640	20107.62
Maximum	19498.68	2.38E+10	7.15E+12	9.21E+09	1.95	3.71	1370	14.29	81.60	3993.67	6.25E+09	9.11E+09	26584.28
Minimum	213.24	12712600	5.23E+10	102128	0.12	-4.18	1050.60	0.29	22.48	2655.30	112	24819	15676.26
Std. Dev.	3993.56	3.74E+09	1.89E+12	1.26E+09	0.58	1.61	75.77	2.15	13.40	219.36	1.27E+09	8.68E+08	3029.071
Skewness	1.38	2.396616	1.63	2.56	0.44	0.61	-0.79	3.4	0.13	0.34	1.72	5.78	0.288409
Kurtosis	4.35	9.582570	4.50	11.94	1.87	2.85	2.76	16.08	2.37	3.37	4.97	43.42	1.961839
Jarque-Bera	512.47	3052.806	617.74	4900.7	92.34	72.54	111.2	10007.74	14.4	38.57	725.86	84750.23	92.34106
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.000000
Sum	3977810	2.48E+12	1.59E+15	8.54E+11	909.65	-1876.61	1373423	2086.55	57763.30	3488369	8.81E+11	3.49E+11	909.6100
Sum Sq. Dev.	1.83E+10	1.55E+22	2.67E+27	1.82E+21	385.53	2908.55	6337933	5311.38	179711.7	53034154	1.86E+21	8.60E+20	327.3950
Observations	1105	1105	1105	1105	1105	1105	1105	1105	1105	1105	1105	1105	1105

Table 2
Phillips-Ouliaris cointegration test

Dependent	*tau-statistic*	*Prob.**	*z-statistic*	*Prob.**
BTCPRICE	-3.92	0.4025	55.13	0.0174
BTCV	-9.68	0.0000	335.31	0.0000
DIFFICULTY	-4.97	0.0524	63.91	0.0042
GOOGLE	-4.29	0.2306	53.63	0.0219
ETHERV	-5.63	0.0073	90.71	0.0000
TETHV	-8.09	0.0000	150.006	0.0000
XRPV	-6.62	0.0001	193.46	0.0000

Note: *MacKinnon (1996) p-values
The null hypothesis is: The series are not cointegrated

Table 3
Long-run results

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
BTCV	6.55E-07	3.02E-08	21.72	0.0000
DIFFICULTY	4.49E-10	6.26E-11	7.17	0.0000
ETHERV	-1.51E-07	5.99E-08	-2.52	0.0118
GOOGLE	452.13	26.14	17.29	0.0000
TETHV	-3.06E-07	8.30E-08	-3.69	0.0002
XRPV	-9.88E-08	5.04E-08	-1.96	0.0501
C	-648.47	62.72	-10.33	0.0000

Note: BTCPRICE is the dependent variable

are the non-cointegrated ones. The stability of the VAR is verified with the unit circle. The information criteria (AIC and HQ) lead us to retain one lag.

We then move to the VECM. The endogenous variables are: bitcoin price (BTCPRICE), bitcoin volume (BTCV), mining difficulty (DIFFICULTY), ether volume (ETHERV), tether volume (TETHV), ripple volume (XRPV) and Google searches (GOOGLE). The exogenous variables are: Financial Stress Index growth rate (TFSI), Federal Funds Rate growth rate (TFFR) oil price growth rate (TOIL), gold price growth rate (TGOLD), Shanghai Stock Exchange growth rate (TSSE) and Dow Jones Index rate (TDJI). We choose one co-integration equation and model 3 (presence of a constant in the model). The results are shown in Table 3.

The speed of adjustment is negative and significant, the VECM is valid, and we can analyze the long-run and short-run dynamics between the variables. First, the long-run dynamic (Table 4): there is a positive long-run relationship between bitcoin price (BTCPRICE), bitcoin volume (BTCV),

Table 4
Short-run results

Variable	*Coefficient*	*Std. Error*	*t-Statistic*	*Prob.*
C	8.28	8.86	0.94	0.3499
D(BTCPRICE(-1)	-0.004	0.03	-0.13	0.8999
D(BTCV(-1))	1.05E-07	1.50E-08	7.01	0.0000
D(DIFFICULTY(-1))	-4.27E-10	2.54E-10	-1.68	0.0927
D(TETHV(-1))	-2.35E-07	3.83E-08	-6.13	0.0000
D(ETHERV(-1))	-2.97E-08	2.99E-08	-0.99	0.3218
D(GOOGLE(-1))	101.54	27.73	3.66	0.0003
D(XRPV(-1))	-1.46E-07	2.07E-08	-7.08	0.0000

