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WHERE IS THE INFORMATION ON USD/BITCOIN HOURLY PRICES?

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ABSTRACT

This paper analyses the price discovery in the USD/Bitcoin market since Mar-2014 to Nov-2016. The results show a positive relationship between the informational relevance of exchanges and their market shares. Information is mostly transmitted between exchanges within an hour, at least for the main exchanges, although lagged feedbacks occur from the major exchanges. Minor exchanges are merely satellite ones and react to price information with some delay. Bitfinex is the most important exchange: the lagged feedback from this exchange to the market is 18.3%, while the reverse feedback accounts only for 0.6% of the total feedback. Volatility in the major exchanges is the main factor explaining the feedback measures, which sustains the claim that the relative importance of the information-based component of volatility increases with the relative dimension of the exchange.

Keywords: Bitcoin; price discovery; high frequency; Geweke feedback measures; volume; volatility.

1. INTRODUCTION

Bitcoin is a decentralised open source peer-to-peer (P2P) crypto-currency protocol, firstly presented in a self-published paper by the mysterious Satoshi Nakamoto on 31-Oct-2008. Nakamoto (2008) describes a mathematical system that can be used to produce and manage a virtual currency, mainly designed for supporting online transactions. Its main merit, which is the basis for its success in relation to other virtual currencies, is to solve the double spending problem (when an individual, conducting an online transaction, sends the same money to two counterparts at the same time) without the need for a third trusted intermediary. Moreover, while other online payment systems, such as PayPal and eBay, still have impediments in cross-border transactions, Bitcoin allows its holders to trade across borders, in an increasingly global marketplace (ECB, 2012; Lancelot and Tatar, 2013; Pagliery, 2014; Pieters, 2016).

As a crypto-currency, Bitcoin is digital, without physical existence nor country of origin. Bitcoin is issued and controlled by its users and is accepted among the members of an increasing virtual community, therefore is not subjected to any regulation or supervision from a monetary authority. Bitcoins are created by solving a complex mathematical algorithm in a process known as "mining", which is transparent, decentralised, and overseen by the Bitcoin protocol users. The winning miner is awarded a given amount of new Bitcoins, while the losers get nothing. Hence, this activity is characterized as a "competitive bookkeeping" by Harvey (2016). Bitcoins are sent and received via Bitcoin addresses. However, because there is no central processing authority, transactions between users must be confirmed by consensus: a private Bitcoin key of one user has to match the public Bitcoin key of another user. This is made possible through the Bitcoin's "blockchain", which is essentially a public chronological log of every confirmed Bitcoin transaction (ECB, 2012). The Bitcoin supply has increased at a predictable rate, depending on the number of "miners" and traders, technological advances and energy costs.

Bitcoin tends to be subjected to a deflationary process as the demand becomes higher than the supply (Nakamoto, 2008; Fink and Johann, 2014). The historical appreciation of Bitcoin has been impressive. Some anecdotal evidence can grasp this: the first product bought using Bitcoins was two pizzas on 21-May-2010, for a price of 10000 BTC, roughly 25 USD at that time (Fink and Johann, 2014). At the time of writing, the price for one Bitcoin is around 1188.46 USD; so, at the actual prices, this is probably the most expensive meal in the history of mankind! The exponential appreciation of Bitcoin seems to be behind the increasing interest that Bitcoin is gaining in the online trading community.

Since its online creation in 2009, Bitcoin has grown from a new digital currency traded essentially between enthusiasts, to a booming payment system receiving substantial media attention for its conceptual merits. The market capitalisation of Bitcoin surpassed 25 billion USD recently, and the transaction volume keeps growing in a more global and diversified scale. By now, approximately 16.9 million Bitcoins are in circulation (the absolute maximum is 21 million BTC) and there are more than fifty Bitcoin exchanges offering trades against different currencies, with USD and CNY being the most important ones (data on 3-May-2017).

In 2010, the first currency exchanges emerged, with Mt.Gox claiming the market leadership, holding a market share of more than 80% during the next two years (Brandvold et al., 2015). Later, exchange-trading volumes at Bitstamp, BTC-e and Bitfinex rose as Mt.Gox's fell down, due to several technical incidents and legal issues. In the second half of 2013, those three exchanges took more than 50% of USD/BTC market share and, in Feb-2014, Mt.Gox suspended all transactions after a serious security breach.

In terms of economic literature, the study of the Bitcoins phenomenon is still relatively limited, namely in respect to the price discovery process on the currency exchanges. This paper addresses this issue by examining transaction data on fourteen Bitcoin exchanges that were active at least one year since the Mt.Gox bankruptcy (1-Mar-2014) until the aftermath of the hack attack on Bitfinex (30-Nov-2016).

The remainder of the paper is organised as follows. Section 2 presents a brief literature review. Section 3 refers to the data and presents a preliminary analysis. Section 4 describes the methodology, namely the Geweke feedback measures and the procedure for the panel regression analysis. The results of the empirical application are shown in Section 5. The paper concludes in Section 6.

2. LITERATURE REVIEW

Most papers and books on Bitcoin are from the fields of computer sciences and cryptography, therefore focusing essentially on the explanation of technical and methodological features of the Bitcoin network, mining activity and blockchain knowledge.[1]

Barber et al. (2012), Bradbury (2013), Eyal and Sirer (2014) and Böhme et al. (2015) discuss technical aspects of the Bitcoin project, trying to understand the reasons behind its success. Tu and Meredith (2015) and Karame et al. (2015) analyse security and legal issues in crypto-currency systems. Reid and Harrigan (2013) and Ron and Shamir (2013) dedicate more attention to the analytical aspects related to the information contained in the blockchain. The latter authors show, in particular, that a large fraction of issued Bitcoins is "dormant", in the sense that they were issued and never traded again.

