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ORIGINAL ARTICLE

Price discovery on Bitcoin markets

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Abstract
Trading of Bitcoin is spread about multiple venues where buying and selling is offered in various currencies. However, all exchanges trade one common good and by the law of one price, the different prices should not deviate in the long run. In this context, we are interested in which platform is the most important one in terms of price discovery. To this end, we use a pairwise approach accounting for a potential impact of exchange rates. The contribution to price discovery is measured by Hasbrouck's and Gonzalo and Granger's information share. We then derive an ordering with respect to the importance of each market which reveals that the Chinese OKCoin platform is the leader in price discovery of Bitcoin, followed by BTC China. Overall, the exchange rate is neither affected by Bitcoin trading nor does it contribute decisively to its price discovery.

Keywords Price discovery · Bitcoin · Hasbrouck information shares

JEL Classification C58 · C32 · G23

1 Introduction

The XXI century gave birth to the new concept of a cryptocurrency, a decentralized peer-to-peer digital currency that uses cryptography to ensure that payments are sent and received in a safe manner. While there are numerous cryptocurrencies currently traded on the market, only a few of them reach a significant size in terms of market capitalization. Indeed, as of 26 September 2017, only 4 cryptocurrencies out of the total 1128 hold about 78.4% of the total cryptocurrency market capitalization:

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Bitcoin (with a market share of approximately 47.7%), followed by Ethereum, Bitcoin Cash, and Ripple (roughly 20.1%, 5.5%, and 5.1%, respectively).

The focus of this article is Bitcoin, arguably the most important as well as most widely known digital currency nowadays. Introduced by a programmer (or a team of programmers) under the pseudonym of Satoshi Nakamoto (2008), Bitcoin was launched in 2009 and sparked widespread interest in this new form of digital currency. To give an idea of the spectacular growth and fluctuations that Bitcoin has lately experienced, in 2017, its market capitalization started from 15.6 billion USD in January, reached 20 billion USD in March, doubled to 40 billion USD by the end of May and then doubled again to 80 billion USD on the first of September. However, the recent cryptocurrency crackdown in China made this value drop drastically, even though it still hovers around 65.5 billion USD as of 26 September 2017.

Given the innovative nature of this new phenomenon, academic studies devoted to Bitcoin cover a broad range of issues. Many researchers focus on the fundamental aspects as well as on the mechanisms behind the functioning of the cryptocurrency (cp. Segendorf 2014; Dwyer 2015) which is of particular interest to central banks (cp. ECB 2012; Velde et al. 2013; ECB 2015). A detailed description of the Bitcoin mining process is provided by Kroll et al. (2013). The legal status of Bitcoin and the legal issues linked to its use are considered by Doguet (2012) or Murphy et al. (2015). Other studies focus on the potential of Bitcoin to constitute not only an alternative medium of exchange (Rogojanu and Badea 2014), but also a real monetary standard, analyzing the related advantages and drawbacks (Weber 2014). Lastly, Trimborn and Härdle (2016) propose a method to create an index for the cryptocurrency market, referred to as CRIX, which is supposed to reflect the state of the overall cryptocurrency market.

One of the core questions in the context of Bitcoin is whether it should be conceived as a currency or as a speculative asset. Yermack (2015) defends the speculative nature of Bitcoin since its features—like the huge volatility and the scarce correlation with gold and other currencies—do not meet the typical ones of a well-established fiat currency. The analysis of Bouoiyour and Selmi (2015) confirms the speculative behavior of Bitcoin and its limited usefulness as a medium of exchange. Baur et al. (2018) draw the same conclusion by analyzing transaction data of the cryptocurrency. The analysis of Bitcoin realized volatility of Baur and Dimpfl (2017) further supports that Bitcoin cannot serve as a currency given the enormous price fluctuations (up to factor 30) compared to other currencies like the US Dollar.

A key element of Bitcoin is that it is traded against various currencies as well as on multiple venues. As reported by Brière et al. (2015), prices vary substantially among the platforms in which the cryptocurrency is traded. For a trader it is, however, of utmost importance to know where she can find an accurate and fair price to carry out her transactions to minimize transaction costs. Still, the literature trying to address the question where price discovery takes place related to Bitcoin markets is not very large. A notable exception are Brandvold et al. (2015) who analyze the contributions to price discovery of a (at the time) representative set of Bitcoin exchanges. They select Bitcoin platforms according to trading volume, including five big exchanges (Bitfinex, Bitstamp, BTC-e, BTC China, and Mt.Gox) and two smaller ones (Bitcurex and Canadian Virtual Exchange (Virtex)) to capture eventual differences in the behavior of the two categories. These exchanges covered approximately 90% of Bitcoin trading at that time. They conclude that the price discovery leaders are Mt.Gox and BTC-e during the investigated period from 1 April 2013 to 25 February 2014. Moreover, Brandvold et al. (2015) argue that the information shares linked to Bitcoin exchanges are dynamic and change significantly over time. As a consequence, bearing in mind that Mt.Gox went bankrupt on 28 February 2014 and taking into account their argument about the evolution of the information shares, it seems reasonable to claim that their conclusion regarding the leader platforms cannot hold anymore. We, therefore, contribute to the literature by an analysis of Bitcoin price discovery which in particular accounts for the fact that one and the same asset (Bitcoin) is traded against different currencies. Furthermore, we link our results to trading volume and argue that in the absence of fundamental pricing factors, trading itself is informative and price discovery is led by the market which attracts the highest trading volume.

Price discovery is a widely studied topic in finance. The leading tool to measure contributions to price discovery is the information share methodology proposed by Hasbrouck (1995). This technique allows to derive upper and lower bounds for each market's contribution to the total variance of the fundamental efficient price which is taken as the respective market's contribution to price discovery. There are various applications in all contexts of financial markets (cp. Hasbrouck 2003; Blanco et al. 2005; Dimpfl et al. 2017; Hatheway et al. 2017), propositions to solve the non-unique decomposition (Grammig and Peter 2013; Lien and Shrestha 2009), as well as attempts to resolve the impact of market microstructure effects (Yan and Zivot 2010; Putniņš 2013). In the context of foreign exchange, price discovery is analyzed by Covrig and Melvin (2002) and Chen and Gau (2010).

Another methodological pillar in the price discovery context is the common factor weight approach of Gonzalo and Granger (1995). Both measures are generally used in the context of one security traded on two markets. In contrast to Hasbrouck's information shares, the common factor weights are uniquely identified as they evaluate the relative size of the adjustment of each market price to the common permanent trend component. References related to the use of the Gonzalo and Granger (1995) common factor weights with respect to the foreign exchange market can be found, for instance, in Alberola et al. (1999) and Maeso-Fernandez et al. (2002). Besides, price discovery literature on exchange rates also contains several studies which make use of both the aforementioned techniques, such as Tse et al. (2006), Cabrera et al. (2009) and Rosenberg and Traub (2009).

