Scientific Annals of Economics and Business
65 (2), 2018, 97-117
DOI: 10.2478/saeb-2018-0013

Information Transmission Between Cryptocurrencies: Does Bitcoin Rule the Cryptocurrency World?

Pedro Bação[*], António Portugal Duarte[**], Helder Sebastião[***], Srdjan Redzepagic[§]

Abstract

This paper investigates the information transmission between the most important cryptocurrencies - Bitcoin, Litecoin, Ripple, Ethereum and Bitcoin Cash. We use a VAR modelling approach, upon which the Geweke's feedback measures and generalized impulse response functions are computed. This methodology allows us to fully characterize the direction, intensity and persistence of information flows between cryptocurrencies. At the available data granularity, most of information transmission is contemporaneous, that is, it occurs within a day. However, it seems that there are some lagged feedback effects, mainly from other cryptocurrencies to Bitcoin. The generalized impulse-response functions confirm that there is a strong contemporaneous correlation and that there is not much evidence of lagged effects. The exception appears to be related to the overreaction of Bitcoin returns to contemporaneous shocks.

Keywords: Bitcoin; cryptocurrencies; causality; Geweke feedback measures; generalized impulse response.

JEL classification: G10; G14; G15.

1. INTRODUCTION

Cryptocurrencies, sometimes referred to as virtual or digital currencies, may be considered a medium of exchange in certain contexts, but they do not yet possess all the properties and features usually attributed to money. According to the traditional view (based on Jevons, 1896), money has three main functions: i) it serves as a medium of exchange, ii) it is used as a unit of account and iii) it serves as a store of value. Cryptocurrencies have no legal tender and therefore their acceptance as a medium of payment is not guaranteed anywhere, even in the virtual network. Additionally, given their high price volatility,

[*] Centre for Business and Economics Research (CeBER), Grupo de Estudos Monetários e Financeiros (GEMF), Faculty of Economics, University of Coimbra, Portugal; e-mail: *pmab@fe.uc.pt*.

[**] Centre for Business and Economics Research (CeBER), Grupo de Estudos Monetários e Financeiros (GEMF), Faculty of Economics, University of Coimbra, Portugal; e-mail: *portugal@fe.uc.pt* (corresponding author).

[***] Centre for Business and Economics Research (CeBER), Grupo de Estudos Monetários e Financeiros (GEMF), Faculty of Economics, University of Coimbra, Portugal; e-mail: *helderse@fe.uc.pt*.

[§] University Nice Sophia Antipolis, Université Côte d'Azur, CNRS, GREDEG, France; e-mail: *srdjan.redzepagic@unice.fr*.

cryptocurrencies are certainly not a good way to store nominal or real value. In fact, it is now well-know that cryptocurrencies behave differently from traditional currencies. For instance, the returns on cryptocurrencies are more volatile and exhibit heavier tails, and hence cryptocurrencies are riskier than "real currencies" (Gkillas and Katsiampa, 2018). At most, cryptocurrencies can be viewed as a new kind of tradable speculative asset, which can work as imperfect substitutes for traditional currencies.

Nevertheless, cryptocurrencies quickly became a global phenomenon. Coinciding with the international financial crisis of 2008, and the associated lack of confidence in the financial system status, cryptocurrencies started to have an important place in the international financial landscape, attracting extensive attention from media, financial and government institutions, institutional and individual investors, academic researchers, and the public in general (Yermack, 2014; Dyhrberg and Haubo, 2016; Osterrieder *et al.*, 2017; Phillip *et al.*, 2018).

The early work on cryptocurrencies, naturally concentrated on Bitcoin (the first cryptocurrency), came from the fields of computer sciences, cryptography and law, therefore focusing on the technical and methodological features of the Bitcoin network, on mining activity, on blockchain knowledge and on the security and legal issues of the cryptocurrency concept (see, for instance: Barber *et al.*, 2012; Bradbury, 2013; Reid and Harrigan, 2013; Ron and Shamir, 2013; Eyal and Sirer, 2014; Böhme *et al.*, 2015; Karame *et al.*, 2015; Tu and Meredith, 2015). Since then, the cryptocurrency literature approaching the issue from a financial perspective has been growing at an exponential pace. This has been driven in part by the explosive price behaviour (and high media coverage), but it is also due to the academic community's perception that the world of cryptocurrencies is an excellent worldwide financial laboratory, with a huge number of players, low entry costs and a lot of publicly available information. Still, most of the literature has been focused on Bitcoin.

Our paper contributes to the existing literature by investigating the connections between a broad spectrum of cryptocurrencies. Our main goal is to assess the direction, intensity and persistence of information flows between the five most important cryptocurrencies (at the time of writing): Bitcoin, Ethereum, Ripple, Litecoin and Bitcoin Cash. Arguably, these cryptocurrencies compete between them and share the same price formation determinants. Therefore their prices should be closely related, not only in the long- but also in the short-run. In fact, our results show that most information transmission between the prices of these cryptocurrencies occurs within a day. Nevertheless, some lagged information flows are visible. One would expect that, if these lagged effects exist, the information would flow from the Bitcoin market to the other cryptocurrencies, as Bitcoin's is the oldest and most mature cryptocurrency market, and is also the most important in terms of blockchain and exchange trading volume. Surprisingly, what we find is that not only there is not any Bitcoin dominance in terms of information flows, but in fact most of the lagged feedback occurs in the other direction, from other cryptocurrencies to Bitcoin.

The remainder of the paper is organized as follows. Section 2 describes the main features of cryptocurrencies and presents the five most important cryptocurrencies. Section 3 provides a brief literature review, with a focus on market efficiency. Section 4 presents the data and characterizes the cryptocurrencies' markets in term of several trading variables, such as volume, capitalization, price and return. Section 5 presents the VAR analysis, Geweke feedback measures and generalized impulse response functions. Section 6 concludes the paper.

2. THE WORLD OF CRYPTOCURRENCIES

Cryptocurrencies have been feeding both dreams and nightmares. They embody a new technology that – some hope and others fear - will change the way we do many things, not just payments. The new avenues opened up by this technology – and the corresponding benefits and risks - are still under construction/discussion (see, e.g. Guesmi *et al.*, 2018). In the meantime, both potential users and speculators are pouring into cryptocurrencies. To them, cryptocurrencies offer lower transaction costs, peer-to-peer (P2P) transactions, a market where government intervention is still small, and the possibility of cross-border usage (Baur *et al.*, 2018).

Following the seminal work of Nakamoto (2008) on electronic payment systems based on cryptographic proofs, and the creation of Bitcoin in 2009 as the first decentralized ledger currency, a multiplicity of cryptocurrencies, most of them created via initial coin offerings (ICOs), and exchanges have emerged over the last decade. Bitcoin is considered the first successful attempt at creating a digital currency. However, academic interests in anonymous communication research date back to the early eighties. The first commercial digital currency, called DigiCash, was launched in 1990, offered anonymity through cryptographic protocols (Chaum, 1981; Phillip *et al.*, 2018). But the double-spending problem wasn't properly solved, i.e., there was no mechanism to prevent the currency holder from using it in more than one payment. This problem was only solved by the algorithm and cryptographic protocol, the so-called blockchain, created in 2008 by a person or group of persons under the pseudonym Satoshi Nakamoto.

The success of Bitcoin and other cryptocurrencies is astonishing, considering the increasing number of coins and tokens, total market capitalization, trading volume and price appreciation. Currently, the Wikipedia site lists 47 active cryptocurrencies. However, some aggregation sites that compile trade information, such as CoinMarketCap (https://coinmarketcap.com/), claim that there are over 1500 cryptocurrencies with a market capitalization of around 400 billion USD, and more than 10 thousand exchanges that are venue to a total daily trading volume that surpasses 30 billion USD (information obtained on May 1, 2018, from CoinMarketCap). These astonishing figures, coupled with the recent explosive price appreciation of the most important cryptocurrencies, have attracted many speculators and investors. Thus, it is not surprising that nowadays interest in cryptocurrency markets is not limited to technology enthusiasts and to those who value anonymity (Wei, 2018).

Despite Bitcoin's capitalization being already less than half of the total market capitalization of cryptocurrencies (37% on May 1, 2018), Bitcoin continues to be, without any doubt, the most widely known digital currency, with the highest capitalization index and the largest number of users in digital networks and online exchanges. Bitcoin was projected as an anonymous alternative to the centralized banking system, as a decentralized peer-to-peer (P2P) network that allows for the proof and transfer of its ownership without the need for an intermediary or any central monetary authority. All transfers are grouped into blocks and recorded in a large distributed public ledger, the blockchain, which thus contains the whole history of accepted Bitcoin online transactions. Bitcoins are sent and received via Bitcoin addresses, which are cryptographic identities, and, for the trade to take place, a private Bitcoin key of one user has to match the public Bitcoin key of another user. Because there is no central processing authority, transactions between users must be confirmed by consensus, and hence the overall blockchain is constantly validated by Bitcoin participants. Two key advantages emerge. First, it offers protection against fraud. Second, it eliminates intermediaries, reducing the costs and delays in transactions. In other words, this framework increases efficiency (Sebastiao *et al.*, 2017; Guesmi *et al.*, 2018; Ziegeldorf *et al.*, 2018).