An issue that has also attracted some attention in the academic world is the discussion on if Bitcoin is in fact a currency. Naturally, central banks have been quite concerned with this issue, for instance the ECB (2012) argues that, like any currency, Bitcoin depends on trust, which is not supported by its intrinsic value or on the belief in a central monetary authority solvency, but rather on cryptography and computer technology. Although several concepts of money have been associated to the Bitcoin phenomenon, such as "crypto-currency" (Elias, 2011; Evans, 2014; Böhme et al., 2015), "digital currency" (Grinberg, 2011; Dwyer, 2015) or "virtual currency" (ECB, 2012; Tu and Meredith, 2015), for some authors Bitcoin cannot be considered a currency. Yermack (2013), for instance, argues that the Bitcoin exhibits excess volatility, has no correlation with classical currencies and is not regulated. Brière et al. (2015) also argue that Bitcoins seem to be a valuable asset for portfolio diversification

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[1] Velde (2013) presents a comprehensive overview of the Bitcoin project. A literature review on Bitcoin can be found in Li and Wang (2017).

and Fink and Johann (2014) defend that, in its current usage, Bitcoin is more an investment vehicle than a currency.

A set of few studies have also investigated the Bitcoin exchange market. Some of these studies focus their attention on the existence of speculative bubbles (Cheung et al., 2015; Cheah and Fry, 2015) and Glaser et al. (2014) have even questioned the motivations behind the implementation of Bitcoin and the resemblance of its exchange activities to pure speculative trading.

More recently, the economic literature on Bitcoin was directed predominantly towards the conduction of econometric analyses regarding the identification and explanation of the main determinants of the Bitcoin exchange rate. Kristoufek (2013) shows a very high correlation between the Google Trends, Wikipedia views on Bitcoins and the Bitcoin exchange rate, and, in a later paper, Kristoufek (2015) shows that speculative behaviour and the exchange--trade ratio play a significant role at lower frequencies. Bouoiyour and Selmi (2015) also identify several determinants of the Bitcoin exchange rate, including Google searches, hash rate, ratio of exchange-trade volume and stock market dynamics, while Polasik et al. (2015) conclude that Bitcoin returns are mainly driven by news volume, news sentiment and the number of traded Bitcoins.

In what concerns to price discovery process in Bitcoin currency exchanges, to the best of our knowledge, the existing literature is quite scarce. Fink and Johann (2014) study several aspects of the Bitcoin exchange market, showing that Bitcoin prices experience extreme returns and high volatility and that the market is not informationally efficient, while the largest Bitcoin exchanges are cointegrated. According to the authors, transaction frequency, ownership, and size are broadly dispersed across more than fifteen million Bitcoin users, which shows that the Bitcoin is traded by both retail and professional traders with different strategies. The price discovery leader was the Mt.Gox exchange before its bankruptcy, but after that event the market shares and price discovery across Bitcoin exchanges are more balanced. Brandvold et al. (2015) conclude that for the whole sample period (1-Apr- 2013 to 25-Feb-2014) Mt.Gox, together with the BTC-e, were the market leaders, while the rest of the exchanges were less informative, but still providing some information to the Bitcoin exchange market. They also determine that information shares are dynamic and evolving significantly over time. While Mt.Gox dominated the price discovery process, its information share decreased significantly but still was higher than its activity share. BTC-e was one of the most informative exchanges and was much more informative than other exchanges during the shutdown of the Silk Road.

3. Data and Preliminary Analysis

The data for this study was mainly collected from the site www.bitcoincharts.com. This aggregation site compiles transaction data on several exchanges that trade Bitcoins against different currencies, being the USD and CNY the most important ones. Although Bitcoin high frequency data is available for free in other public sites, it seems that this database is quite reliable and has already been used in several academic papers (for instance, in Fink and Johann, 2014; Brandvold et al., 2015; Pieters, 2016).

In this paper, we just focus on the USD/BTC market. The main reason for this, relies on the fact that there has been some rumours that the main exchanges dealing with the Chinese Yuan, which of course, have their headquarters in China, tend to exaggerate their trading volume in order to attract more traders.[2]

The sample period was defined by two particular events. On 25-Feb-2014, Mt.Gox closed permanently for business. Before its bankruptcy, Mt.Gox was by far the dominant exchange in the USD/BTC market with a share of 74.83% of trading volume (from Jan--2010 to Feb-2014). Even at the closing day, the daily market share of Mt.Gox (33.46%) was still above the market share of any of its rivals (Bitstamp 28.01%, Bitfinex 20.60%, and BTC-e 17.12%). On the early afternoon of 2-Aug-2016, Bitfinex halted trading after discovering that roughly 120 thousand BTCs were stolen. Bitfinex stayed closed for seven days, until 8-Aug-2016. On 8-Dec-2017, the site bitcoincharts ended publishing Bitfinex data, due to a change in their API.[3] Given these events and the data available, we selected a sample period of 1006 days, since 1-Mar-2014 until 30-Nov-2016.

We also had to decide on the sampling frequency. There is a trade-off between gathering as much information as one can and avoiding the effects of microstructural noise and non-synchronous trading. For instance, Fink and Johann (2014) use a 1-minute interval while Brandvold et al. (2015) use a 5-minutes interval. Here, because we intend to study also low trading frequency exchanges, we choose a sampling interval of one hour. At this frequency, we collect information on hourly price indexes weighted by trading volume and trading volume in BTC. The use of price indexes instead of transaction prices (e.g. last price before the sampling point) smooths the price time series and diminishes the impact of extreme trades documented in Brandvold et al. (2015). On the other hand, it allows us to take into account that Bitcoin may be traded at small quantities. One Bitcoin can be divided down to one satoshi, i.e. 10^{-8} of a unit, and trades with volumes lower than 0.1 BTC are the most common ones (Brandvold et al., 2015).