In many contexts, trading of the same security on different markets is spread across countries and, hence, involves the denomination of trading prices in different currencies. Hence, the foreign price will not only reflect the fundamental value, but will also be marked by the exchange rate. Hence, an investigation of price discovery may also account for exchange rate impacts. Grammig et al. (2005) apply the Hasbrouck (1995) information share approach to cross-listed stocks on the New York Stock Exchange and the Toronto Stock Exchange, taking the USD/CAD exchange rate into account. In this way, the authors are able to determine both which market is the leader in the price formation mechanism and whether the exchange rate plays a role in the mechanism itself. Furthermore, they show that the use of bivariate systems involving only market prices would lead to a bias towards overestimating the information share belonging to the market whose price is converted into the foreign currency. This finding highlights the relevance of estimating trivariate systems modeling the exchange rate explicitly rather than only bivariate ones where prices are converted into one common currency.

In this article, we evaluate the price discovery process of Bitcoin in light of trading in different currencies for the period ranging from 2 January 2014 to 6 March 2017. To this end, prices from six Bitcoin trading platforms (Bitfinex, Bitstamp, BTC-e, Kraken, OKCoin, and BTC China) which together account for a market share of more than 50% in terms of traded volume are analyzed. The contribution of each exchange to price discovery is determined by relying on the Hasbrouck (1995) and Gonzalo and Granger (1995) techniques applied to bivariate and trivariate Vector Error Correction Models (VECMs). The bivariate VECMs involve two price series when the exchanges trade in the same currency, whereas the trivariate ones investigate the relationships between prices of exchanges trading against different currencies and include the exchange rate (as in the study of Grammig et al. 2005). Indeed, modeling the exchange rates we are able to assess their contribution to price discovery.

The main results can be summarized as follows. We find a clear ranking with regard to the importance of each exchange in the price formation process. Specifically, over the investigated period, the Chinese OKcoin is the leading market for the price discovery, followed by BTC China, which in turn precedes the American Bitfinex and Bitstamp, the European Kraken and the American BTC-e. Thus, we note that the Chinese exchanges enjoy a leading position when it comes to price discovery, while one cannot generally argue that the American exchanges—led by Bitfinex—are more important than the European one, given that Kraken turns out to be more informative than BTC-e. Moreover, BTC-e emerges as the least informative platform—among those analyzed—from a price discovery perspective. The latter finding is in contrast to the ranking of Brandvold et al. (2015) who found that BTC-e is one of the leading exchanges. Still, it confirms their claim that the information shares are dynamic and evolve significantly over time and is in line with the shift of trading volume away from BTC-e towards the other exchanges. Hence, high trading volume and a high information share seem to be complementary events. Lastly, we find the effect of the exchange rate on Bitcoin prices to be rather week which suggests that the cryptocurrency is not a global player in the FX markets.

The remainder of this article proceeds as follows. Section 2 outlines the methodology employed. Section 3 provides a description of the data and the market environment, preliminary analyses as well as the VECM estimation results. Section 4 presents the estimated information share results in the context of cross-currency trading of Bitcoin. Section 5 derives an overall ranking of the exchanges in terms of their contributions to price discovery and Sect. 6 concludes.

2 Methodology

The core issue addressed by the current study is to determine which Bitcoin trading platform leads price discovery. To answer such a question, we start from a fundamental microstructure model for Bitcoin where trading prices of Bitcoin can be observed in multiple markets which might trade in different currencies. This results in bivariate (trivariate) models involving two market prices at a time (and the corresponding exchange rate when the two exchanges considered trade in different currencies). To determine the contribution of each exchange to price discovery, we rely on the Hasbrouck (1995) information share approach, accounting for the potential influence of the exchange rate as in Grammig et al. (2005), as well as on the Gonzalo and Granger (1995) common factor weights. Ultimately, a comparison of the bi-market models reveals an ordering of the exchanges according to their importance in the price discovery process.

In the present context, all markets trade one common asset: Bitcoin. Even though trading the asset takes place in different currencies, the law of one price states that prices related to the same asset should not deviate in the long run. Strictly speaking, the no-arbitrage condition implies that

$$P_t^{i,x} = P_t^{j,y} \cdot R_t^{x/y}, \tag{1}$$

where $P_t^{i,x}$ and $P_t^{j,y}$ denote the prices of Bitcoin on exchanges i and j at time t traded against the currencies x and y, respectively, and $R_t^{x/y}$ is the exchange rate at time t between the two currencies. Taking logs on both sides of Eq. (1), the relationship becomes

$$p_t^{i,x} = p_t^{j,y} + r_t^{x/y}, \tag{2}$$

where $p_t^{i,x}$ and $p_t^{j,y}$ denote log prices at time t and $r_t^{x/y}$ indicates the log of the exchange rate. Of course the relationships illustrated in Eqs. (1) and (2) do not necessarily hold exactly for every point in time t. However, when the Bitcoin prices are expressed in a common unit of measure, the deviations must not be too large as this would present opportunities for arbitrage trading. Assuming that both the observed prices and the exchange rate are best described by random walks, and denoting the short term, i.i.d. pricing error by w_t, Eq. (2) forms the basis for a cointegration relationship. Hence,

$$p_t^{i,x} = p_t^{j,y} + r_t^{x/y} + w_t, \tag{3}$$

which implies a theoretical cointegrating vector of $(1, -1, -1)$.

Market microstructure theory suggests that the fundamental, but unobserved value m_t of Bitcoin follows a random walk $m_t = m_{t-1} + v_t$ with i.i.d. innovations v_t. Similar to Lehmann (2002), we assume that the prices which are observed on the respective markets are given as

$$\tilde{p}_t = \iota_2 m_t + u_t, \tag{4}$$

where $\tilde{p}_t$ is a (2×1) vector which contains the trading prices, ι_2 is a (2×1) vector of ones, and u_t is a (2×1) vector of zero-mean market microstructure noise which is not necessarily uncorrelated. Note that in contrast to Lehmann (2002), we might observe one price in a different currency such that Eq. (2) holds.

Given the cointegration structure in Eq. (3), the Granger representation theorem (cp. Engle and Granger 1987) provides a suitable model to study the price dynamics: the VECM. Collecting the variables in the vector $p_t = (r_t^{x/y}, p_t^{i,x}, p_t^{j,y})'$, the model is of the form

$$\Delta p_t = \alpha\beta' p_{t-1} + \sum_{i=1}^{k-1} \zeta_i \Delta p_{t-i} + \varepsilon_t, \tag{5}$$

with α a (3×1) vector containing the adjustment coefficients, β the (3×1) cointegrating vector, ζ_i the (3×3) parameter matrices, k the autoregressive order, and ε_t a multivariate zero-mean white noise process with variance–covariance matrix Σ_ε.

To determine the contribution of each exchange to price discovery, it is useful to write the VECM in Eq. (5) in its corresponding vector moving average (VMA) representation

$$\Delta p_t = \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_2 \varepsilon_{t-2} + \ldots = \Psi(L)\varepsilon_t, \tag{6}$$

where L denotes the lag operator and Ψ_j are (3×3) VMA coefficient matrices. $\Psi(L)$ is the matrix polynomial in the lag operator $\Psi(L) = I_3 + \Psi_1 L + \Psi_2 L^2 + \ldots$ and I_3 is the (3×3) identity matrix.