Note: BTCPRICE is the dependent variable

Table 5
VECM

	Model
Cointegration	-0.028***
D(BTCPRICE (-1))	-0.012*
D(BTCV(-1))	1.31E-07 ***
D(DIFFICULTY(-1))	-1.12E-09
D(TETHV(-1))	-7.81E-07
D(ETHERV(-1))	-7.29E-08**
D(XRPV(-1))	1.52E-07 ***
D(GOOGLE(-1))	61.88*
TFSI	-6.27
TFFR	43.01
TGOLD	724.2
TOIL	-140.72
TSSE	338.56
DJI	-262.1
C	-6.78*

Note: Dependent variable: D(BTCPRICE). *** significant at 1% level, ** significant at 5% level, * significant at 10% level.

mining difficulty (DIFFICULTY) and Google searches (GOOGLE). There is a negative long-run relationship between bitcoin price (BTCPRICE), ether volume (ETHERV), tether volume (TETHV) and ripple volume (XRPV). We verify the robustness of these results by a unit root test on the residuals. There is no unit root, the long-run dynamic is robust. In the short run (Table 5), there is a positive relationship between bitcoin price (BTCPRICE), bitcoin volume (BTCV) and Google Searches (GOOGLE). There is a negative short-run relationship between bitcoin price (BTCPRICE), mining difficulty (DIFFICULTY), ripple volume (XRPV) and tether volume (TETHV).

3. Results and Discussion

In our model all the macroeconomic variables have a non-significant relationship with bitcoin price, as suggested in the literature. A positive and significant relationship between bitcoin price and the FSI would have led to an asymmetrical volatility that would give bitcoin safe haven status.[11] This safe haven feature challenges the benefits of holding bitcoins in your wallet. Before the price crash of 2013, bitcoin price rose during periods of high volatility in the financial market, conveying a message of uncertainty that pushed investors to invest more. Conversely, in the case of a fall in prices, investors interpret this as a drop in uncertainty on the markets and abandon bitcoin for traditional assets. This characteristic would enable investors to hedge the risk on traditional markets, but it seems to have disappeared following the price crash of 2013. In our results, the absence of a positive and significant relationship between FSI and bitcoin price allows us to deduce, like Azzi *et al.* (2016), that bitcoin cannot be considered as a safe haven.[12] "*Bitcoin is a speculative vehicle*" (De la Fuente *et al.,* 2019) For the other macroeconomic components that have a non-significant relationship with bitcoin price, we could explain this phenomenon by the fact that bitcoin does not yet play an important role in the financial system. It is not used sufficiently in the traditional financial system because "bitcoins are held speculatively and are therefore hoarded" (Baur *et al.*, 2017, p. 9). Hence the general state of the global economy, reflected by stock, gold, oilVan Wijk, 2013 and fiat currency markets, does not have an impact on bitcoin price.

The difficulty of mining bitcoins is computed 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 Proof of Work (PoW[13]"*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.). This validation technique considers as accurate the results obtained following the largest investment in computing power (CPU). This requires substantial investment in IT equipment and electricity. Combined with the increasing difficulty imposed by the logarithm, investment in bitcoin mining can be very expensive and loss-making. This suggests a negative relationship between bitcoin price and mining difficulty, because increasing this difficulty could discourage investment in bitcoin and lead to a drop in bitcoin price. So our results in the short run confirm this hypothesis. In the long run, however, we find a positive relationship between bitcoin price and mining difficulty. This result is consistent with the literature. Kristoufek

(2015) believes that bitcoin price growth may encourage investment in computer mining hardware, which would lead to indirect bitcoin holdings and increase the difficulty. This increased difficulty implies that the least efficient miners would exit the system. If the remaining miners use mining as an alternative to direct investment, they will become mere buyers of bitcoins and thus increase demand and price.

Bitcoin's volume has only a positive long-run relationship with bitcoin price. This result is explained by the fixed amount of bitcoins. Bitcoin has a deflationary process which implies that bitcoin price increases when total bitcoin reaches its total stock of 21 million. This result is consistent with the fact that bitcoin price increases with the scarcity of non-issued bitcoins.