Finally, we had to decide what exchanges we would use in this study from the 52 exchanges that trade USD/BTC and have data available at the bitcoincharts site. The criterion was to consider those exchanges that were active at least one year during the sample period (1-Mar-2014 to 30-Nov-2016). We end up with 14 exchanges, which account for 74.34% of the total Bitcoins traded against USD during the sample period (72.71 million BTC in all exchanges). Table 1 presents some information on these exchanges with a focus on its trading activity.

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[2] For instance, the total traded volume of BTC against CNY, since 15-Mar-2015 until 14-Mar-2017, according to the site data.bitcoinity.org, was approximately 1.3 billion, which roughly means a market share of 94% during that period, while the USD market share was only 4.06%. About this issue see, for instance, the news article "Chinese Bitcoin Exchange OKCoin Accused of Faking Trading Data", written by Eric Mu on 21-Dec-2013 (available at: http://www.coindesk.com).

[3] API means Application Programming Interface and it is a set of commands, protocols, functions and objects aimed to create software or to interact with an external system.

Table 1: Exchange information

Exchanges	Headquarters	Data availability	Volume	Average time lag	Volume per trade
Bitfinex	Hong Kong	Full sample	22.148 (30.46%)	10s	2.548
Bitstamp	Luxembourg	Full sample	11.099 (15.27%)	12s	1.532
BTC-e	Bulgaria	Full sample	7.3712 (10.14%)	5s	0.424
Coinbase	San Francisco USA	Since1-Dec-2014	5.0439 (6.94%)	7s	0.406
ItBit	New York USA	Full sample	3.6011 (4.95%)	1m59s	4.930
LakeBTC	Shanghai China	Until 19-Jun-2015	2.1103 (2.90%)	24s	0.583
LocalBitcoins	Finland	Since 11-Mar-2013	1.6223 (2.23%)	52s	0.971
Kraken	San Francisco USA	Full sample	0.4260 (0.59%)	3m11s	0.936
HitBTC	UK	Full sample	0.3526 (0.48%)	1m36s	0.389
Onecoin	Bulgaria	9-Mar-2014 to 4-Apr-2015	0.2318 (0.31%)	1m54s	0.029
Rock	Malta	Full sample	0.0206 (0.03%)	23m34s	0.335
CampBX	Atlanta USA	Until 19-Oct-2016	0.0150 (0.02%)	36m49s	0.267
BitKonan	Croatia	Full sample	0.0096 (0.01%)	58m6s	0.385
Bitbay	Poland	Since 16-May-2014	0.0091 (0.01%)	19m12s	0.121

Notes: This table shows some information on the 14 exchanges used in this study, namely: Headquarters, period of data availability at www.bitcoincharts.com, total trading volume USD/BTC in millions of BTC (where the values in parenthesis present the volume of each exchange relative to the total trading volume of the overall USD/BTC market – 72.71 million BTC according to https://data.bitcoinity.org), average time-lag between consecutive trades in minutes and seconds and average volume per trade during the sampling period (1-Mar-2014 to 30-Nov-2016).

Bitfinex, Bitstamp and BTC-e stand out as the three main exchanges with a total volume of roughly 56% of the USD/BTC market, in a second level are Coinbase and ItBit with roughly 12% of the total volume. In order to analyse the price discovery process among all exchanges we need a continuous time series without many gaps, hence we decide to isolate Bitfinex, Bitstamp, BTC-e and ItBit from all the other 10 exchanges, compiled into a pool of exchanges, which we denominate by "Others". The exchange Coinbase is included into this basket not because its trading volume is low but due to its late opening on the 01-Dec-2014, nine months after the sample beginning. The trading volume for

Others is simply obtained by adding up the trading volume of these 10 exchanges, while the price is computed as an average of the prices in these exchanges, using the trading volume as a weighting scheme.

From now on, we will assume that the USD/BTC market was totally composed, since 1-Mar-2014 until 30-Nov-2016, by Bitfinex with a market share, given by the relative trading volume, of 40.97%, Bitstamp, 20.53%, BTC-e, 13.64%, ItBit, 6.66% and Others, 18.20%. In this last case, it means an average market share per exchange of 1.82%. Table 2 shows the preliminary statistics of the hourly logarithmic returns for the exchanges under scrutiny.

Table 2: Descriptive statistics on returns

	Bitfinex	Bitstamp	BTC-e	ItBit	Others
No. of zeros	203 (0.8%)	108 (0.4%)	653 (2.7%)	3580 (14.8%)	0
Mean (10^{-5})	1.2531	1.3131	1.3203	1.1261	1.0927
Minimum	-0.1656	-0.1390	-0.1498	-0.5056	-0.4771
Percentile 5	-0.0086	-0.0087	-0.0080	-0.0082	-0.0257
Median	0.0000	0.0001	0.0000	0.0000	0.0003
Percentile 95	0.0085	0.0083	0.0080	0.0079	0.0248
Maximum	0.1053	0.1178	0.1016	0.5428	0.4967
Stand. deviation	0.0063	0.0062	0.0062	0.0081	0.0179
Skewness	-1.0749	-0.6081	-0.9125	2.1412	-0.0693
Kurtosis	43.590	34.074	48.419	151.76	68.504
Jarque-Bera (10^6)	1.6620 ***	0.9728 ***	2.0786 ***	2307.6 ***	4.3163 ***
Autocorr(1)	0.1282 ***	0.1416 ***	0.1139 ***	0.0089	-0.3578 ***
Autocorr(2)	-0.0879 ***	-0.0772 ***	-0.0589 ***	-0.2176 ***	-0.0187 ***
Autocorr(3)	-0.0466 ***	-0.0488 ***	-0.0365 ***	-0.0154 **	0.0092
BIC	3	3	3	5	52