It is worth noting the importance of $\Psi(1)$ in assessing the long-run effect that a shock exerts on the series involved in each model. As a matter of fact, the elements of this matrix express the permanent impact of the composite shocks, i.e. the $\varepsilon = (\varepsilon_t, \varepsilon_{t-1}, \ldots)$ innovations, on the long-run evolution of Bitcoin prices (and the exchange rate). In the present context, the $\Psi(1)$ matrix is obtained through the VECM parameters as follows (cp. Johansen 1998):

$$\Psi(1) = \beta_\perp \left[\alpha'_\perp \left(I_3 - \sum_{i=1}^{k-1} \zeta_i \right) \beta_\perp \right]^{-1} \alpha'_\perp, \tag{7}$$

where $\alpha_\perp$ and $\beta_\perp$ denote the orthogonal complement of α and β, respectively.

The permanent effect exerted by shocks on the three prices is contained in the vector $\Psi(1)\varepsilon_t$, as shown by Stock and Watson (1988), which can be explicitly written as

$$\Psi(1)\varepsilon_t = \begin{bmatrix} \psi_{1,1} & \psi_{1,2} & \psi_{1,3} \\ \psi_{2,1} & \psi_{2,2} & \psi_{2,3} \\ \psi_{3,1} & \psi_{3,2} & \psi_{3,3} \end{bmatrix} \cdot \begin{bmatrix} \varepsilon_t^r \\ \varepsilon_t^i \\ \varepsilon_t^j \end{bmatrix}. \tag{8}$$

The element $\psi_{i,j}$ captures the long-run impact of a unit composite shock in the jth market price on the ith price. Taking a look at the ith element of the vector $\Psi(1)\varepsilon_t$, this is nothing else but a weighted sum of the specific innovations, having the row elements of $\Psi(1)$ as weights: it expresses the permanent effect of the specific innovations enclosed in the ith market price.

As far as the elements of the $\Psi(1)$ matrix are concerned, there is one important aspect: we assume that the exchange rate is exogenous to the Bitcoin price given the relatively low market volume of the cryptocurrency compared to the traditional currencies' volumes.[1] In other words, trading of Bitcoin in different currencies does not (immediately, if at all) affect the exchange rate of the respective currencies. Thus, it is reasonable to expect that $\psi_{1,2} = \psi_{1,3} = 0$.

After the $\Psi(1)$ matrix is computed, the long-run impact variances must be decomposed to obtain the Hasbrouck (1995) information shares. The long-run impact variances, i.e. $\sigma_l^2 = Var(\psi_{l,1}\varepsilon_t^r + \psi_{l,2}\varepsilon_t^i + \psi_{l,3}\varepsilon_t^j)$, where $l = 1, 2, 3$ are the ones contained on the main diagonal of the $\psi\Sigma_\varepsilon\psi'$ matrix. In the present application, the matrix of the innovations Σ_ε is not diagonal. To obtain a unique decomposition, it is necessary to impose further restrictions. One common approach in the literature is to use Cholesky decomposition of the composite innovation variance–covariance matrix. The matrix Σ_ε can then be decomposed as $\Sigma_\varepsilon = FF'$, where F is lower triangular. Subsequently, market j's information share in the Hasbrouck sense can be derived as

$$IS_{i,j} = \frac{([\psi' F]_{i,j})^2}{[\psi\Sigma_\varepsilon\psi']_{i,i}}. \tag{9}$$

Intuitively, the information share represents the fraction of the innovation variance in the price of the market i which is due to shocks in the price of market j.

It must be stressed that in the context of our trivariate system the methodology employed here is slightly different from the one proposed by Hasbrouck (1995). While Hasbrouck's approach investigates price discovery related only to the case of one security traded on multiple markets, the current one accounts for exchange rate effects. As a consequence, Hasbrouck's technique is based on the core assumption that one common stochastic trend exists (the common efficient stock price m_t), whereas in the present context the number of common trends is two, one for the efficient stock price and another one for the exchange rate. This implies the presence of one cointegrating relation (i.e. one cointegrating vector) in the current trivariate setup as set out in Eq. (3). For those models where we consider Bitcoin prices denoted in the same currency, the methodology reduces to what is set out in Hasbrouck (1995).

While the use of the Cholesky factorization overcomes the issue of identification, it is burdened with a substantial limitation. Given the lower triangular form of the matrix F, structural innovations cannot have any contemporaneous impact on the markets which have a higher rank in the hierarchical structure imposed by the Cholesky decomposition. Thus, information share results obviously depend on the particular order of variables chosen for the triangularization of the variance–covariance matrix. In many applications, no theoretical justification is available to provide an exact order of variables. In the present case, an important economic consideration allows to determine at least the variable which should be ordered first: the exchange

[1] For example, the average daily US Dollar foreign exchange trading volume was 1.65 trillion US Dollar in 2016 as opposed to 14 billion trading of Bitcoin in US Dollar.

rate. It is reasonable to assume that the exchange rate between two currencies should not be affected by the dynamics of a generic Bitcoin exchange price. The main reason is, as discussed above, the relatively low market volume of the cryptocurrency compared to traditional fiat currencies. As we do not have an economic reasoning for the ordering of the Bitcoin markets, their order is switched as is standard in the literature. This strategy results in upper and lower bounds of the Hasbrouck (1995) information shares.

As an additional information share measure, an adaptation of the Gonzalo and Granger (1995) common factor weights to the present context is proposed. This measure will be referred to as adjustment share, as it deals with the adjustment coefficients retrieved from the VECM estimation. To compute the adjustment shares, the adjustment coefficient related to the exchange rate is restricted to zero, which is the substantial difference with respect to the Gonzalo and Granger (1995) common factor weight approach. The theoretical consideration behind this decision is that exogenous exchange rates should not adjust to disequilibrium, which implies that the first element of the adjustment coefficient vector $\alpha_1 = 0$, if the exchange rate is ordered first in Δp_t. Under this constraint, the adjustment share related to the Bitcoin exchange i is computed as

$$AS_i = \frac{\alpha_{i,\perp}}{\alpha_{i,\perp} + \alpha_{j,\perp}}, \tag{10}$$

where $\alpha_{i,\perp}$ and $\alpha_{j,\perp}$ indicate the orthogonal complements of the adjustment coefficients associated with the Bitcoin exchanges i and j, respectively. This measure, in contrast to Hasbrouck's information shares, is uniquely identified without imposing any further restrictions. It should be noted that the two shares do not measure the same: while the Hasbrouck information share quantifies the proportion of the total variance of the VECM due to a specific innovation, the adjustment share assesses the magnitude of the adjustment to the underlying common stochastic trend.

The methodology presented so far aimed at the analysis when Bitcoin is traded in different currencies. In case that two markets use the same currency, the relationship in Eq. (2) reduces to $p_t^{i,x} = p_t^{j,x}$ and the VECM in Eq. (5) to a bivariate model where $p_t = (p_t^{i,x}, p_t^{j,x})'$. All other derivations still hold and are directly applicable, in particular the information shares of Hasbrouck (1995) and Gonzalo and Granger (1995).