At the core of the Bitcoin P2P electronic payment system is the mining process. Bitcoin "miners" invest computing power to validate trades (by solving a complex mathematical algorithm) and to facilitate the protection of transaction records through hashing. New Bitcoins are generated as recompenses to the "miners". This is in fact the only way to create new Bitcoins. Arguably, these validating costs are cheaper when compared with the costs of a traditional payment system. According to the cryptographic protocol, the number of new Bitcoins generated per block started at 50BTC and decreases by half every 210,000 blocks. Given that a block is generated on average approximately every 10 minutes (Li and Wang, 2017), the issuance rate of Bitcoins is expected to diminish over time at a predictable rate, depending on the number of "miners" and traders, technological advances and energy costs. Contrary to fiat currency, where the money supply can be discretionarily increased by the central monetary authority, the total number of Bitcoins to be issued was previously capped at 21 million. At the current pace, this number will be reached in 2140 (see, e.g., Bariviera *et al.*, 2017). This has strong implications for the market value of Bitcoins as it introduces a potential deflationary trend.

The rapid market capitalization growth and the exponential growth of the globalized use of Bitcoins led to the emergence of other cryptocurrencies. Amongst more than 1500 cryptocurrencies currently operating in the various networks and exchanges, Ethereum, Ripple, Litecoin and Bitcoin Cash stand out by its price, trading volume and competitive power against Bitcoin. Together, these five cryptocurrencies represent currently about 90% of the total cryptocurrency market capitalization. Although there are some similarities to the Bitcoin's decentralized P2P network, there are also several differences between those cryptocurrencies and Bitcoin, which warrant a more detailed presentation of these cryptocurrencies.

Ethereum is also a P2P network, but, unlike Bitcoin, it has no theoretical supply limit. Nevertheless, the protocol will achieve an "ice age" were mining difficulty increases exponentially, such that in fact supply is capped at 100 million coins. The Ethereum protocol focuses on providing a platform that facilitates building applications on its public blockchain and such that any user can use it as a decentralized ledger. For instance, Ethereum provides additional features that enable the digital platform to run smart contracts (Ciaian *et al.*, 2018). These characteristics help explain the interest that Ethereum has attracted since its creation in 2015. However, being new, decentralized and with a relatively small market capitalization, its market is considerably more volatile than Bitcoin's (Ciaian *et al.*, 2018).

As in the case of Bitcoin, Ripple is built upon an open source decentralized consensus protocol, where all transactions and their orders of execution are publicly available. This feature is crucial for preventing double-spending and malformed market transactions. Ripple's protocol also fixes a maximum for the total of coins supply that can be put in circulation through the mining activity (Schwartz *et al.*, 2014). The growth rate of additionally minted Ripple coins is also decreasing over time, and converges to zero when the supply of coins approaches its maximum. Hence, the Ripple market is also expected to become deflationary. As in the case of other cryptocurrencies with capped supplies, this characteristic encouraged a faster adoption of this virtual currency, as users and "miners" have incentives to acquire coins as soon as possible in order to benefit from a potential future price increase. Created in 2012, Ripple inherently supports faster transactions than Bitcoin, as almost all ledgers are closed within just a few seconds. This feature may explain the fast capitalization of Ripple in recent years and its current prominent position among the most active cryptocurrencies (Ciaian *et al.*, 2018).

Another cryptocurrency that also tried to complement and to improve upon the Bitcoin's blockchain technology was Litecoin. Launched in 2011, with a fixed supply of 84 million units, this cryptocurrency was also designed to save on the computing power required for the mining process, by requiring miners to solve a less complex problem. Actually, Litecoin is very similar to Bitcoin in its technical implementation, but it primarily differs from Bitcoin by having a smaller block generation time (it is four times faster than Bitcoin, e.g., a block is generated in 2.5 minutes on average), which increases the overall processing speed (Nolting and Muller, 2017).

More recently, on August 1, 2017, Bitcoin Cash was created, once again aiming to improve on certain Bitcoin characteristics. It can be simply characterized as a "sort of upgrade" of the Bitcoin system. In fact, Bitcoin Cash kept the pre-existing blockchain records, but launched a new, slightly modified version of the Bitcoin code for future blocks (Neudecker, 2017). The goal was to make the code much more transaction friendly, which was achieved through a significant increase in the maximum size of a block. On the day of its implementation, holders of Bitcoin received one Bitcoin Cash for each Bitcoin held, much like as in the case of a share spin off. By giving a new token to the holders of each Bitcoin, Bitcoin Cash instantly achieved a wide distribution. Bitcoin Cash operates therefore as a new cryptocurrency, able to handle a large volume of small transactions and suitable for ordinary day-to-day use as a medium of payment. However, as with all these new blockchain assets, it remains to be seen whether Bitcoin Cash will be successful in the long-run. It is precisely the unexpectedness of events such as those that surrounded the creation of Bitcoin Cash that today make this new world of cryptocurrencies as admirable as uncertain.

3. LITERATURE REVIEW

Early studies on the formation of cryptocurrencies' prices and market efficiency can be traced back to Fink and Johann (2014). In that paper, volatility, turnover, liquidity, returns, price efficiency, and price cointegration of Bitcoin are analysed. The authors show that Bitcoin prices experience extreme returns and high volatility, and that the Bitcoin market is not informationally efficient.

The speculative nature of Bitcoin is well documented in the literature. For instance, Glaser *et al.* (2014) are peremptory in questioning the motivations behind the implementation of Bitcoin and highlight the resemblance of its exchange activities to pure speculative trading. Yermack (2014) points out that the Bitcoin price exhibits excess volatility, while Bouri *et al.* (2016) find long-memory features in its volatility. Cheung *et al.* (2015) observe several short-lived bubbles and three huge bubbles in Bitcoin prices during the period 2011-2013. The existence of speculative bubbles in Bitcoin prices is also evidenced by Cheah and Fry (2015).

The basic idea that Bitcoin is a pure speculative asset, without any fundamental relationship to macroeconomic and financial variables, triggered another strand of studies examining the speculative nature of Bitcoin. Ciaian *et al.* (2016) find that market forces and investor attractiveness are the main drivers of Bitcoin prices, and there is no evidence that macro-financial developments have any impact on Bitcoin prices in the long run. Kristoufek (2013) shows a very high correlation between the Google Trends measure, the number of Wikipedia views on Bitcoins and Bitcoin prices. Kristoufek (2015) argues that the Bitcoin price cannot be explained by economic theory; instead the Bitcoin price is driven by speculative investments. Bouoiyour and Selmi (2014) attempt to describe the evolution of Bitcoin's value by regressing its price on several variables such as the market price of gold, Google searches, and the velocity of Bitcoin measured by transaction data. The authors find that only the lagged Google searches were significant at the 1% level. Polasik *et al.* (2015) also show that Bitcoin price formation is the result primarily of its popularity and the transactional needs of its users, hence concluding that Bitcoin returns are mainly driven by news volume, news sentiment and the number of traded Bitcoins. Dastgir *et al.* (2018) study the causal relationship between Bitcoin attention (measured by the Google Trends) and Bitcoin returns for the period from January 1, 2013, to December 31, 2017. They observe a bi-directional causal relationship, with the exception of the central distributions from 40% to 80%, meaning that this bidirectional causality mainly exists in the tails of the distribution.

There are several studies aiming to test Bitcoin's informational efficiency directly. Urquhart (2016) uses six different types of efficiency tests and concludes that Bitcoin is inefficient. However, Urquhart also argues that, after an initial transitory phase, as the market matures, Bitcoin is in the process of moving towards efficiency. Nadarajah and Chu (2017) apply eight different tests to a simple power transformation of the Bitcoin returns and conclude for the efficiency of Bitcoin returns. Bariviera (2017) also re-examines the efficient market hypothesis for Bitcoin using Range over Standard Deviation or Rescaled Range and De-trended Fluctuation Analysis methods to detect long memory and variations in informational efficiency, respectively. The author reports that daily returns exhibit persistent behaviour in the first half of the period under study, whereas its behaviour is more efficient since 2014. Tiwari *et al.* (2018) use a battery of computationally efficient long-range dependence estimators for the period since July 18, 2010 until June 16, 2017, and find that the market is informationally efficient. Vaddepalli and Antoney (2018) compare the time-varying weak-form efficiency of Bitcoin prices in terms of US dollars and euro at a high-frequency level by using permutation entropy. They find that these markets have become more informationally efficient since the beginning of 2016, and that Bitcoin is slightly more efficient in USD prices than in EUR prices. They also find that the higher the frequency, the lower the pricing efficiency is and that liquidity (volatility) has a significant positive (negative) effect on the informational efficiency of Bitcoin.

As we mentioned earlier, most studies on cryptocurrencies focus solely on Bitcoin, but there are some exceptions. Gandal and Halaburda (2014) analyse the competition between several cryptocurrencies and between four online exchanges. The authors found that arbitrage opportunities do not exist for the majority of cryptocurrencies. However, this result might be biased by the small sample size. The authors also conclude that due to the trading frictions between cryptocurrencies and national fiat money, other cryptocurrencies tend to be more efficient and less volatile when their prices are measured in Bitcoins instead of USD.

Kim *et al.* (2016) employ user comments in online cryptocurrency communities to predict fluctuations in the daily prices and transactions of Bitcoin, Ethereum, and Ripple, with positive results, especially for Bitcoin. Phillips and Gorse (2017) show that hidden Markov models based on the behaviour of novel online social media indicators provide the basis for successful trading strategies on several cryptocurrencies. Gkillas and Katsiampa (2018) study the tail behaviour of returns of the major five cryptocurrencies (Bitcoin, Ethereum, Ripple, Bitcoin Cash and Litecoin), using extreme value analysis and estimating Value-at-Risk and Expected Shortfall as tail risk measures. The authors find that Bitcoin Cash is the riskiest, while Bitcoin and Litecoin are the least risky cryptocurrencies.