Notes: This table summarises the statistics for the hourly logarithmic returns of the USD/BTC exchange rates. The sample covers the period since 1-Mar-2014 until 30-Nov-2016, for a total of 1006 days (24143 hourly observations). The exchanges are Bitfinex, Bitstamp, BTC-e, ItBit and "Others". This last one refers to a compilation of several minor exchanges (Coinbase, LakeBTC, LocalBitcoins, Kraken, HitBTC, Onecoin, Rock, CampBx, BitKonan and Bitbay). The Others' price upon which the returns are computed is the price index averaged by volume. BIC denotes the Bayesian-Information Criterion for choosing the lag length in an autoregressive process. The autocorrelations significance levels were inferred using Bartlett's standard errors. Values significant at the 10%, 5% and 1% levels are marked by *, ** and ***, respectively.

The number of staled prices seems only to be a problem for ItBit, where 14.8% of the returns is zero. The mean and median returns are almost zero, but the returns show positive and negative extreme values. This is particularly true for ItBit, with a minimum and a maximum hourly returns of -50.56% and 54.28%, and for the basket Others with a minimum of -47.71% and a maximum of 49.67%. The standard deviation is inversely related with the exchange's dimension; for instance, the standard deviation of Others is more than twice the standard deviation of the four bigger exchanges. The returns are obviously non-normal, presenting negative skewness (except for the ItBit) and leptokurtosis. ItBit also shows a higher kurtosis than the other exchanges. The first order autocorrelations are significantly positive, except for Others that is negative. The second and third order autocorrelations are all significantly negative (except the third order autocorrelation for Others). Although persistence should be inversely related to the trading intensity and should be higher in Others as a result of the averaging procedure, it revealed to be quite higher than expected. The Bayesian-Information Criterion indicates that modelling the returns of Others by an autoregressive process would imply using a lag length of 52, which means using self-information for more than two days.

Before proceeding with the estimation of the feedback measures, we verified if all return series were stationary by applying ADF tests, without constant and trend, and with a lag length inferred by the BIC. For all the returns series the tests were categorical in rejecting the null hypotheses of a unit root at a 1% significance level.

4. Methodology

In order to assess the informational relationship between exchanges we use the feedback measures of Geweke (1982). These measures are applied pairwise for each pair of exchanges and between each exchange and the rest of the market, formed by all the other exchanges. We also proceed with a second stage analysis by conducting panel regressions of the feedback measures on market variables, such as volatility and volume.

The analysis is conducted on a bivariate return process, such that r_{it} and r_{jt} are the returns in market i and j at time t, respectively, computed from the volume weighted prices. Consider that a pair of Bitcoin time series of returns, $\{r_{it}, r_{jt}\}$, sampled at some frequency, say hourly, can be expressed as a bivariate autoregressive process of an arbitrary order p:

$$\begin{bmatrix} r_{it} \\ r_{jt} \end{bmatrix} = \begin{bmatrix} A(L) & B(L) \\ C(L) & D(L) \end{bmatrix} \begin{bmatrix} r_{it} \\ r_{jt} \end{bmatrix} + \begin{bmatrix} \varepsilon_{it} \\ \varepsilon_{jt} \end{bmatrix}, \qquad (1)$$

where $A(L)$, $B(L)$, $C(L)$ and $D(L)$ are polynomials in the lag operator, L, and the innovations are Gaussian (i.e. ε_{kt} are independently and identically $\mathcal{N}(0, \sigma_k^2)$, for $k = i, j$). The innovations covariance matrix is

$$\Omega = cov \begin{bmatrix} \varepsilon_{it} \\ \varepsilon_{jt} \end{bmatrix} = \begin{bmatrix} \sigma_i^2 & \sigma_{ij} \\ \sigma_{ji} & \sigma_j^2 \end{bmatrix}. \tag{2}$$

Absence of Granger causality, denoted by "$\nRightarrow$" implies that the coefficient matrix is triangular in the VAR representation. **For a bivariate process, there are two lagged feedback hypotheses: $H_{i \nRightarrow j}$: $C(L) = \mathbf{0}$ and $H_{j \nRightarrow i}$: $B(L) = \mathbf{0}$.** Under these hypotheses, the VAR simplifies to:

$$\begin{bmatrix} r_{it} \\ r_{jt} \end{bmatrix} = \begin{bmatrix} A(L) & \mathbf{0} \\ \mathbf{0} & D(L) \end{bmatrix} \begin{bmatrix} r_{it} \\ r_{jt} \end{bmatrix} + \begin{bmatrix} \xi_{it} \\ \xi_{jt} \end{bmatrix}. \tag{3}$$

Additionally, if there is no contemporaneous linear relationship between the series, $H_{i \nLeftrightarrow j}$, then $cov(\xi_{it}, \xi_{jt}) = 0$. The hypothesis of no linear link between the two variables is given by the conjunction of the previous hypotheses: $H_{i \cdot j} = H_{i \nRightarrow j} \cap H_{i \nLeftrightarrow j} \cap H_{j \nRightarrow i}$. The measures proposed by Geweke (1982) allow testing these hypotheses:

Measure of lagged feedback from i to j:

$$F_{i \rightarrow j} = ln(\sigma_{\xi j}^2 / \sigma_{\varepsilon j}^2). \tag{4}$$

Measure of lagged feedback from j to i:

$$F_{j \rightarrow i} = ln(\sigma_{\xi i}^2 / \sigma_{\varepsilon i}^2). \tag{5}$$

Measure of contemporaneous feedback between i and j:

$$F_{i \leftrightarrow j} = ln(\sigma_{\varepsilon i}^2 \sigma_{\varepsilon j}^2 / |\Omega|). \tag{6}$$

Measure of total feedback between i and j:

$$F_{i,j} = ln(\sigma_{\xi i}^2 \sigma_{\xi j}^2 / |\Omega|). \tag{7}$$

Where $|\Omega|$ denotes de determinant of the innovations covariance matrix in the unrestricted model. Under the null hypothesis, these measures, multiplied by the number of observations, T, are asymptotically independent and follow chi-squared distributions with p, p, 1 and $2p+1$ degrees of freedom, respectively.