To calculate standard errors, we rely on the parametric bootstrap proposed by Li and Maddala (1997). To this end, we draw from the vector of VECM residuals obtained from estimating Eq. (5) with replacement to obtain a vector of innovations. By means of the new innovation vector and the estimated VECM parameters, bootstrap time series are generated. These artificial data are then used to re-estimate the VECM parameters. We rely on 1000 bootstrap replications to obtain the distribution of each parameter of interest and to compute their standard errors.

3 Data description, preliminary analysis and estimations

This section provides a description of the data, followed by a preliminary analysis which comprises stationarity and cointegration tests and finally presents the VECM estimation results. The cointegration model is estimated using Johansen's (1988; 1991) full information maximum likelihood approach. All the analyses and estimations are performed using Matlab version R2016b.

The dataset is composed of six Bitcoin price time series obtained from bitcoincharts.com and three exchange rate time series obtained from Bloomberg for the period 2 January 2014–6 March 2017. The chosen Bitcoin platforms belong to the most important trading venues in the considered time frame in terms of transaction volume. According to data from bitcoinity.org, the market share of these platforms varied between 25% in January 2014 and more than 75% in February 2015. On average, it is well above 50%.

For three exchanges, we consider Bitcoin traded against the US Dollar (Bitfinex, Bitstamp, BTC-e), two against the Chinese Renminbi (BTC China, OKCoin) and one against the Euro (Kraken). Accordingly, the USD/CNY, EUR/USD and EUR/CNY exchange rates are needed. Both Bitcoin and the exchange rates are traded continuously 24 h on 7 days a week. Hence, we do not face any restrictions to overlapping trading hours like Grammig et al. (2005). All time series are sampled at a 5-min interval. To illustrate the price dynamics of Bitcoin during the considered period, Fig. 1 presents a time series plot of the Bitstamp price time series. To align the data, we have removed pairs of observations when one of the variables was missing. This happened in particular for the EUR/CNY exchange rate for which we could only obtain data starting from mid-2014. In case of the Bitcoin prices, we also have

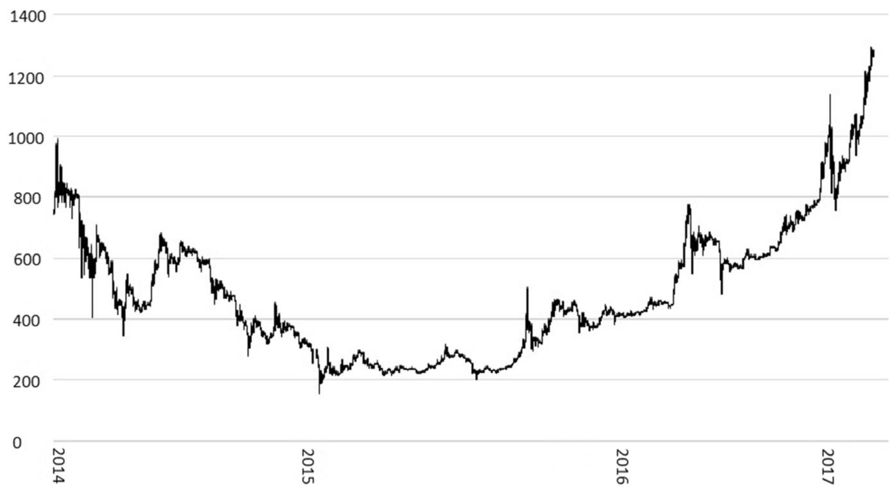

Fig. 1 Bitstamp price series (USD). The graph from above shows the dynamics of the Bitstamp price series—expressed in US Dollars—during the analyzed period 2 January 2014–6 March 2017. Prices are sampled at a 5-min interval

missing data which are most likely due to recording errors in the database. The data quality seems very good for Bitstamp while the most missing days are observed for OKCoin.[2] The exclusion is implemented individually for each of the models considered which leads to different numbers of observations in each model.

To derive the information shares, we rely on bivariate and trivariate VECMs. To this end, the six Bitcoin price series are combined in pairs and, if they are traded in different currencies, complemented by the respective exchange rate. This leads to a total of eleven trivariate and four bivariate models which are numbered and described in columns one and two in Table 1. The table also reports the resulting number of observations for each model.

Price discovery is arguably related to trading volume and to the level of trading activity on the involved exchanges. Figures 2 and 3, therefore, present the relative trading volume and the relative trading activity (in terms of number of transactions) of the considered exchanges. As one can see, trading activity and volume are concentrated to a large extent on OKCoin, in particular from mid-2015 to mid-2016. Volume started to shift (allegedly to markets in Japan and South Korea, cp. Xiao et al. 2017) at the end of 2016 when the Chinese government first announced that stricter controls of Bitcoin will be implemented (which ultimately led to a close of the markets in China in September 2017). However, due to its overwhelming market share, we expect that OKCoin is the dominant market in terms of price discovery.

As far as the preliminary analysis of the data is concerned, prices and exchange rates are first tested for stationarity. To this end, Augmented Dickey–Fuller (ADF) and KPSS (Kwiatkowski et al. 1992) tests are conducted for each resulting time series after cleaning of the data. Results are presented in the last four columns of Table 1. In general, the test results support the fact that both prices and exchange rates are non-stationary in levels, as well as that their first differences are stationary. For example, while the ADF test just weakly indicates the non-stationarity of the EUR/CNY exchange rate in levels in models 10 and 11 with a p value only slightly above 5%, the KPSS test solidly points towards a unit root. The latter consideration allows to proceed with the analysis as non-stationarity of the series in levels is the prerequisite for the time series to be cointegrated.

To test for cointegration, the Johansen trace test and the Johansen maximum eigenvalue test are performed. It is reasonable to expect that the tests will reveal a cointegrating rank $r = 1$, such that $g = 3 - r = 2$ common stochastic trends will be present in the trivariate model or $g = 2 - r = 1$ in the bivariate models. Indeed, the tests should indicate the presence of one trend associated with the efficient exchange rate (if part of the model) and another one for the common efficient Bitcoin price. Results are presented in Table 2. Overall, both tests point to the same conclusion for almost all of the models: a cointegrating rank $r = 1$. The only model for which

[2] We have not interpolated the data in the usual way, keeping the last observation as the still valid one until a change is recorded as we believe that the missing data are due to recording errors, not non-trading. Introducing a day's worth of zero returns, however, substantially discriminates against the respective platform in terms of price discovery. We, therefore, keep only full-time spans in the spirit of Grammig et al. (2005) who restrict the estimation to overlapping trading hours.