Sovbetov (2018) examines the factors that influence weekly prices of Bitcoin, Ethereum, Dash, Litecoin, and Monero over 2010-2018. The author shows that these prices are cointegrated and that factors such as market beta, trading volume, and volatility appear to be significant both in short- and long-run. Attractiveness of cryptocurrencies also matters, but only in long-run. Phillips and Gorse (2018) investigate if the relationships between online and social media factors and the prices of several cryptocurrencies (Bitcoin, Ethereum, Litecoin and Monero) depend on the market regime (bubbles versus other events). The authors use wavelet coherence as a metric for the co-movement between a cryptocurrency price and the factors. The authors find that medium-term positive correlations strengthen significantly during bubble-like regimes, while short-term relationships appear to be caused by particular market events (such as hacks / security breaches).

4. DATA AND PRELIMINARY ANALYSIS

The data for our study was collected from the Coin Metrics site (https://coinmetrics.io/). At the time of writing, this aggregation site compiles daily data on 22 cryptocurrencies and 29 tokens. Our attention is focused only on the 5 most important cryptocurrencies, by market capitalization and trading volume, namely: Bitcoin (btc), Litecoin (ltc), Ripple (xrp), Ethereum (eth) and Bitcoin Cash (bch). (This ordering of the cryptocurrencies follows the date of launching, and not its capitalization or trading volume ranking.) For each cryptocurrency, the CSV files available at the Coin Metrics site contain the date (day), on-chain transaction volume and counts, market capitalization, price, exchange volume, generated coins and fees. The daily observations are timestamped at 00:00 UCT. The on-chain transaction volume indicates the total value of outputs on the blockchain, on a given day, i.e. the value denominated in USD that circulates on the blockchain per day. The on-chain count refers to the number of transactions occurring on the blockchain per day. As clearly stated by the site, these two series are only approximations to the actual values and thus quite noisy and incomparable between cryptocurrencies such as Bitcoin and Ethereum. Market capitalization is the unit price in USD multiplied by the number of units in circulation. Unfortunately these are also noisy time series, with the noise level being inversely related to the ratio between actual circulating units to the total number of units. Prices and exchange volumes are also denominated in USD and were collected by Coin Metrics from the CoinMarketCap site (https://coinmarketcap.com/). Generated coins are the number of new coins brought into existence per day. Lastly, fees are the amounts payed in cryptocurrency to use the blockchain. According to the Coin Metrics site, “on-chain volume and transaction count can both be faked and can be tricky to estimate. Exchange volume must be viewed fairly sceptically. Market cap has a whole host of methodological issues. Generated coins and fees, however, are much more concrete.”

Given that the cryptocurrencies in our sample did not come into existence all at the same time, we partitioned the overall sample (May 1, 2013, until March 14, 2018) into four segments according to the existing cryptocurrencies: S1 is the first segment (May 2, 2013 – August 7, 2013) when there is only Bitcoin and Litecoin, S2 is the second segment (August 8, 2013 – August 10, 2015) formed by btc, ltc and xrp, S3 is the third segment (August 11, 2015 – August 3, 2017) formed by btc, ltc, xrp and eth, and finally, S4 is the fourth segment (August 4, 2017 – March 14, 2018) which includes all cryptocurrencies under scrutiny.

Table no. 1 presents some information on the cryptocurrencies’ markets during the last segment (August 4, 2017 – March 14, 2018). We only show the last segment because it has the most updated information and allows the comparison between all cryptocurrencies (with the caveats outlined before).

Table no. 1 – Information on the cryptocurrencies' markets (August 4, 2017 – March 14, 2018)

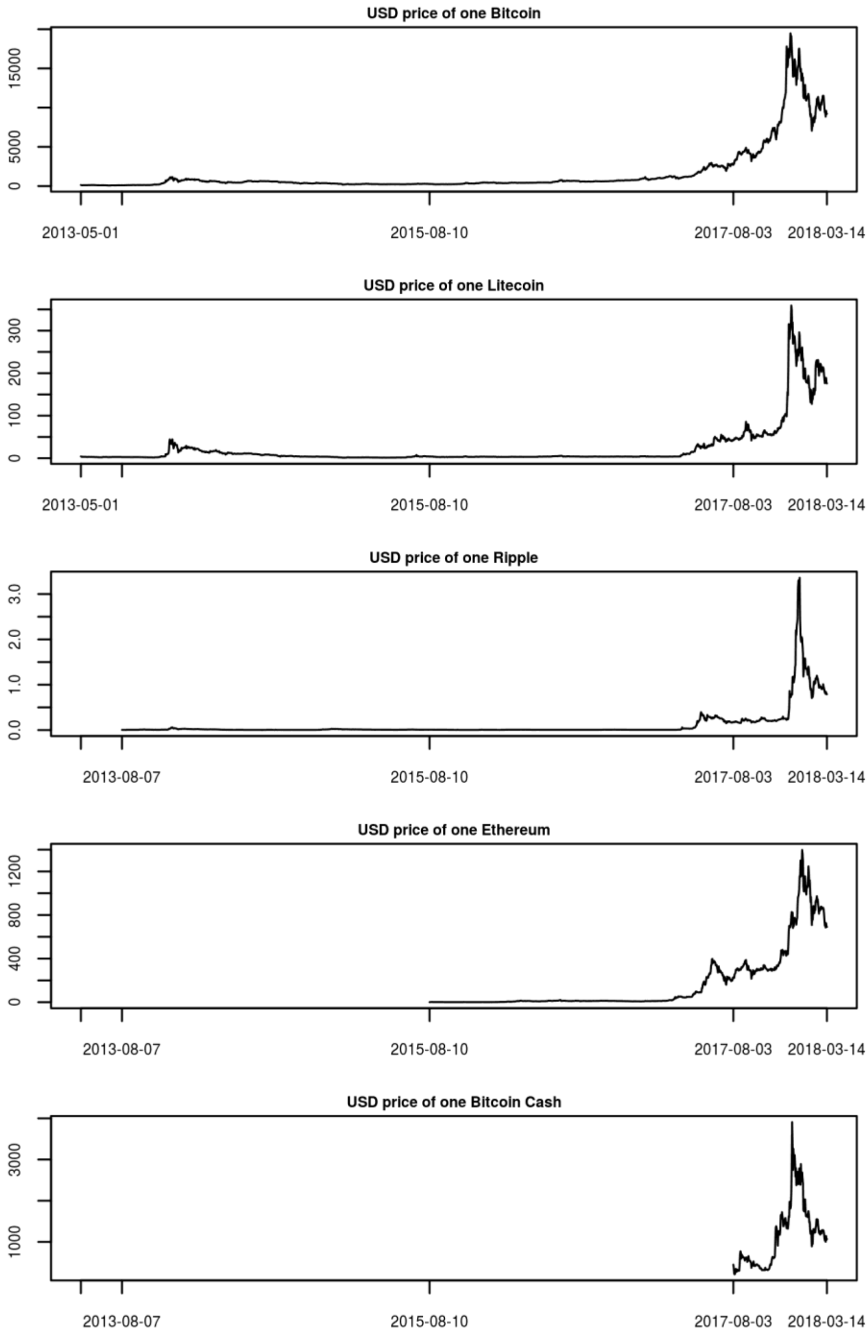
	btc	ltc	xrp	eth	bch
Maximum supply (Millions of Crypto)	21	84	99993	100	21
Ratio of circulating supply to maximum supply (%)	81	66	39	98	81
Daily average on-chain volume per count (Thousands USD)	48.78	26.49	12.61	7.78	58.84
Average market capitalization (Billions USD)	143.81	6.98	25.66	54.85	19.38
Daily average exchange transaction volume (Millions USD)	6.58	0.69	1.07	2.02	1.06
Daily average generated coins (Thousands Crypto)	1.94	14.93	n.a.	19.01	2.40
Daily average fees (Units Crypto).	296	97	n.a.	771	4

Note: Data obtained from the Coin Metrics site (https://coinmetrics.io/). Computations performed by the authors.

On March 14, 2018, the circulating supply of Ethereum was almost at its maximum cap of 100 million units, Bitcoin and Bitcoin Cash achieved a circulating supply of 81% of its maximum, Litecoin supply was 66%, and Ripple had a circulating supply of only 39% of a maximum of approximately 100 billion units. Daily average on-chain transaction volume per count ranges from 7.78 thousand USD for Ethereum to 58.84 thousand USD for Bitcoin Cash. Bitcoin has the highest market capitalization (143.8 billion USD), followed by Ethereum (54.85 billion USD), Ripple (25.66 billion USD), Bitcoin Cash (19.38 billion USD) and Ripple (6.98 billion USD). Considering the total average market capitalization of these five cryptocurrencies, Bitcoin has a market share of 57.37%. Bitcoin also comes first in terms of exchange transaction volume (6.58 billion USD), with an exchange trading volume market share of 57.62%. The difficulty in mining Bitcoins is expressed by the small number of generated coins, especially if one takes into account the higher values of on-chain transaction volume per count, market capitalization and daily average exchange transaction volume. Although the maximum supply has almost been reached, that difficulty in mining is not visible in Ethereum (roughly 19 thousand coins are generated each day). In terms of total average daily fees, Ethereum presented a value of 771 units (1.02 per count), Bitcoin's daily fees are 296 (1.08 per count), Litecoin has fees of 97 units (1.94 per count) and the value reported for Bitcoin Cash is only 4 units (0.18 per count).