The feedback measures are just the log-likelihood ratio statistics for the null hypotheses, and, therefore, if feedback is present, their asymptotic distributions are well defined. Under

the alternative hypothesis, these measures, multiplied by the number of observations, are asymptotically non-central chi-squared:

$$T\hat{F}_{i\rightarrow j} \sim \chi'^2(p, TF_{i\rightarrow j}), \tag{8}$$

$$T\hat{F}_{j\rightarrow i} \sim \chi'^2(p, TF_{j\rightarrow i}), \tag{9}$$

$$T\hat{F}_{i\leftrightarrow j} \sim \chi'^2(1, TF_{i\leftrightarrow j}), \text{ and} \tag{10}$$

$$T\hat{F}_{i,j} \sim \chi'^2(2p+1, TF_{i,j}), \tag{11}$$

The Geweke feedback measures have several advantages over other methodologies, such as the Wald F-test: (i) under the alternative hypothesis these statistics represent cardinal measures of the extent of linear dependence in the two series, (ii) these measures are additive: $\hat{F}_{i,j} = \hat{F}_{i\rightarrow j} + \hat{F}_{i\leftrightarrow j} + \hat{F}_{j\rightarrow i}$, (iii) comparison between the feedback in two pair of variables is straightforward as long as the measures are estimated using the same number of observations, and (iv) these metrics are unaffected by prefiltering the series by any invertible lag operator (Parzen, 1982), which suggests that they are less sensitive to the effects of non-synchronous trading and other microstructural idiosyncratic sources of noise.

In the second stage of our analysis, we compute a time series of the feedback measures for each different pair of exchanges using a non-overlapping rolling window with the same length. This rolling window procedure is also used to compute the time series of the trading intensity, measured by the log-volume in Bitcoins, *vol*, and of the volatility for each exchange. Although volume and volatility are usually highly correlated, they may account for different types of information arrival processes (Andersen, 1996). For measuring volatility, we use the range estimator of Parkinson (1980):

$$HL = \left[(1/D) \sum_{d=1}^{D} \frac{(ln(H_d/L_d))^2}{4ln(2)} \right]^{\frac{1}{2}}. \tag{12}$$

Where D is the number of days in the window, and H_d and L_d are the maximum and minimum prices (weighted by volume) recorded on day d. Although the Parkinson estimator assumes no drift and it tends to underestimate volatility, it seems a good candidate to measure volatility in a continuous trading market (other more efficient range volatility estimators, such as Garman and Klass, 1980; Rogers and Satchell, 1991; Yang and Zhang, 2000, also consider the opening and closing prices). Moreover, one should notice that the bias present in the Parkinson estimator is not an important issue here since we are using the estimator for comparing the volatility between markets, in just a few days, instead of using it to compare volatilities through time.

The regression analysis was conducted as follows. Firstly, the feedback measures were normalized using the procedure prescribed by Geweke (1982). If $T\hat{F} \sim \chi'^2(df, TF)$, where df is the degree of freedom and TF is the non-centrality parameter, then

$$n\hat{F} = (| T\hat{F} - (df - 1)/3 |)^{\frac{1}{2}} \sim \mathcal{N}((| T\hat{F} - (df - 1)/3 |)^{\frac{1}{2}}, 1). \tag{13}$$

Secondly for each pair of markets, i and j, and for each normalized measure, $n\hat{F}_{i \to j}$, $n\hat{F}_{j \to i}$, $n\hat{F}_{i \leftrightarrow j}$ and $n\hat{F}_{i,j}$, we construct a matrix of regressors, $[HL_i, HL_j, vol_i, vol_j]$. With the purpose of simplifying the interpretation of the results, the pair (i, j) is constructed considering in the first entry the exchange with the highest market share (given by the trading volume). So, for N exchanges we have $N(N-1)/2$ time series on each feedback measure. Finally, for each feedback measure we run the following panel regression:

$$n\hat{F}_{(i,j)t} = \beta_0 + \beta_1 HL_{it} + \beta_2 HL_{jt} + \beta_3 vol_{it} + \beta_4 vol_{jt} + \vartheta_{(i,j)t}. \tag{14}$$

The regression analysis on the feedback measures has been used elsewhere. For instance, Kawaller et al. (1993) use this methodology to study the interrelationship between stock index and stock index futures, Bracker et al. (1999) study the evolution of integration, measured by contemporaneous feedback, between several national stock markets. In this last paper, the authors use a pooled regression and combine the two lagged feedback measures, arguing that they are analogous in economic and statistical terms.

Our perspective is different. Firstly we do not superimpose the data pooling and instead let the data tell us what is the best model (pooled regression, panel with fixed effects or panel with random effects). Secondly, we do not aggregate the lagged feedback measures and instead we model them separately. Obviously the two measures are statistically similar but they may be economically different, the impact of volatility and volume from a particular exchange on a feedback measure may be different depending on if it is a leader or a follower exchange.

The methodological design allows us to formulate several hypotheses. Basically, most of these hypotheses are drawn upon the Wall Street adage "It takes volume to make prices move". On other hand, we also assume that volatility is mostly information-driven, especially if it is from the leader exchange and therefore volatility should increase the exchanges' proximity.

From the pairwise estimations of the feedback measures we can test the following hypothesis:

H1: The ranking of the pairs of exchanges by the total feedback is the same as its ranking by the combined volume of the two exchanges.