Table 1 Models and stationarity test results

Model		N. Obs	ADF		KPSS	
			p_t	Δp_t	p_t	Δp_t
1.	CNY/USD	46856	0.9889	< 0.001	< 0.01	< 0.1
	Bitfinex		0.5035	< 0.001	< 0.01	< 0.1
	OKCoin		0.6113	< 0.001	< 0.01	< 0.1
2.	CNY/USD	52917	0.9423	< 0.001	< 0.01	< 0.1
	Bitstamp		0.8343	< 0.001	< 0.01	0.0894
	OKCoin		0.8540	< 0.001	< 0.01	0.0798
3.	CNY/USD	51178	0.9467	< 0.001	< 0.01	< 0.1
	BTC-e		0.8432	< 0.001	< 0.01	0.0740
	OKCoin		0.8703	< 0.001	< 0.01	0.0749
4.	CNY/USD	58790	0.9764	< 0.001	< 0.01	< 0.1
	Bitfinex		0.5531	< 0.001	< 0.01	< 0.1
	BTC China		0.6818	< 0.001	< 0.01	0.0760
5.	CNY/USD	64915	0.9275	< 0.001	< 0.01	< 0.1
	Bitstamp		0.8924	< 0.001	< 0.01	0.0632
	BTC China		0.9051	< 0.001	< 0.01	0.0428
6.	USD/EUR	63421	0.9273	< 0.001	< 0.01	< 0.1
	BTC-e		0.8836	< 0.001	< 0.01	0.0486
	BTC China		0.9042	< 0.001	< 0.01	0.0434
7.	USD/EUR	212132	0.6284	< 0.001	< 0.01	< 0.1
	Bitfinex		0.5104	< 0.001	< 0.01	< 0.1
	Kraken		0.6703	< 0.001	< 0.01	< 0.1
8.	USD/EUR	224549	0.5856	< 0.001	< 0.01	< 0.1
	Bitstamp		0.7158	< 0.001	< 0.01	< 0.1
	Kraken		0.8536	< 0.001	< 0.01	< 0.1
9.	USD/EUR	219899	0.5918	< 0.001	< 0.01	< 0.1
	BTC-e		0.7270	< 0.001	< 0.01	< 0.1
	Kraken		0.8524	< 0.001	< 0.01	< 0.1
10.	EUR/CNY	58855	0.0679	< 0.001	< 0.01	< 0.1
	OKCoin		0.9427	< 0.001	< 0.01	< 0.1
	Kraken		0.9195	< 0.001	< 0.01	< 0.1
11.	EUR/CNY	81341	0.0533	< 0.001	< 0.01	< 0.1
	BTC China		0.9848	< 0.001	< 0.01	< 0.1
	Kraken		0.9647	< 0.001	< 0.01	< 0.1
12.	Bitfinex	304468	0.5558	< 0.001	< 0.01	< 0.1
	Bitstamp		0.5668	< 0.001	< 0.01	< 0.1
13.	Bitfinex	298098	0.5581	< 0.001	< 0.01	< 0.1
	BTC-e		0.5776	< 0.001	< 0.01	< 0.1
14.	Bitstamp	324419	0.8846	< 0.001	< 0.01	< 0.1
	BTC-e		0.8930	< 0.001	< 0.01	< 0.1
15.	BTC China	235626	0.8650	< 0.001	< 0.01	< 0.1
	OKCoin		0.8511	< 0.001	< 0.01	< 0.1

Table 1 (continued) The first and second columns show the label of the models along with the respective price and exchange rate series. The third column holds the number of observations associated with each model. The fourth and fifth columns show the results of the ADF test, whereas the sixth and the seventh columns present the ones related to the KPSS test. The ADF tests in levels are conducted including a constant but no time trend, same for the KPSS tests. Both tests are conducted using an optimal lag length determined according to the Bayes–Schwarz information criterion. The minimum p value reported by MATLAB is 0.001 for the ADF and 0.01 for the KPSS tests, while the maximum p value reported for the KPSS test is 0.1

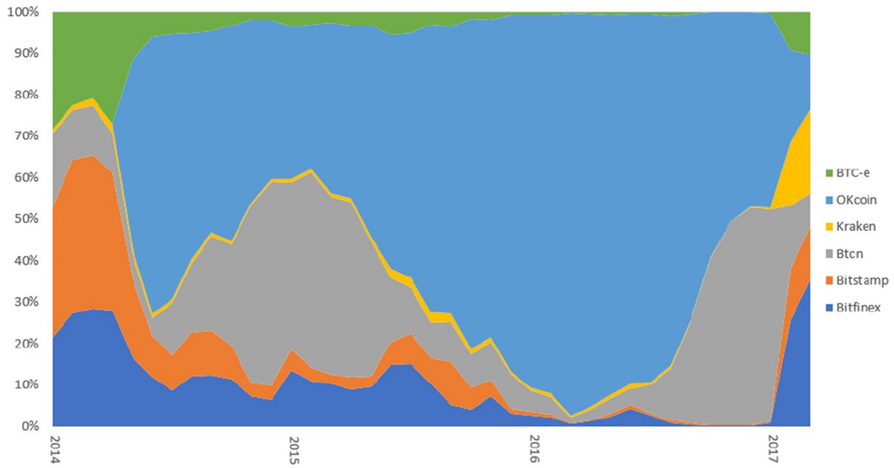

Fig. 2 Trading volume decomposition. The graph illustrates the distribution of Bitcoin trading volumes across the analyzed exchanges during the sample period 2 January 2014–6 March 2017. Volumes are sampled on a monthly basis

the two tests report conflicting outcomes is the first one which involves Bitfinex, OKCoin and the USD/CNY exchange rate. However, the p value of the trace test for $r = 1$ is only slightly smaller than 5% so that we decide to continue under the assumption that all models have a cointegrating rank $r = 1$.

Subsequently, we estimate the cointegrating vector for all of the models to see whether the empirical ones would be compatible with the theoretical cointegrating vector derived from Eq. (3). We find that for all models the estimated vectors are numerically very close to the theoretical vector. Notwithstanding, for the trivariate model, the null hypothesis that the true cointegrating vector is the theoretical one is only not rejected in 3 out of 11 cases. Similarly, for the bivariate models the test does not support that the estimated vector equals the theoretical one on a 5% significance level. Despite the test results, we will use the theoretical vector as in Hasbrouck (1995). To ensure that our results are robust to this restriction, we repeat the

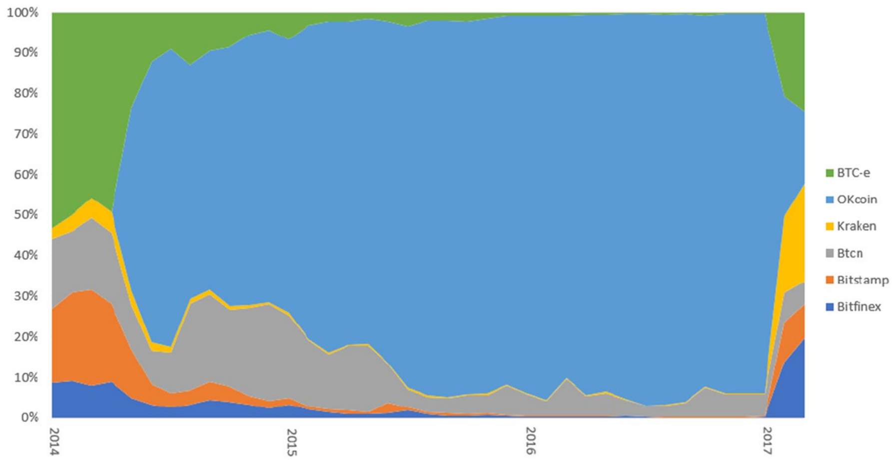

Fig. 3 Trading activity decomposition. The figure illustrates the distribution of the number of trades across the analyzed exchanges during the sample period 2 January 2014–6 March 2017. The number of trades is counted on a monthly basis

entire analysis using the estimated cointegrating vector and find that the conclusions are not qualitatively altered.[3]