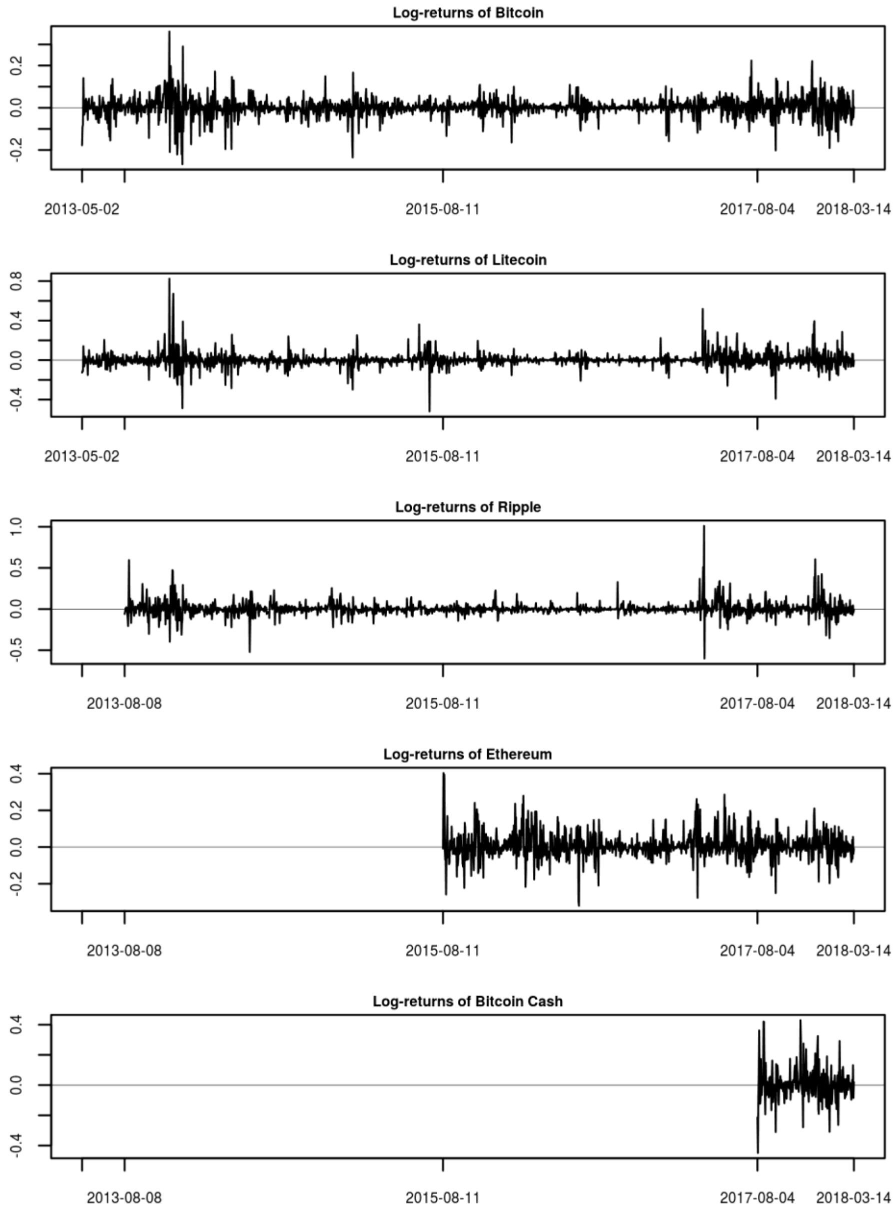
Figure no. 1 shows the evolution of the USD prices of the five cryptocurrencies. Until the end of 2016 prices were relatively low, but in 2017 prices showed an explosive behaviour. The first quarter of 2018 was marked by bearish markets. Also it is noteworthy that the price scales are quite diverse, not only between different cryptocurrencies but also for each cryptocurrency through its time path. For the overall sample, btc prices ranged from 68.5USD to 19475.8USD, ltc prices ranged from 1.15USD to 359.13USD, xrp ranged from 0.003USD to 3.36USD, eth ranged from 0.43USD to 1397.48USD and bch ranged from 212.18USD to 3909USD.

Figure no. 2 shows the data used in our empirical analysis (the daily log-returns, i.e., the first differences of the logarithms of the daily USD prices of the cryptocurrencies).



Source: CoinMetrics site (https://coinmetrics.io/, accessed March 19, 2018).

Figure no. 1 – Prices of bitcoin, litecoin, ripple, ethereum and bitcoin cash in USD



Source: Coin Metrics (https://coinmetrics.io/, accessed March 19, 2018)

Figure no. 2 – Log-returns of bitcoin, litecoin, ripple, ethereum and bitcoin cash

At first glance, looking at Figure no. 1, one would expect the price variability to be quite higher in 2017 and in the first quarter of 2018 than in the earlier part of the sample. However that it is just an illusory effect resulting from the difference in price scales at the beginning and end of each sample. As one can see from Figure no. 2, in the log-returns there is no discernible pattern in the volatility scale or clustering throughout the overall sampling.

Table no. 2 – Descriptive statistics of the log returns

	btc	ltc	xrp	eth	bch
Number obs.	1778	1778	1680	947	223
Mean	0.0024	0.0021	0.0031	0.0073	0.0039
Median	0.0022	0.0000	-0.0026	0.0000	-0.0079
Minimum	-0.2674	-0.5193	-0.6017	-0.3198	-0.4492
Maximum	0.3614	0.8246	1.0110	0.4035	0.4297
Std. deviation	0.0450	0.0700	0.0801	0.0717	0.1151
Skewness	-0.1266	1.7664	2.0435	0.4957	0.5530
Exc. kurtosis	8.0618	24.779	26.457	4.0688	3.2834

Note: Daily price data obtained from the Coin Metrics site (https://coinmetrics.io/). Computations performed by the authors.

The descriptive statistics of the log-returns are in Table no. 2. The mean daily return ranges from 0.21% for Litecoin to 0.73% for Ethereum. The median is zero for Litecoin and Ethereum, negative for Ripple and Bitcoin Cash, and positive for Bitcoin. There has been a very high degree of variability in the prices of cryptocurrencies: the daily log-returns have varied between -0.602 (a 45% daily loss) and 1.01 (a daily gain over 170%). These two extreme values are for Ripple, but the other series' minima and maxima are not very far. In terms of standard deviation, Bitcoin Cash shows the highest value (0.115) while Bitcoin reports the lowest value (0.045). The series present positive skewness (Ripple has the highest value, 2.04), with the exception of Bitcoin (skewness of -0.127). All series present excess kurtosis, especially Litecoin and Ripple (24.8 and 26.5, respectively).

Table no. 3 – Augmented Dickey-Fuller test statistics

Series	log-prices		log-returns	
Deterministic component	constant and trend	constant	constant	none
btc	-1.3714 [0.869]	-0.2975 [0.923]	-7.6290 [0.000]	-7.4455 [0.000]
ltc	-0.9382 [0.950]	-0.1593 [0.941]	-13.7021 [0.000]	-13.6506 [0.000]
xrp	-1.2228 [0.905]	-0.2471 [0.930]	-11.2152 [0.000]	-11.1544 [0.000]
eth	-2.0140 [0.593]	-0.3320 [0.918]	-16.5838 [0.000]	-16.3519 [0.000]
bch	-1.7444 [0.731]	-1.6690 [0.447]	-12.8799 [0.000]	-12.8879 [0.000]

Note: p-values in square brackets.

Standard Augmented Dickey-Fuller tests strongly indicate that the log-price series have a unit root, whereas the first differences of the prices (the log-returns) are stationary - see Table no. 3. This result holds regardless of the assumption concerning the deterministic component (trend in log-prices and constant in log-returns, or no trend in log-prices and no deterministic term in log-returns).

5. FEEDBACK MEASURES AND IMPULSE RESPONSE FUNCTIONS

Our goal in this section is to determine the intensity and direction of the information flow, on a daily sample, between the five main cryptocurrencies. To that end we use a VAR modelling approach. This approach allows us to compute Geweke's feedback measures

(Geweke, 1982), which are used to assess the direction and intensity of causality, and to compute impulse responses. All estimations were performed in Gretl version 2018a.

Given that the cryptocurrencies in our sample did not come into existence all at the same time, we estimate separate VAR models for the four segments of our sample. To compute Geweke's feedback measures, for each possible pair of cryptocurrencies in each segment, we apply the following procedure. First we estimate univariate autoregressive models for each log-return series in each segment. We set the maximum lag-order of the AR model to seven. This allows for the possibility of day-of-the-week effects. Nevertheless, we do not expect the autocorrelation to be very strong, otherwise it might be possible to use the forecasts from an AR model to devise a profitable trading strategy (after taking transaction costs into consideration). The number of lags is selected by optimizing the Bayesian Information Criterion (BIC). The results are presented in Table no. 4. All estimates point to just one lag, except in the case of Ripple. For Ripple, the optimal lag length is two in S2 and three in S3.

Table no. 4 – Lag-orders of the AR and VAR models

Series	**Segment**			
	S1	**S2**	**S3**	**S4**
btc	1	1	1	1
ltc	1	1	1	1
xrp	-	2	3	1
eth	-	-	1	1
bch	-	-	-	1
VAR order	1	2	3	1

Note: The order of the autoregressive model for each series in each segment was chosen according to the Bayesian Information Criterion (BIC). The maximum number of lags allowed was 7. The order selected for the VAR model is the maximum of the lag-orders selected for the univariate models in each segment.