H2: At an hourly sampling, the great contributor for the total feedback is the contemporaneous feedback, and its contribution increases with the combined volume of the two exchanges.

H3: In each pair, the lagged feedback runs mostly from the exchange with higher volume to the other exchange, and the difference between the lagged feedbacks is positively related to the difference in trading volumes.

In the same line of reasoning, we can also formulate hypotheses on the expect signs of the regressors in Eq. (14).

H4: All the variables in the contemporaneous feedback regression have positive signs.

H5: All the variables in the total feedback regression have positive signs.

H6: In the lagged feedback regressions, $i \to j$, volume and volatility of exchange i have positive signs, while volume and volatility of exchange j have negative signs.

In the next section we present the empirical results that allow us to infer about the validity of these hypotheses.

5. Results

Firstly, we estimate the feedback measures pairwise, considering the exchanges Bitfinex, Bitstamp, BTC-e, ItBit and Others, where this last one is a pool of minor exchanges (Coinbase, LakeBTC, LocalBitcoins, Kraken, HitBTC, Onecoin, Rock, CampBx, BitKonan and Bitbay). The estimates were obtained from fitting VARs with a lag structure truncated at lag 52, which is the longest lag structure inferred by the Bayesian-Information Criterion applied to the univariate time series of hourly continuous returns. Using such lag length enable us to capture all the autocorrelation and lagged cross-correlation structure, even in the Others returns. Results are presented in Table 3.

Table 3: Pairwise estimation of feedback measures

Exch. (i)	Exch. (j)	Average Share	$F_{i \to j}$	$F_{j \leftrightarrow i}$	$F_{j \to i}$	$F_{j.i}$
Bitfinex	Bitstamp	30.75%	0.0495 (3.41%)	1.3948 (96.11%)	0.0070 (0.47%)	1.4512
Bitfinex	BTC-e	27.31%	0,059 (6.24%)	0.8783 (92.82%)	0.0089 (0.94%)	0.9463
Bitfinex	ItBit	23.82%	0.1361 (23.13%)	0.4485 (76.21%)	0.0039 (0.67%)	0.5886
Bitstamp	BTC-e	17.09%	0.0412 (4.35%)	0.8838 (93.33%)	0.0220 (2.32%)	0.9469
Bitstamp	ItBit	13.60%	0.1211 (19.81%)	0.4830 (79.02%)	0.0071 (1.17%)	0.6112
BTC-e	ItBit	10.15%	0.0888 (19.90%)	0.3447 (77.24%)	0.0128 (2.87%)	0.4463
Bitfinex	Others	5.38%	0.1615 (64.70%)	0.0864 (34.61%)	0.0017 [a] (0.69%)	0.2497
Bitstamp	Others	3.52%	0.1653 (62.51%)	0.0974 (36.82%)	0.0018 [a] (0.67%)	0.2645
BTC-e	Others	2.89%	0.1300 (60.49%)	0.0811 (37.74%)	0.0038 (1.77%)	0.2149
ItBit	Others	2.26%	0.1033 (52.78%)	0.0758 (38.70%)	0.0167 (8.52%)	0.1958

Notes: Geweke´s feedback measures were estimated for all pairs of exchanges using hourly logarithmic returns. The column "Average Share" gives the total market share of the exchanges divided by the number of exchanges (2 for all pairs, except for the pairs that include Others, where the divisor is 11). The "Average Share" is used to order the pairs in the table. Others refers to a compilation of several minor exchanges (Coinbase, LakeBTC, LocalBitcoins, Kraken, HitBTC, Onecoin, Rock, CampBx,w BitKonan and Bitbay). The feedback measures were obtained from fitted VAR models with a lag structure truncated at 52. The lagged feedback from i to j and from j to i are denoted by $F_{i \to j}$ and $F_{j \to i}$ respectively, while the simultaneous feedback is denoted by $F_{j \leftrightarrow i}$ and the total feedback is $F_{i'j'}$. The relative weight (i.e. divided by the total feedback) of the lagged feedbacks and simultaneous feedback are shown in parentheses. All the estimates are significant at the 1% level, except the lagged feedback from Others to Bitfinex and to Bitstamp that are not significant at the 10% level. These two estimates are marked by [a].

As expected, the total feedback is highly correlated with the average market share, implying that the interrelationship between exchanges increases with their relative volume. However, the ordering is not exactly the same and the total feedbacks between Bitstamp and BTC-e and between Bitstamp and ItBit are higher than the total feedback between Bitfinex and ItBit, despite this last pair sharing a higher trading volume. This probably means that market proximity, in terms of trading volume, also tightens prices together.

The contemporaneous feedback is the main contributor to the total feedback, except when Others is included in the pair. In this case, the contemporaneous feedback only accounts for about to 34% to 39% of the total feedback, and most of the feedback runs from the major exchange to Others (52.78% to 64.70%). The contemporaneous feedback ranges from 96.11% of the total feedback in the Bitfinex/Bitstamp pair and only 34.61% of the total feedback in the Bitfinex/Others pair. The lagged feedback is asymmetrical and runs dominantly from the major exchange than the other way around. These figures range from 0.0495 (3.41% of total feedback) in the Bitfinex/Bitstamp pair to 0.1615 (64.70%) in the Bitfinex/Others pair. The feedback from the minor exchanges is quite marginal, with a maximum absolute value of 0.022 in the Bitstamp/BTC-e pair and a maximum relative value of 8.52% in the ItBit/Others pair. In fact, the only estimates that are not significant (even at the 10% level) are the lagged feedback from Others to the two major exchanges, Bitfinex and Bitstamp.