In the next step, the VECM specified in Eq. (5) is estimated. The optimal lag length k is determined by means of the Bayes–Schwarz information criterion based on the vector autoregressive (VAR) representation of the model in first differences. Table 3 presents selected estimation results. Recall that we use the assumption that the exchange rate does not adjust to the common trend component to derive Eq. (10) in the trivariate context. The estimation results support this restriction as the order of magnitude of the adjustment coefficient α related to the exchange rate is comparatively small and in most cases not statistically significant.

After the estimation of the VECM parameters, we obtain the long-run impact matrix $\Psi(1)$ through the formula in Eq. (7). $\Psi(1)$ matrix estimates are shown in Table 3. First, in line with theory, the exchange rate does not seem to be affected by shocks in the Bitcoin prices, given the relatively modest weight of the elements $\psi_{1,2}$ and $\psi_{1,3}$. Taking a look at the results obtained in the last six models, though, reveals that the magnitude of the $\psi_{1,2}$ and $\psi_{1,3}$ entries is considerably higher than in the first five models. However, in each model these two coefficients are still low compared to the other ones belonging to the same long-run impact matrix. Second, the size of $\psi_{2,1}$ and $\psi_{3,1}$ reveals that the exchange rate has a small, but mostly statistically significant effect on the long-run evolution of the Bitcoin exchange prices. Third, in all cases, an innovation in the exchange price ordered first (second) always exerts a

[3] Repeating the analysis using the estimated cointegrating vector leads to almost identical conclusions with respect to the identification of the leadership. More precisely, the leadership results are identical when considering the Hasbrouck (1995) information shares. Considering the Gonzalo and Granger (1995) common factor weights, there is one model (model 11) for which the price discovery leadership is altered.

Table 2 Cointegration tests

Model	Lags	Trace			Max Eigenvalue		
		$r = 0$	$r = 1$	$r = 2$	$r = 0$	$r = 1$	$r = 2$
1.	5	< 0.001	0.0435	0.0502	< 0.001	0.1422	0.0502
2.	6	< 0.001	0.1141	0.1851	< 0.001	0.1671	0.1851
3.	3	< 0.001	0.1209	0.1839	< 0.001	0.1782	0.1839
4.	5	< 0.001	0.0393	0.0653	< 0.001	0.1092	0.0653
5.	6	< 0.001	0.1315	0.2237	< 0.001	0.1804	0.2237
6.	4	< 0.001	0.1190	0.1915	< 0.001	0.1713	0.1915
7.	19	< 0.001	0.4671	0.4772	< 0.001	0.5141	0.4772
8.	17	< 0.001	0.3602	0.3153	< 0.001	0.4588	0.3153
9.	15	< 0.001	0.2643	0.3432	< 0.001	0.3435	0.3432
10.	9	< 0.001	0.8042	0.5860	< 0.001	0.8469	0.5860
11.	7	< 0.001	0.7239	0.5171	< 0.001	0.7797	0.5171
12.	17	< 0.001	0.9542	–	< 0.001	0.9542	–
13.	17	< 0.001	0.9538	–	< 0.001	0.9538	–
14.	18	< 0.001	0.7723	–	< 0.001	0.7723	–
15.	20	< 0.001	0.7650	–	< 0.001	0.7650	–

The second column reports the number of lagged differences included in the VECM estimation, determined using the Bayes–Schwarz information criterion based on a VAR in first differences. The maximum number of lags allowed in conducting the analysis is 20. Columns three to five illustrate the p values associated with the Johansen Trace test for cointegration, whereas columns six to eight present the p values related to the Johansen Max Eigenvalue test, with r being the number of cointegrating relations. The null hypothesis $r = 0$ indicates the absence of cointegration, while $r = 1$ and $r = 2$ indicate the presence of cointegration with cointegrating ranks of 1 and 2, respectively. The specification of the model tested does not include any constant or time trend, neither in the equation nor in the cointegrating relationship. Both tests are conducted on a 5% significance level. The minimum p value reported by MATLAB is 0.001 for both tests

larger long-run impact towards the exchange ordered first (second), rather than on the exchange price ordered second (first). While this difference is subtle for the first five models, it is more predominant from model 6 onwards.[4]

4 Price discovery analysis in the presence of exchange rate effects

Hasbrouck (1995) information shares for the models that consider Bitcoin traded in different currencies are reported in Table 4, while Table 5 presents the respective Gonzalo and Granger (1995) adjustment shares. The bounds of the information shares are found to be wide which suggests a considerable amount of

[4] Detailed VECM estimation results for the remaining models 12–15 are not reported as there are no economic implications that would restrict α or $\Psi(1)$ in the bivariate models.