In the second step of our procedure we want to pair the variables and estimate a bivariate VAR model with each pair. The bivariate VAR model must encompass the univariate AR models, to make it possible to test the restrictions that lead from the VAR model to the univariate models. Consequently, we set the order of the VAR equal to the maximum order of the univariate models. Given the results presented in Table no. 4, the estimated VAR models will thus be of orders one, two, three and one in segments S1, S2, S3 and S4, respectively.

In step three of our procedure, we use the estimates from the VAR models of step two and from the AR models of step one to compute Geweke's feedback measures. The measures are the following.

Measure of lagged feedback from variable 1 to variable 2 in the pair:

$$F_{1\Rightarrow 2} = ln(\tilde{\sigma}_2^2 / \hat{\sigma}_2^2) \tag{1}$$

Measure of lagged feedback from variable 2 to variable 1 in the pair:

$$F_{2\Rightarrow 1} = ln(\tilde{\sigma}_1^2 / \hat{\sigma}_1^2) \tag{2}$$

Measure of contemporaneous feedback between the variables in the pair:

$$F_{2\Leftrightarrow 1} = ln(\hat{\sigma}_1^2 \, \hat{\sigma}_1^2 / |\Omega|) \tag{3}$$

Measure of total feedback between the variables in the pair:

$$F_{1.2} = ln(\tilde{\sigma}_1^2 \, \tilde{\sigma}_1^2 / |\Omega|) = F_{1\Rightarrow 2} + F_{2\Rightarrow 1} + F_{1\Leftrightarrow 2} \tag{4}$$

In equations (1) - (4), $\tilde{\sigma}_1^2$ is the variance of the residual of the univariate AR model for the first variable in the pair under analysis, $\tilde{\sigma}_2^2$ is the variance of the residual of the univariate AR model for the second variable in the pair, $\hat{\sigma}_1^2$ is the variance of the residual (of the VAR model) corresponding to the first variable in the pair, $\hat{\sigma}_2^2$ is the variance of the residual (of the VAR model) corresponding to the second variable in the pair, $|\Omega|$ is the determinant of the variance-covariance matrix of the residuals of the VAR model. Note that $\hat{\sigma}_1^2$ and $\hat{\sigma}_2^2$ are the elements in the main diagonal of Ω.

Under the null hypothesis that the lags of variable 1 are not significant in the equation for variable 2 (in the VAR model), $T \cdot F_{1\Rightarrow 2} \sim \chi^2(p)$ asymptotically, where T is the number of observations and p is the order of the VAR model. Similarly, $T \cdot F_{2\Rightarrow 1} \sim \chi^2(p)$ can be used to test the significance of the lags of variable 2 in the equation for variable 1. Thus, these two measures provide a way of testing Granger causality. For the contemporaneous feedback measure we have $T \cdot F_{1\Leftrightarrow 2} \sim \chi^2(1)$ under the null hypothesis that there is no correlation between the error terms in the bivariate VAR model. Finally, we can use $T \cdot F_{1.2} \sim \chi^2(2p+1)$ to test the null hypothesis that all the previous three hypothesis are true, i.e., that there is no linear relation (no information flowing) between the variables in the pair under analysis.

The results of applying this procedure are presented in Table no. 5 (for segments S1, S2 and S3 of our sample) and Table no. 6 (for segment S4).

Table no. 5 – Pairwise feedback measures - segments S1, S2 and S3

1	2	$F_{1\Rightarrow 2}$	$F_{2\Rightarrow 1}$	$F_{1\Leftrightarrow 2}$	$F_{1.2}$
S1 (May 2, 2013 – August 7, 2013)					
btc	ltc	0.0026	0.0061	0.6375***	0.6462***
		(0.4%)	(0.9%)	(98.7%)	
S2 (August 8, 2013 – August 10, 2015)					
btc	ltc	0.0079*	0.0179***	0.6973***	0.7231***
		(1.1%)	(2.5%)	(96.4%)	
btc	xrp	0.0328***	0.0029	0.1953***	0.2310***
		(14.2%)	(1.2%)	(84.5%)	
ltc	xrp	0.0150***	0.0259***	0.1271***	0.1680***
		(8.9%)	(15.4%)	(75.7%)	
S3 (August 11, 2015 – August 3, 2017)					
btc	ltc	0.0011	0.0093*	0.3091***	0.3195***
		(0.3%)	(2.9%)	(96.7%)	
btc	xrp	0.0006	0.0081	0.0210***	0.0297***
		(2.0%)	(27.3%)	(70.6%)	
btc	eth	0.0062	0.0013	0.0407***	0.0482***
		(12.9%)	(2.7%)	(84.4%)	
ltc	xrp	0.0826***	0.0431***	0.0392***	0.1649***
		(50.1%)	(26.1%)	(23.8%)	
ltc	eth	0.0065	0.0006	0.0141***	0.0213**
		(30.7%)	(2.9%)	(66.5%)	
xrp	eth	0.0009	0.0055	0.0037	0.0102
		(8.7%)	(54.5%)	(36.8%)	

Notes: The results come from estimating AR and VAR models of order 1 (for S1), 2 (for S2) and 3 (for S3) – see Table no. 3. $F_{1\Rightarrow 2}$, $F_{2\Rightarrow 1}$, $F_{1\Leftrightarrow 2}$ and $F_{1.2}$ are Geweke's feedback measures given by Equations (1)-(4). The asterisks denote the significance level of the product of the number of observations by Geweke's feedback measures, under Chi-square distributions with *p*, *p*, *1* and *2p+1* degrees of freedom, respectively, where *p* is the order of the VAR. "*": significance at the 10% significance level. "**": significance at the 5% significance level. "***": significance at the 1% significance level. The percentages in brackets are the weight of each feedback measure in the corresponding $F_{1.2}$ measure.

The results show that the contemporaneous measure is almost always the most important component (by far) of the feedback between the log-returns. In fact, the contemporaneous measure is not significant only in segment S3 for the pair composed of Ripple and Ethereum. Interestingly, there appears to be information concerning Bitcoin returns in lagged Litecoin returns in all segments of the sample except the first. Furthermore, in segment S4, Bitcoin returns appear to incorporate information flowing from lagged values of all the other cryptocurrencies in our sample. In segments S2 and S3 it appears that there is a close relationship between Litecoin and Ripple returns, but only the contemporaneous relation survives in segment S4. In fact, in segment S4, lagged Ripple returns appear to contain information relevant to the returns of all the other cryptocurrencies except Litecoin.

Table no. 6 – Pairwise feedback measures – Segment S4

1	2	$F_{1\Rightarrow 2}$	$F_{2\Rightarrow 1}$	$F_{1\Leftrightarrow 2}$	$F_{1.2}$
btc	ltc	0.0025	0.0329***	0.4326***	0.4680***
		(0.5%)	(7.0%)	(92.4%)	
btc	xrp	0.0046	0.0140*	0.1120***	0.1307***
		(3.6%)	(10.7%)	(85.7%)	
btc	eth	0.0003	0.0282**	0.4503***	0.4788***
		(0.1%)	(5.9%)	(94.0%)	
btc	bch	0.0140*	0.0399***	0.1282***	0.1821***
		(7.7%)	(21.9%)	(70.4%)	
ltc	xrp	0.0000	0.0084	0.2061***	0.2145***
		(0.0%)	(3.9%)	(96.1%)	
ltc	eth	0.0001	0.0035	0.7888***	0.7924***
		(0.0%)	(0.4%)	(99.5%)	
ltc	bch	0.0074	0.0003	0.1490***	0.1567***
		(4.7%)	(0.2%)	(95.1%)	
xrp	eth	0.0155*	0.0005	0.3033***	0.3194***
		(4.9%)	(0.2%)	(95.0%)	
xrp	bch	0.0198**	0.0014	0.0967***	0.1178***
		(16.8%)	(1.2%)	(82.0%)	
eth	bch	0.0020	0.0009	0.2301***	0.2330***
		(0.8%)	(0.4%)	(98.8%)	

Notes: Segment S4 of our sample corresponds to the August 4, 2017 – March 14, 2018 period. The results come from estimating AR and VAR models of order 1 – see Table no. 3. $F_{1\Rightarrow 2}$, $F_{2\Rightarrow 1}$, $F_{1\Leftrightarrow 2}$ and $F_{1.2}$ are Geweke's feedback measures given by Equations (1)-(4). The asterisks denote the significance level of the product of the number of observations by Geweke's feedback measures, under Chi-square distributions with *p*, *p*, *1* and *2p+1* degrees of freedom, respectively, where *p* is the order of the VAR. "*": significance at the 10% significance level. "**": significance at the 5% significance level. "***": significance at the 1% significance level. The percentages in brackets are the weight of each feedback measure in the corresponding $F_{1.2}$ measure.

The generalized impulse-response functions (Pesaran and Shin, 1998) in Figure no. A1 to Figure no. A4 in Annex, provide an alternative way of assessing the relations between the log-returns of the cryptocurrencies. These functions confirm that there is a strong contemporaneous correlation between the log-returns. There is not much evidence of lagged effects. The clearest exceptions appear to be the above-mentioned relationship between Litecoin and Ripple with a lag of three periods, and the fact that, in segment S4, Bitcoin returns appear to overreact to contemporaneous shocks, leading to a correction in the period immediately after the shock.