Bitcoin is an asset with no economic fundamentals and no value from its exploitation; it depends entirely on investors' confidence in its sustainability. To achieve this confidence, the communication made around bitcoin makes it possible to reduce the costs of access to information and increase its attractiveness.[14] Google searches are a good measure of this attractiveness. The positive short-run and long-run relationships between bitcoin price and Google searches are consistent with the literature.

Our VECM shows a negative relationship between bitcoin price and the crypto-asset volumes (ether, ripple and tether). These crypto-assets could be used in arbitrage operations with bitcoin or at least in price manipulation procedures. These 3 crypto-assets have in common the fact that they are mainly held by their issuers or the first buyers (Ethereum for ether, Tether Limited for tether and Ripple Company for ripple). This may offer the holders the opportunity to perform pump and dump operations. Tether, for example, is issued on a discretionary basis. It is first sold on Bitfinex before spreading to other crypto-asset exchange platforms. On these platforms Griffin and Shams (2018) see correlations between the printing of tethers and the evolution of bitcoin price.We find the same results in our correlations table. There is a positive correlation between bitcoin price and the volume of the other crypto-assets.

Typically, tether issuers arbitrate the conversion of the tether into dollars and then its conversion into another, better-known crypto-asset, with a higher valuation in dollars, i.e. bitcoin. They print tethers that support bitcoin price in phases when prices are lower, below a "floor price". The support provided by the issuers of tethers prevents other investors losing confidence in bitcoin. Thus the bitcoin price is artificially high. However, according to their policy of transparency, the issuers of tether are obliged to communicate their bank account statements on their website at the end of each month to justify that the number of tethers in circulation is well backed by the same number of monetary units in dollars. They sell the bitcoins in their possession, which allows them to build up their reserve of dollars and increase the company's capitalization. Analysis of the crypto-assets market on coinmarket.com from 2016 to 2018 shows how tether's capitalization and rank evolved. We clearly see an increase in bitcoin's capitalization following a fall in tether's capitalization in the previous week. Whenever we have a fall in bitcoin price, tether capitalization has increased two or three days before and tether has climbed two steps or more in the ranking of the highest capitalizations. This phenomenon is difficult to see with ether and ripple because they were already among the top crypto-assets in terms of capitalization. As we know, however, the supply of ripples is controled entirely by the Ripple Company, which holds 2/3 of the volume of ripples. This assumes a possible use of ripples for manipulation purposes like tether. Bitcoin's market is a favourable space for these manipulations because it is inefficient (Selmi *et al.*, 2018 and Urquhart, 2018).

4. Conclusion

Following the price spike of December 2017, research on the reasons for the evolution of the bitcoin price has gradually shifted from traditional variables (Google searches, macroeconomic environment, variables typical to bitcoin) to variables of the crypto-assets ecosystem. Our analysis has shown that there is a negative and significant long-run relationship between bitcoin price and the volumes of ethers, ripples and tethers, and a negative short-run relationship between bitcoin price and the volumes of ripples and tethers. The VECM shows that there is indeed a link between the volume of these crypto-assets and bitcoin price, but is unable to distinguish any better the operating phenomenon of when exactly the bitcoin is bought and resold, at least for crypto-assets such as ether and ripple. For us, this opens the way to the use of more advanced econometric techniques like a wavelet to better understand these pump and dump phenomena for crypto-assets other than tether and the impact of the recent pandemic of Covid-19 on these pump and dump phenomena.

Notes

1. Also called 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 December 2020, 88% of the 21 million bitcoins were issued.
5. https://www.buybitcoinworldwide.com/fr/minage/pools/

6. Between August 2016 and August 2017, China was responsible for more than two thirds of bitcoin issuance. See "The rise of virtual currencies in China: authorities between mistrust and support" Treasury General Directorate, Beijing, October 26, 2017.
7. We also use this variable because it is updated and easily available, but we have to acknowledge that it is not accurate enough to represent the impact of China (State and miners) on bitcoin price.
8. De la Fuente *et al.* (2019) used a GJR-GARCH on the same variables to explain bitcoin demand in the short and long run.
9. The same is true for the price of gold. A positive and significant relationship between bitcoin price and gold price would mean that bitcoin is a safe haven asset (Bouoiyour and Selmi, 2019 and Dyhrberg, 2016).
10. "*Bitcoin is a speculative vehicle*" (De la Fuente *et al.*, 2019)
11. "*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.
12. *"Investment demand depends on the costs associated with seeking information on potential investment opportunities available in the market"* Ciaian *et al.* (2015), p.17.

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