Table 3 Adjustment coefficients and $\Psi(1)$ matrix for the trivariate models

Model		α	$\Psi(1)$		
1.	CNY/USD	− 0.0001 (0.00007)	0.9260 (0.0102)	− 0.0073 (0.0039)	0.0087 (0.0042)
	Bitfinex	− 0.0088 (0.00188)	− 0.1988 (0.2599)	0.4702 (0.1003)	0.5264 (0.1063)
	OKCoin	0.0078 (0.00174)	0.7273 (0.2613)	0.4630 (0.1008)	0.5351 (0.1070)
2.	CNY/USD	− 0.0001 (0.00006)	0.9376 (0.0130)	− 0.0057 (0.0051)	0.0071 (0.0055)
	Bitstamp	− 0.0060 (0.00141)	− 0.4582 (0.3396)	0.4195 (0.1247)	0.5785 (0.1336)
	OKCoin	0.0043 (0.00135)	0.4794 (0.3399)	0.4138 (0.1248)	0.5855 (0.1337)
3.	CNY/USD	− 0.0001 (0.00004)	0.9420 (0.0143)	− 0.0150 (0.0074)	0.0170 (0.0079)
	BTC-e	− 0.0042 (0.00092)	− 0.7315 (0.3373)	0.3762 (0.1680)	0.6428 (0.1799)
	OKCoin	0.0024 (0.00088)	0.2105 (0.3393)	0.3613 (0.1688)	0.6598 (0.1809)
4.	CNY/USD	− 0.0001 (0.00005)	0.9090 (0.0093)	− 0.0049 (0.0039)	0.0070 (0.0042)
	Bitfinex	− 0.0067 (0.00137)	− 0.4519 (0.2318)	0.4545 (0.0990)	0.5424 (0.1067)
	BTC China	0.0056 (0.00123)	− 0.4572 (0.3556)	0.4496 (0.1669)	0.5494 (0.1818)
5.	CNY/USD	− 0.0000 (0.00004)	0.9239 (0.0126)	− 0.0031 (0.0049)	0.0051 (0.0054)
	Bitstamp	− 0.0046 (0.00103)	− 0.6644 (0.3103)	0.4086 (0.1162)	0.5876 (0.1279)
	BTC China	0.0032 (0.00094)	0.2595 (0.3110)	0.4055 (0.1166)	0.5927 (0.1283)
6.	CNY/USD	− 0.0001 (0.00003)	0.9094 (0.0145)	− 0.0126 (0.0068)	0.0154 (0.0074)
	BTC-e	− 0.0038 (0.00066)	− 1.0538 (0.3547)	0.2484 (0.1664)	0.7843 (0.1812)
	BTC China	0.0011 (0.00064)	− 0.1444 (0.3556)	0.2358 (0.1669)	0.7996 (0.1818)
7.	USD/EUR	− 0.0008 (0.00008)	0.8690 (0.0119)	− 0.0354 (0.0039)	0.0397 (0.0041)
	Bitfinex	− 0.0037 (0.00069)	− 0.0670 (0.0794)	0.6467 (0.0265)	0.1741 (0.0280)
	Kraken	0.0135 (0.00065)	0.8020 (0.0790)	0.6133 (0.0263)	0.2139 (0.0278)
8.	USD/EUR	− 0.0009 (0.00008)	0.8187 (0.0146)	− 0.0500 (0.0051)	0.0512 (0.0049)
	Bitstamp	− 0.0049 (0.00072)	− 0.1038 (0.1009)	0.5660 (0.0354)	0.2704 (0.0346)
	Kraken	0.0100 (0.00070)	0.7149 (0.1005)	0.5160 (0.0352)	0.3217 (0.0344)
9.	USD/EUR	− 0.0002 (0.00004)	0.8569 (0.0213)	− 0.0331 (0.0073)	0.0413 (0.0087)
	BTC-e	− 0.0038 (0.00036)	− 0.2952 (0.1412)	0.2783 (0.0474)	0.4913 (0.0572)
	Kraken	0.0020 (0.00031)	0.5617 (0.1421)	0.2452 (0.0477)	0.5326 (0.0576)
10.	EUR/CNY	− 0.0006 (0.00017)	0.6974 (0.0252)	− 0.0842 (0.0213)	0.0794 (0.0228)
	Kraken	− 0.0032 (0.00101)	− 0.2889 (0.1926)	0.3960 (0.1617)	0.5403 (0.1730)
	OKCoin	0.0020 (0.00106)	0.4085 (0.1908)	0.3118 (0.1600)	0.6197 (0.1713)
11.	EUR/CNY	− 0.0006 (0.00013)	0.6207 (0.0236)	− 0.0890 (0.0186)	0.0943 (0.0213)
	Kraken	− 0.0021 (0.00058)	− 0.2658 (0.1377)	0.5088 (0.1114)	0.4644 (0.1268)
	BTC China	0.0020 (0.00062)	0.3548 (0.1397)	0.4198 (0.1131)	0.5587 (0.1287)

Note: the third column holds the estimated adjustment coefficients resulting from the VECM estimation using the fixed cointegrating vector $(1, 1, -1)$. Columns 4–6 present the estimates of the long-run impact matrices $\Psi(1)$. The order of the variables is reported in column 2. Bootstrap standard errors based on a sample of 1000 bootstrap replications are reported in parentheses

contemporaneous correlation of the VECM residuals. In particular, the greatest spread between upper and lower bounds is found for model 1 which considers Bitfinex and OKCoin. The estimated information shares may, therefore, appear

Table 4 Information share bounds (trivariate models)

Model			Innovation		
			r	p_i	p_j
1.	CNY/USD	r	98.37	0.02–1.29	0.34–1.61
	Bitfinex	p_i	0.33	7.79–91.04	8.63–91.88
	OKCoin	p_j	0.90	7.50–90.25	8.85–91.61
2.	CNY/USD	r	98.89	0.00–0.79	0.31–1.11
	Bitstamp	p_i	0.17	6.41–88.61	11.22–93.34
	OKCoin	p_j	0.63	6.27–87.96	11.41–93.10
3.	CNY/USD	r	93.97	0.08–4.74	1.30–5.96
	BTC-e	p_i	0.11	4.72–86.48	13.41–95.18
	OKCoin	p_j	0.51	4.31–85.50	14.00–95.18
4.	CNY/USD	r	98.96	0.00–0.64	0.41–1.04
	Bitfinex	p_i	0.02	8.96–89.73	10.25–91.02
	BTC China	p_j	0.30	8.72–89.25	10.45–90.99
5.	CNY/USD	r	99.38	0.02–0.27	0.36–0.60
	Bitstamp	p_i	0.00	8.13–86.12	13.88–91.86
	BTC China	p_j	0.22	7.97–85.74	14.04–91.81
6.	CNY/USD	r	94.39	0.10–4.14	0.36–1.46
	BTC-e	p_i	0.02	2.65–76.18	23.80–97.33
	BTC China	p_j	0.07	2.37–75.38	24.55–97.56
7.	USD/EUR	r	87.80	2.92–8.58	3.63–9.28
	Bitfinex	p_i	0.02	60.59–96.21	3.77–39.39
	Kraken	p_j	1.53	54.92–92.70	5.78–43.56
8.	USD/EUR	r	81.07	5.22–15.59	3.34–13.72
	Bitstamp	p_i	0.04	41.52–92.00	7.95–63.67
	Kraken	p_j	1.20	35.13–87.34	11.45–63.67
9.	USD/EUR	r	81.97	7.52–14.42	3.61–10.51
	BTC-e	p_i	0.26	24.70–63.69	36.05–75.04
	Kraken	p_j	0.81	19.12–56.92	42.27–80.07
10.	EUR/CNY	r	86.62	1.22–12.49	0.89–12.16
	Kraken	p_i	2.73	5.17–86.72	10.55–92.10
	OKCoin	p_j	0.15	3.27–85.69	14.16–96.58
11.	EUR/CNY	r	80.97	1.24–14.71	4.32–17.79
	Kraken	p_i	0.23	14.26–86.97	12.81–85.51
	BTC China	p_j	1.12	9.42–80.91	17.98–89.46

The table presents the estimated information share bounds obtained through the permutation of the last two variables of each model in the Cholesky decomposition of the variance–covariance matrix. Column 4 illustrates bounds for the contribution of the exchange rate on the total VECM variance for each of the variables listed in column 2, while columns 5 and 6 show bounds for the contribution of the prices ordered second and third, respectively, in the particular structure provided again in column 2. Given that the exchange rate is always ordered first, information shares related to an innovation in the exchange rate are unique and, therefore, only one value is shown. Values are illustrated in percentage terms