6. CONCLUSION

This paper investigates the information transmission between the most important cryptocurrencies, namely between Bitcoin, Litecoin, Ripple, Ethereum and Bitcoin Cash, using a daily sample since May 1, 2013, until March 14, 2018. To that end we use a VAR modelling approach. This approach allows us to compute Geweke's feedback measures, which are used to assess the direction of causality, and to compute impulse responses.

The cryptocurrencies are closely related, and most of the information transmission occurs within the day, however some lagged information transmission is visible in our sample. It would seem reasonable to expect that Bitcoin tends to dominate the other cryptocurrencies in terms of information transmission, given its dominance in terms of trading volume, market capitalization and exchange trading volume. However, our results present some evidence against this hypothesis, with the lagged information transmission occurring mainly from the other cryptocurrencies, especially from Litecoin, to Bitcoin. Additionally, the feedback from other cryptocurrencies to Bitcoin intensified in the more recent period (August 4, 2017 to March 14, 2018) when Bitcoin returns appear to overreact to contemporaneous shocks and to correct in the day immediately after the shock. According to our results, if we had to choose, among all these five cryptocurrencies, an information transmission leader, that would be, without any doubt, Litecoin.

These results must be interpreted with caution. It might be the case that, because mining and trade validation are more difficult for Bitcoin than for other cryptocurrencies, Bitcoin prices are recorded with a greater delay. If such delay exists then our results are biased against Bitcoin. This problem is potentially more serious in 2017 and in the first quarter of 2018 when there was a Bitcoin trading frenzy.

In future work we intend to test the robustness of these results using other cryptocurrency databases available online. We also intend to investigate the determinants of the information flows between cryptocurrencies, such as, for instance, the relative trading volume, price trend and internet sentiment.

References

Barber, S., Boyen, X., Shi, E., and Uzun, E., 2012. Bitter to Better -- How to Make Bitcoin a Better Currency. In A. Keromytis (Ed.), *Financial Cryptography and Data Security, 7397* (pp. 399-414). Berlin, Heidelberg: Springer. doi:http://dx.doi.org/10.1007/978-3-642-32946-3_29

Bariviera, A. F., 2017. The Inefficiency of Bitcoin Revisited: A Dynamic Approach. *Economics Letters, 161*, 1-4. doi: http://dx.doi.org/10.1016/j.econlet.2017.09.013

Bariviera, A. F., Basgall, M. J., Hasperue, W., and Naiouf, M., 2017. Some Stylized Facts of the Bitcoin Market. *Physica A, 484*, 82-90. doi: http://dx.doi.org/10.1016/j.physa.2017.04.159

Baur, D. G., Hong, K., and Lee, A. D., 2018. Bitcoin: Medium of Exchange or Speculative Assets? *Journal of International Financial Markets, Institutions and Money*.

Böhme, R., Christin, N., Edelman, B., and Moore, T., 2015. Bitcoin: Economics, Technology, and Governance. *The Journal of Economic Perspectives, 29*(2), 213-238. doi: http://dx.doi.org/10.1257/jep.29.2.213

Bouoiyour, J., and Selmi, R., 2014. What Bitcoin Looks Like? . *MPRA Working Paper, 58091*.

Bouri, E., Azzi, G., and Dyhrberg, A. H., 2016. On the Return-volatility Relationship in the Bitcoin Market around the Price Crash of 2013. *Kiel Institute for the World Economy, Economics Discussion Papers*(2016-41).

Bradbury, D., 2013. The Problem with Bitcoin. *Computer Fraud & Security, 2013*(11), 5-8. doi: http://dx.doi.org/10.1016/S1361-3723(13)70101-5

Chaum, D., 1981. Untraceable Electronic Mail, Return Addresses, and Digital Pseudonyms. *Communications of the ACM, 24*(2), 84-90. doi: http://dx.doi.org/10.1145/358549.358563

Cheah, E. T., and Fry, J., 2015. Speculative Bubbles in Bitcoin Markets? An Empirical Investigation into the Fundamental Value of Bitcoin. *Economics Letters, 130*, 32-36. doi: http://dx.doi.org/10.1016/j.econlet.2015.02.029

Cheung, A., Roca, E., and Su, J. J., 2015. Crypto-currency Bubbles: An Application of the Phillips-Shi-Yu (2013) Methodology on Mt.Gox Bitcoin prices. *Applied Economics, 47*(23), 2348-2358. doi: http://dx.doi.org/10.1080/00036846.2015.1005827

Ciaian, P., Rajcaniova, M., and Kancs, d. A., 2016. The Economics of Bitcoin Price Formation. *Applied Economics, 48*(19), 1799-1815. doi: http://dx.doi.org/10.1080/00036846.2015.1109038

Ciaian, P., Rajcaniova, M., and Kancs, d. A., 2018. Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets. *Journal of International Financial Markets, Institutions and Money, 52*, 173-195. doi: http://dx.doi.org/10.1016/j.intfin.2017.11.001

Dastgir, S., Demir, E., Downing, G., Gozgor, G., and Lau, C. K. M., 2018. The Causal Relationship between Bitcoin Attention and Bitcoin Returns: Evidence from the Copula-based Granger Causality Test. *Finance Research Letters*. doi: http://dx.doi.org/10.1016/j.frl.2018.04.019

Dyhrberg, A. H., and Haubo, A., 2016. Bitcoin, Gold and the Dollar-- A GARCH Volatility Analysis. *Finance Research Letters, 16*(C), 85-92. doi: http://dx.doi.org/10.1016/j.frl.2015.10.008

Eyal, I., and Sirer, E. G., 2014. Majority is not Enough: Bitcoin Mining is Vulnerable. 436-454. doi: http://dx.doi.org/10.1007/978-3-662-45472-5_28

Fink, C., and Johann, T., 2014. Bitcoin Markets. *SSRN*. http://dx.doi.org/10.2139/ssrn.2408396.

Gandal, N., and Halaburda, H., 2014. Competition in the Cryptocurrency Market. *CESifo Working Paper Series, 4980*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2506577.

Geweke, J., 1982. Measurement of linear dependence and feedback between multiple time series. *Journal of the American Statistical Association, 77*(378), 304-313. doi: http://dx.doi.org/10.1080/01621459.1982.10477803

Gkillas, K., and Katsiampa, P., 2018. An Application of Extreme Value Theory to Cryptocurrencies. *Economics Letters, 164*, 109-111. doi: http://dx.doi.org/10.1016/j.econlet.2018.01.020

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., and Siering, M., 2014. *Bitcoin - Asset or Currency? Revealing users' hidden intentions*. Paper presented at the Twenty Second European Conference on Information Systems, Tel Aviv.

Guesmi, K., Saadi, S., Abid, I., and Ftiti, Z., 2018. Portfolio Diversification with Virtual Currency: Evidence from Bitcoin. *International Review of Financial Analysis*. doi: http://dx.doi.org/10.1016/j.irfa.2018.03.004

Jevons, W. S., 1896. *Money and the Mechanism of Exchange*. New York: D. Appleton and Company.

Karame, G. O., Androulaki, E., Roeschlin, M., Gervais, A., and Capkun, S., 2015. Misbehavior in Bitcoin: A Study of Double-Spending and Accountability. *ACM Transactions on Information and System Security, 18*(1), 2-32. doi: http://dx.doi.org/10.1145/2732196

Kim, Y. B., Kim, J. G., Kim, W., Im, J. H., Kim, T. H., Kang, S. J., and Kim, C. H., 2016. Predicting Fluctuations in Cryptocurrency Transactions Based on User Comments and Replies. *PLoS One, 11*(8), e0161197. doi: http://dx.doi.org/10.1371/journal.pone.0161197

Kristoufek, L., 2013. BitCoin meets Google Trends and Wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific Reports, 3*(3415), 3415. doi: http://dx.doi.org/10.1038/srep03415

Kristoufek, L., 2015. *What are the Main Drivers of the Bitcoin Price?* : Evidence from Wavelet Coherence Analysis. doi:http://dx.doi.org/10.1371/journal.pone.0123923

Li, X., and Wang, C. A., 2017. The Technology and Economic Determinants of Cryptocurrency Exchange Rates: The Case of Bitcoin. *Decision Support Systems, 95*, 49-60. doi: http://dx.doi.org/10.1016/j.dss.2016.12.001

Nadarajah, S., and Chu, J., 2017. On the Inefficiency of Bitcoin. *Economics Letters, 150*, 6-9. doi: http://dx.doi.org/10.1016/j.econlet.2016.10.033

Nakamoto, S., 2008. Bitcoin: A Peer-to-Peer Electronic Cash System. from https://Bitcoin.org/Bitcoin.pdf

Neudecker, T., 2017. *Bitcoin Cash (BCH) Sybil Nodes on the Bitcoin Peer-to-Peer Network*. Germany: Institute of Telematics, Karlsruhe Institute of Technology.

Nolting, C., and Muller, M., 2017. *CIO Insights Reflections: Cryptocurrencies and Blockchains - Their Importance in the Future". Deutsche Bank Research, Deutsche Oppenheim*: Deutsche Bank AG.