Overall, Table 3 indicates that the three major markets are highly integrated. In these markets, the relative contemporaneous feedback estimates suggest that more than 92% of price variability is communicated between markets within one hour. The level of integration decays with ItBit, which has a relative contemporaneous feedback of around 77% with the three major markets. The basket Others mostly reacts to price changes with a delay of at least one hour and therefore the minor exchanges compiled into Others may be seen as pure satellite exchanges, in the sense of Garbade and Silber (1979). However, we have to keep in mind that this last result is in part due to smoothing the price series across ten minor exchanges.

Although the results suggest that Bitfinex is the dominant market in terms of the transmission of short run price information, we now try to answer directly to this question. In order to position each exchange in the overall USD/BTC market we computed the feedback measures between each exchange and the Market, where its return is computed upon the price index averaged by volume of the remaining exchanges. Table 4 presents these results, where in Panel A the Market includes the basket Others and Panel B considers the Market formed only by the most important four exchanges.

Table 4: Feedback measures between each exchange and the market

Exchange (i)	$F_{i \rightarrow M}$	$F_{j \leftrightarrow M}$	$F_{M \rightarrow i}$	$F_{i.M}$
Panel A: Including Others				
Bitfinex	0.2031 (38.55%)	0.3219 (61.08%)	0.0020 ([a]) (0.40%)	0.5270
Bitstamp	0.1666 (25.53%)	0.4779 (73.21%)	0.0082 (1.26%)	0.6527
BTC-e	0.1122 (22.18%)	0.3786 (74.83%)	0.0151 (2.99%)	0.5060
ItBit	0.0565 (22.18%)	0.2953	0.0737	0.4256
Others	0.0048 (1.95%)	0.0849 (34.73%)	0.1549 (63.32%)	0.24454
Panel B: Excluding Others				
Bitfinex	0.1702 (18.29%)	0.7542 (81.06%)	0.0060 (0.65%)	0.9304
Bitstamp	0.1020 (10.10%)	0.8824 (87.37%)	0.0255 (2.53%)	1.0099
BTC-e	0.0401 (4.72%)	0.7701 (90.50%)	0.0407 (4.79%)	0.8510
ItBit	0.0086 (1.47%)	0.4465 (76.31%)	0.1300 (22.21%)	0.5852

Notes: Geweke's feedback measures were estimated for all pairs exchange/Market, using hourly logarithmic returns. For the Market, denoted by M, the returns are computed upon the price index, weighted by volume, of all remaining exchanges. Panel A includes in the Market the minor exchanges compiled into the basket Others, while Panel B only considers Bitfinex, Bitstamp, BTC-e and ItBit. The feedback measures were estimated from fitted VAR models with a lag structure truncated at 52. The lagged feedback from i to M and from M to i are denoted by $F_{i \rightarrow M}$ and $F_{M \rightarrow i}$, respectively, while the simultaneous feedback is denoted by $F_{i \leftrightarrow M}$ and the total feedback is $F_{i.M}$. The relative weight (i.e. divided by the total feedback) of the lagged feedbacks and simultaneous feedback are presented in parentheses. All the estimates are significant at the 1% level, except the lagged feedback from the Market to Bitfinex that is not significant at the 10% level. This estimate is marked by ([a]).

Not surprisingly, we notice that when we exclude Others from the analysis, all the lagged feedback measures from an exchange to the Market decrease, while all the lagged feedback measures from the Market to an exchange increase. The degree of integration (contemporaneous feedback) is quite higher when minor exchanges are excluded, which also roughly doubles the total feedback. One can observe from Panel A that the contemporaneous feedback is the major contributor to the total feedback, with this measure presenting a relative weight above 61%, except in the case Others/Market, where this figure only reaches 34.73%.

The feedback from the Market to Others is quite high (63.32%) while the inverse lagged feedback is marginal (1.95%). Moreover, when we include Others in the Market, the lagged feedback from the Market to Bitfinex is not significant at the 10% level. This corroborates the previous conclusion that Others doesn't has, on average, important information on the USD/BTC price movements. Given these results, we hereafter study the USD/BTC market formed only by Bitfinex, Bitstamp, BTC-e and ItBit.

Table 4, Panel B, deserves special attention. The four exchanges are well integrated, with more than 75% of the information on prices being transmitted to the overall market within an hour. The feedback from Bitfinex and from Bitstamp to the Market is higher than the reverse feedback, while the opposite happens for BTC-e and ItBit. However, it takes more than an hour for transmitting 18.29% of the short run price movements that have its origin in Bitfinex, while the relative lagged feedback from Bitstamp is 10.10%. The feedback from the Market to Bitfinex and to Bitstamp is only 0.60% and 2.55%, respectively. In sum, one might say that Bitstamp is more integrated with the overall market, but Bitfinex has the short run informational dominance.

Now we analyse how the feedback measures relate to volatility and volume. As described before, we partitioned the sample into non-overlapping rolling windows and estimate the time series of feedback measures. We choose a window with an amplitude of 5 days, which means that the VARs estimates were obtained from subsamples of 119 returns observations. We get 201 estimates for each feedback measure.[4] The estimation results are shown in Table 5.