Osterrieder, J., Strika, M., and Lorenz, J., 2017. Bitcoin and Cryptocurrencies - Not for the Faint-Hearted. *International Finance and Banking, 4*(1), 56-65. doi: http://dx.doi.org/10.5296/ifb.v4i1.10451

Pesaran, M. H., and Shin, Y., 1998. Generalized Impulse Response Analysis in Linear Multivariate Models. *Economics Letters, 58*(1), 17-29. doi: http://dx.doi.org/10.1016/S0165-1765(97)00214-0

Phillip, A., Chan, J. S. K., and Peiris, S., 2018. A New Look at Cryptocurrencies. *Economics Letters, 163*, 6-9. doi: http://dx.doi.org/10.1016/j.econlet.2017.11.020

Phillips, R. C., and Gorse, D., 2017. *Predicting Cryptocurrency Price Bubbles Using Social Media Data and Epidemic Modelling*. Paper presented at the Computational Intelligence (SSCI), 2017 IEEE Symposium Series. doi:http://dx.doi.org/10.1109/SSCI.2017.8280809

Phillips, R. C., and Gorse, D., 2018. Cryptocurrency price drivers: Wavelet coherence analysis revisited. *PLoS One, 13*(4), e0195200. doi: http://dx.doi.org/10.1371/journal.pone.0195200

Polasik, M., Piotrowska, A. I., Wisniewski, T. P., Kotkowski, R., and Lightfoot, G., 2015. Price Fluctuations and the Use of Bitcoin: An Empirical Inquiry. *International Journal of Electronic Commerce, 20*(1), 9-49.

Reid, F., and Harrigan, M., 2013. An Analysis of Anonymity in the Bitcoin System *Security and Privacy in Social Networks* (pp. 197-223): Springer. doi:http://dx.doi.org/10.1007/978-1-4614-4139-7_10

Ron, D., and Shamir, A., 2013. Quantitative Analysis of the Full Bitcoin Transaction Graph. In A. R. Sadeghi (Ed.), *Financial Cryptography and Data Security. FC 2013. Lecture Notes in Computer Science* (Vol. 7859, pp. 6-24). Berlin, Heidelberg: Springer. doi:http://dx.doi.org/10.1007/978-3-642-39884-1_2

Schwartz, D., Youngs, N., and Britto, A., 2014. The Ripple Protocol Consensus Algorithm. from https://Ripple.com/files/Ripple_consensus_whitepaper.pdf

Sebastiao, H., Duarte, A. P., and Guerreiro, G., 2017. Where is the Information on USD/Bitcoin Hourly Prices? *Notas Económicas, 45*(45), 7-25. doi: http://dx.doi.org/10.14195/2183-203X_45_1

Sovbetov, Y., 2018. Factors Influencing Cryptocurrency Prices: Evidence from Bitcoin, Ethereum, Dash, Litcoin, and Monero. *Journal of Economics and Financial Analysis, 2*(2), 1-27.

Tiwari, A. K., Jana, R. K., Das, D., and Roubaud, D., 2018. Informational Efficiency of Bitcoin - An Extension. *Economics Letters, 163*, 106-109. doi: http://dx.doi.org/10.1016/j.econlet.2017.12.006

Tu, K., and Meredith, M., 2015. Rethinking Virtual Currency Regulation in the Bitcoin Age. *Washington Law Review (Seattle, Wash.), 90*, 271-347.

Urquhart, A., 2016. The Inefficiency of Bitcoin. *Economics Letters, 148*, 80-82. doi: http://dx.doi.org/10.1016/j.econlet.2016.09.019

Vaddepalli, S., and Antoney, L., 2018. Are Economic Factors Driving Bitcoin Transactions? An Analysis of Select Economies. *Finance Research Letters*. doi: http://dx.doi.org/10.1016/j.frl.2018.04.002

Wei, W. C., 2018. Liquidity and Market Efficiency in Cryptocurrencies. *Economics Letters, 168*, 21-24. doi: http://dx.doi.org/10.1016/j.econlet.2018.04.003

Yermack, D., 2014. Is Bitcoin a Real Currency? An Economic Appraisal. *NBER Working Paper, 19747*.

Ziegeldorf, J. H., Matzutt, R., Henze, M., Grossmann, F., and Wehrle, K., 2018. Secure and Anonymous Decentralized Bitcoin Mixing. *Future Generation Computer Systems*, *80*, 448-466. doi: http://dx.doi.org/10.1016/j.future.2016.05.018

ANNEX

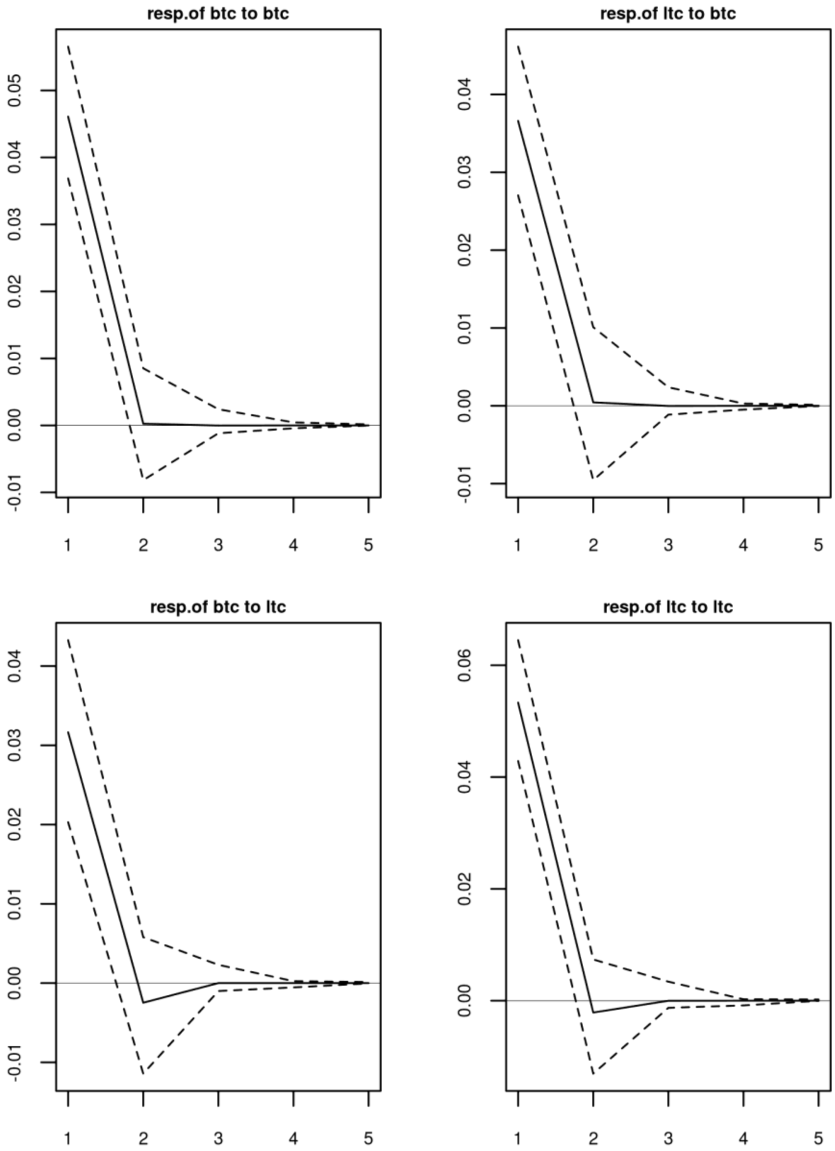


Figure no. A1 – Generalized impulse responses and 95% confidence interval - Segment S1 (May 2, 2013 – August 7, 2013)