Table 5: Panel regressions on the feedback measures

	$nF_{i \to j}$	$nF_{i \leftrightarrow j}$	$nF_{j \to i}$	$nF_{i,j}$
Intercept	4.0900***	−21.091***	1.0296	−16.4148***
	(6.3539)	(−8.6080)	(1.7039)	(−7.5586)
HL_i	18.442***	81.5885**	−6.4511**	76.8656**
	(11.9094)	(3.9798)	(−3.9287)	(3.8838)
HL_j	−16.228**	−65.268***	4.7885	−57.726***
	(−3.9841)	(−5.2993)	(1.6733)	(−4.5083)
vol_i	0.0720	1.5370***	0.0070	1.3934***
	(0.8073)	(4.6319)	(0.3557)	(4.6017)
vol_j	−0.1735**	1.9216***	0.1583*	1.646***
	(−3.2619)	(6.0128)	(2.4148)	(5.6185)
$F_{(4,5)}$	75.058***	654.77***	16.883***	2026.9***
R^2	0.0234	0.4921	0.0215	0.5169

Notes: This table shows the panel regression results on the normalized feedback measures, namely the parameter estimates, the Arellano (2003) t-statistics adjusted for heteroscedasticity and serial correlation (in parentheses), the F test for joint significance of the "named regressors" and the within R^2. The feedback measures were estimated, from fitted VAR models with a lag structure truncated at 5, for all pairs of exchanges, using hourly logarithmic returns for each sub-sample of 5 days. The feedback measures, multiplied by the number of observations, were then normalised. The panel regressions consider 201 time points for 6 cross-section units (each pair of exchanges) for a total of 1206 observations. The normalized lagged feedback from i to j and from j to i are denoted by $nF_{i \to j}$ and $nF_{j \to i}$, respectively, while the simultaneous feedback is denoted by $nF_{i \leftrightarrow j}$ and the total feedback is $nF_{i,j}$. Values significant at the 10%, 5% and 1% levels are marked by *, ** and ***, respectively.

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[4] Before we proceed with the panel regressions we test for unit roots in the series, with special attention to the log--volume series. The Im-Pesaran-Shin panel unit root test, with a constant, without trend or lags allows us to conclude that all series are stationary at the 1% level. Then we select the panel model using the Breusch-Pagan test on the null hypothesis of pooled regression and the Hausman test on the null hypothesis of consistency of the GLS estimates (random effects). All the statistics were significant at the 1% level, which led us to select the panel regression with fixed effects.

The joint test indicates that the overall feedback measures are significant at a 1% level, however the within coefficient of determination is quite low for the lagged feedbacks (around 2%), while its value for the contemporaneous and total feedbacks are 49.21% and 51.69%, respectively. The regressors in the lagged feedback from the major exchanges, $nF_{i \to j}$, have all the expected signs, however only the volatility in exchanges i is significant at the 1% level. The variables of exchanges j are significant at the 5% level. In the equation of the lagged feedback from the minor exchanges, $nF_{j \to i}$, the volatility in exchanges i has the expected sign and is significant at the 5% level, while volume in exchanges j has the expected sign and is significant at the 10% level. These results suggest that the main driving force behind the lagged feedback is the volatility in the major markets, extending the information transmission for more than an hour from the major exchanges and diminishing the reverse feedback. The regression results for the contemporaneous and total feedbacks are quite similar. In fact, the main difference is that the coefficients and the t-statistics in the total feedback are slightly lower. In these two regressions all the variables are significant at the 1% level, and both volume and volatility in the major exchanges contribute positively for the contemporaneous and total feedback. However, volatility in the minor exchanges has a negative sign implying that an increase in that volatility tends to diminish market integration (contemporaneous feedback) and the total linear interconnection between exchanges.

6. Conclusion

The present paper aims to analyse the price discovery process among all relevant exchanges in the USD/Bitcoin market with public available data, even those with low trading intensity. The data was collected from the site www.bitcoincharts.com and reflects the trading information on 14 exchanges for the period since the Mt.Gox bankruptcy until the aftermath of the hack attack on Bitfinex, i.e., since 01-Mar-2014 until 30-Nov-2016, for a total of 1006 days (24143 hourly observations). Given the traded volume and the period of trading, we decided to study Bitfinex, Bitstamp, BTC-e and ItBit separately, while aggregating the remaining 10 exchanges (Coinbase, LakeBTC, LocalBitcoins, Kraken, HitBTC, Onecoin, Rock, CampBx, BitKonan and Bitbay) into a basket, that we denominated by Others. The aggregating procedure uses the price index weighted by trading volume.

The Geweke feedback measures were then estimated pairwise between exchanges, using hourly returns (computed on price indexes weighted by volume) for the overall sampling period. The results highlight the existence of a positive relationship between the total feedback and market share of both exchanges but also with its proximity in terms of trading volume. Most of the information is transmitted between exchanges within an hour, at least for the main four exchanges, while lagged feedback runs mainly from the major exchanges in each pair, being its relative importance positively related to the difference in trading volumes. The minor exchanges, compiled into Others, seem to react to price information with some delay and are merely satellite exchanges.

The Geweke feedback measures were also estimated pairwise between each exchange and the rest of the market. The results supported the main conclusions stated above, namely that the consideration of minor exchanges only brings more noise into the price index process,

Bitstamp is well integrate with the overall market, but, more importantly, Bitfinex stands out as the most important exchange in transmitting information to the market: the relative importance of the lagged feedback from Bitfinex to the market is 18.29% while that quantity for the lagged feedback from the market to Bitfinex is only 0.60%.

The panel regression of the feedback measures on volatility and volume shows that these variables explain a fair part of the contemporaneous and total feedback, with all the signs being significantly positive except the volatility in the minor exchange. This result suggests that pairwise, in relative terms, the volatility in the major exchange is mainly information--based, aligning exchanges together, while volatility in the minor exchange is more noise--based, driving exchanges apart. For the lagged feedback, the most important explaining variable is the volatility in the major exchange, which has an obvious different impact: an increase in that volatility increases the feedback from the major exchange while decreases the feedback from the minor exchange.

Trading Bitcoins involves an important operational risk (the history of Bitcoin exchanges is replete of events such as hack attacks, missing wallets, malpractices, government interventions, temporary and not so temporary trading halts, etc.) and the market industrial organization is in permanent evolution. Therefore, our results are conditional on the sampling period. In fact, it would be quite interesting to see if the informational superiority of Bitfinex still exists after the hack attack occurred on Aug-2016.

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