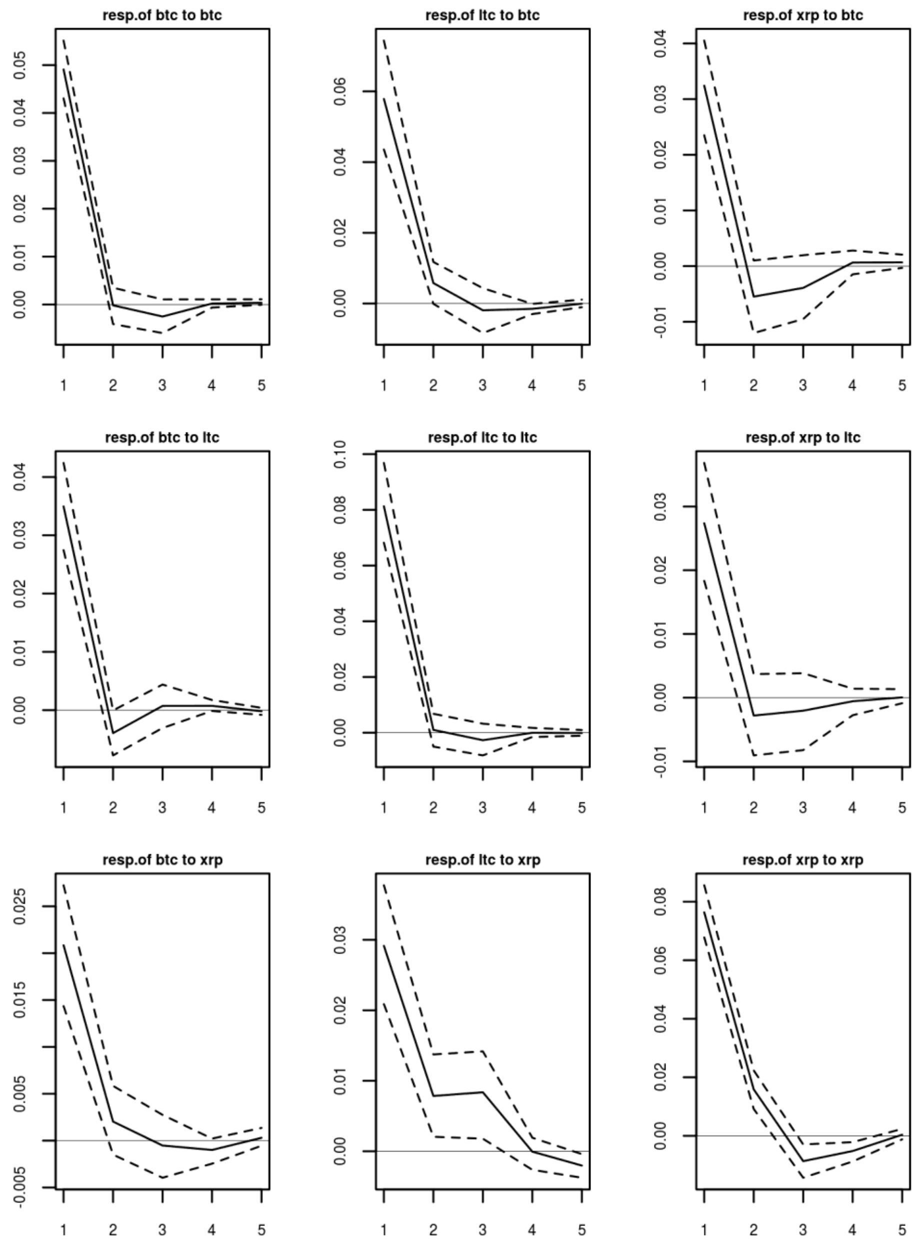


Figure no. A2 – Generalized impulse responses and 95% confidence interval - Segment S2 (August 8, 2013 – August 10, 2015)

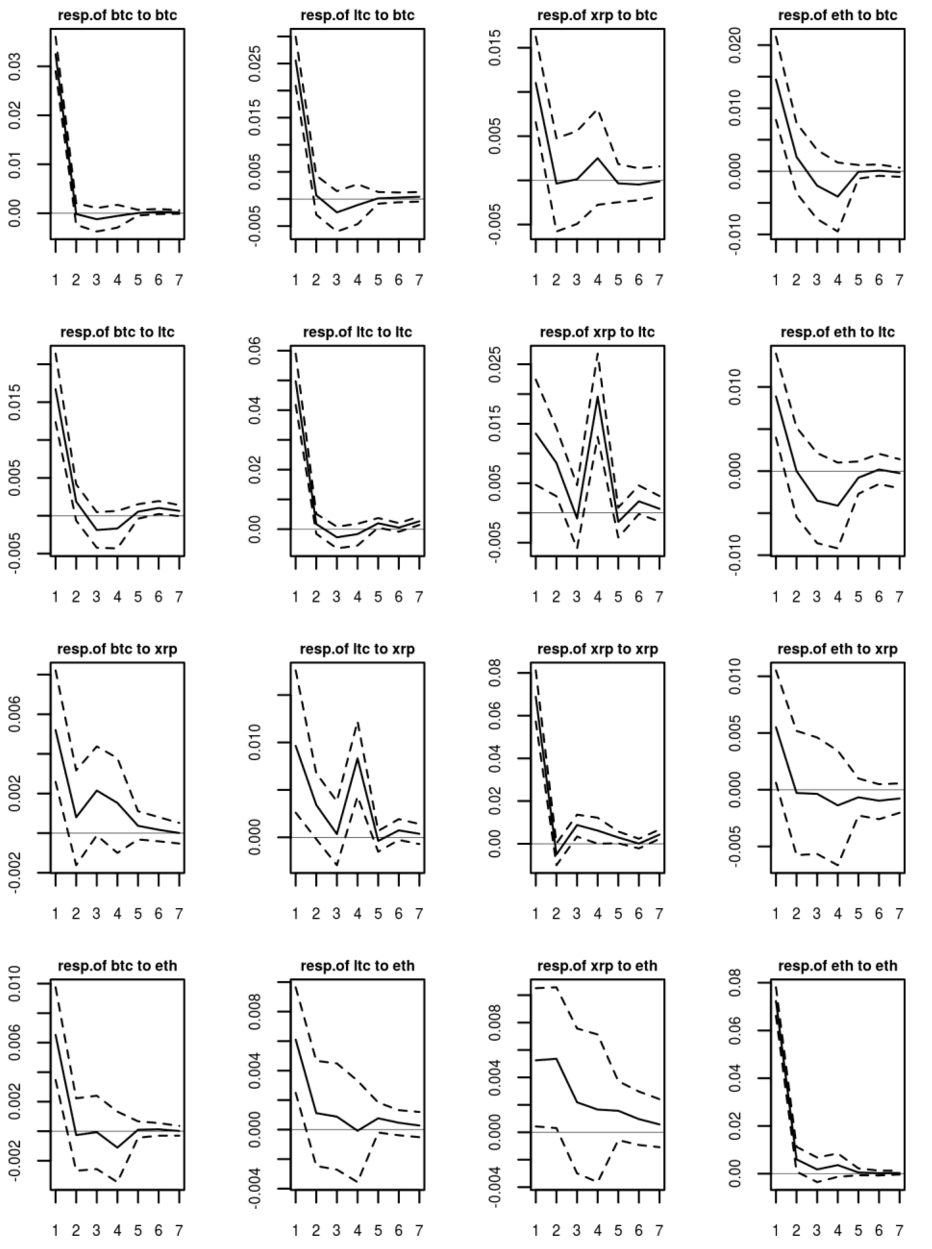


Figure no. A3 – Generalized impulse responses and 95% confidence interval - Segment S3 (August 11, 2015 – August 3, 2017)

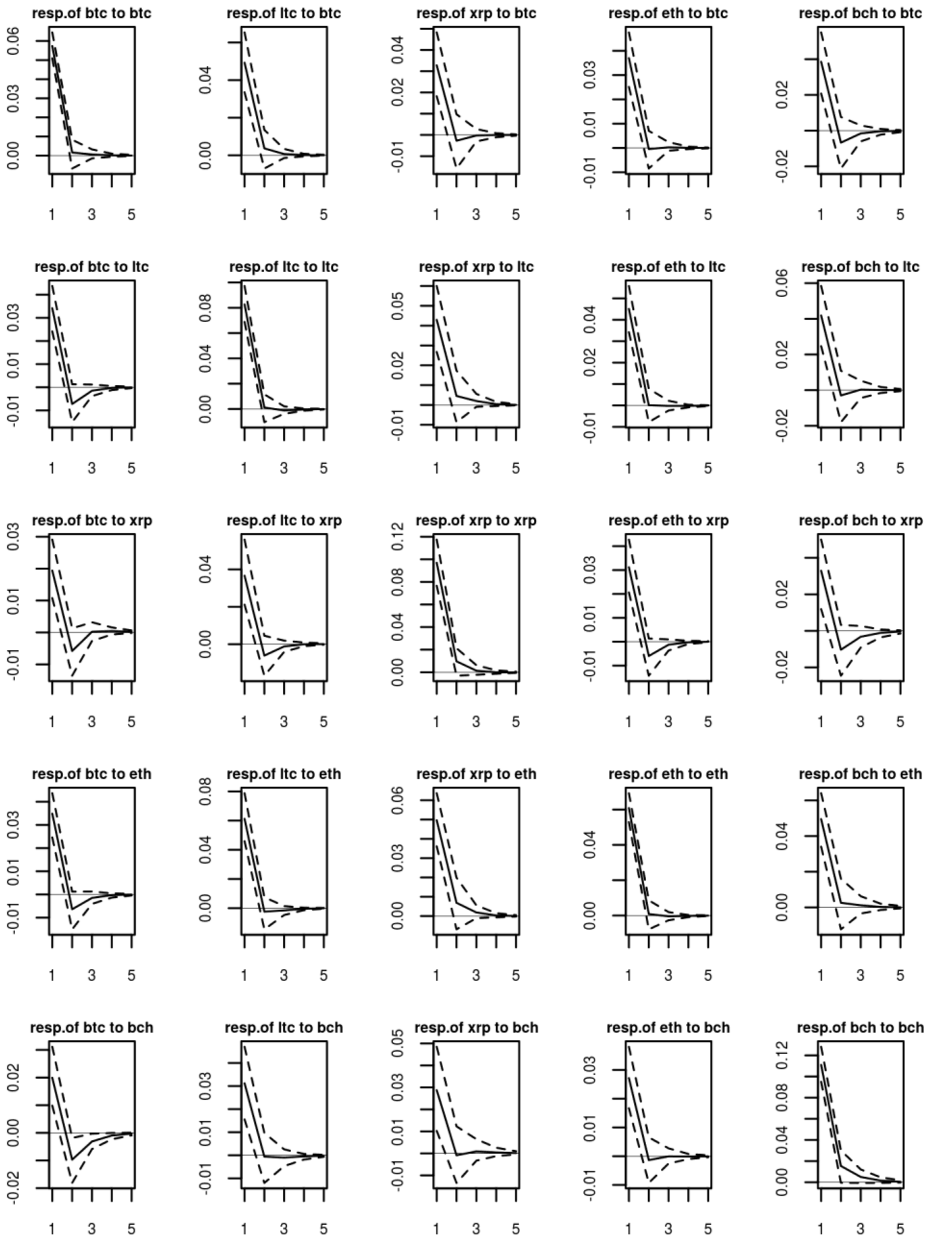


Figure no. A4 – Generalized impulse responses and 95% confidence interval - S4 (August 4, 2017 – March 14, 2018)

Copyright