Table 5 Adjustment shares (trivariate models)

Model		AS
1.	Bitfinex	47.01
	OKCoin	52.99
2.	Bitstamp	41.73
	OKCoin	58.27
3.	BTC-e	35.72
	OKCoin	64.28
4.	Bitfinex	45.30
	BTC China	54.70
5.	Bitstamp	40.73
	BTC China	59.27
6.	BTC-e	22.57
	BTC China	77.43
7.	Bitfinex	78.42
	Kraken	21.58
8.	Bitstamp	66.90
	Kraken	33.10
9.	BTC-e	34.56
	Kraken	65.44
10.	Kraken	38.65
	OKCoin	61.35
11.	Kraken	48.25
	BTC China	51.75

The table presents the results of the adjustment shares. The adjustment share measures are computed as $AS_i = \frac{\alpha_{i,\perp}}{\alpha_{i,\perp}+\alpha_{j,\perp}}$, where $\alpha_{i,\perp}$ and $\alpha_{j,\perp}$ indicate the orthogonal complements of the adjustment coefficients related to the Bitcoin exchanges i and j, respectively. Values are expressed in percentage terms

relatively uninformative because of the substantial width of their bounds. Nonetheless, results obtained from both the information share and the adjustment share measures point to the same conclusions.

Focusing on an exchange level, the first finding is that OKCoin and BTC China dominate price discovery with respect to all the other platforms considered in the analysis which trade against currencies different from the Chinese Renminbi. Indeed, their information shares are always larger than the ones belonging to the platforms to which they are compared to. Second, two of the exchanges trading in US Dollar, namely Bitfinex and Bitstamp, dominate the one trading in Euro (Kraken). Notwithstanding this, they do not exert the same contribution to price discovery as the two Chinese platforms, the shares associated with the latter ones being greater in both cases. Third, BTC-e trading in US Dollar does not contribute to price discovery in the same way or to the same extent as the other two exchanges trading against US Dollar. Indeed, BTC-e is not only overtaken by the exchanges trading in Chinese Renminbi, but also by the one trading in Euro.

Our results suggest that trading in Chinese Renminbi leads the price formation process with respect to the other markets considered in this study. This is an important finding, even though not particularly astonishing, provided that the Chinese market is arguably the one in which most of the trading volume lies during the investigated period (cp. Fig. 2). Another remarkable insight is that trading in US Dollar is not unanimously more informative than trading in Euro from a price discovery point of view albeit trading volume and trading intensity are lower on Kraken than on Bitstamp, Bitfinex, or BTC-e. In fact, the dominance of Kraken over BTC-e does not allow to attest a general supremacy of the US Dollar trading market with respect to Euro trading over the considered time frame.

Another interesting finding regards the magnitude of the exchange rates' contribution to price discovery. It turns out that the exchange rate exerts a very weak impact on the Bitcoin price formation process: this is true for every Bitcoin exchange analyzed in this framework. Indeed, the fraction of total variance of the permanent component due to a shock in the exchange rate ranges from a minimum of 0.00%—towards Bitfinex in model 7—to a maximum of only 2.73%—with respect to Kraken in model 10. The latter is a clear evidence of the fact that the exchange rate is not a fundamental driver in the Bitcoin price discovery mechanism.

In light of the argument that Bitcoin is one major vehicle to avoid capital controls when transferring money out of China[5], this is a remarkable observation. When legal ways are to be avoided, the bypass should allow for a similar transaction. In other words, we would expect that the transfer leads to the same Dollar or Euro amount which would not be feasible using standard ways and the official exchange rate. If the volume of transactions with this purpose is large enough, we would expect that the Bitcoin price would react to exchange rate movements and, thus, the contribution to price discovery of the EUR/CNY or USD/CNY exchange rates should be higher than the EUR/USD contributions. This is not what we find. Table 4 shows that the contribution of any exchange rate is weak and that the contribution of the EUR/USD exchange rate is even marginally higher than the contribution of the other rates. Hence, we conclude that even if one potential use of Bitcoin is to transfer money across countries, it seems to be of minor importance as the heavily traded exchange rates do not exert an impact on Bitcoin prices.

The other way round, i.e. the contribution of Bitcoin towards exchange rate price discovery, seems a bit more important, in particular when trading in Euro is involved. The CNY/USD exchange rate is largely unaffected by Bitcoin with information share upper bounds generally lower than 2%. However, the models that include Kraken prices in Euro reveal a greater impact of Bitcoin trading on the exchange rate. Still, the lower bound of the information share is rather low so that the effect might not be more than a statistical artifact. For markets where trading occurs in Euro and US Dollar, a potential, albeit small, contribution to price discovery is conceivable as money can be freely converted between these currencies and foreign transactions in Bitcoin might be reversed on the fiat currency markets.

[5] See, for example, https://www.newsbtc.com/2016/12/19/bitcoin-remains-viable-option-avoid-capital-controls-china/.

Table 6 Information share bounds and adjustment shares (bivariate models)

Model		IS low	IS up	AS
12.	Bitfinex	41.37	94.77	77.11
	Bitstamp	5.23	58.63	22.89
13.	Bitfinex	76.30	95.95	85.13
	BTC-e	4.05	23.70	14.87
14.	Bitstamp	54.58	88.59	74.01
	BTC-e	11.41	45.42	25.99
15.	BTC China	1.24	85.44	23.26
	OKCoin	14.56	98.76	76.74

The table reports the estimates for the lower bound (third column) and upper bound (fourth column) of the information shares according to Hasbrouck (1995), as well as the Gonzalo and Granger (1995) common factor components (fifth column). Note that the adjustment shares coincide—in this case—to the Gonzalo and Granger common factor weights. Values are expressed in percentage terms

A second explanation could be that the contribution of the Euro-denoted prices is rather low on average so that the exchange rate receives a higher relative contribution albeit it would also be small in absolute terms.

5 Leadership identification

The aim of the present section is to build a comprehensive exchange ranking. Section 4 analyzed the markets where trading takes place in different currencies. These results need to be complemented by an analysis of bivariate models for the markets trading Bitcoin against the same currency. With the considered exchanges, this leaves four additional models to be estimated. The setup is similar to the one described in Sect. 2 with the major exception that the exchange rate component is missing. Hence, the model only considers the observed trading prices as in Eq. 4 without the extra exchange rate component. The Hasbrouck (1995) information shares are computed in the same way, too. The adjustment shares now coincide with the Gonzalo and Granger (1995) common factor weights.

Results of the bivariate models are presented in Table 6. Bounds for the information shares are pretty wide even in this case, although the range—except for the one related to the Chinese exchanges—is in general narrower compared to the one obtained in the trivariate models. For example, the model involving the two Chinese platforms (model 15) exhibits a spread between the lower and upper bounds of 84.20%, whereas the other models report a width of at most 53.40% (Bitfinex and Bitstamp, model 12). These outcomes are again due to substantial contemporaneous correlation in the VECM innovations as discussed in Sect. 4. Again, the issue of dealing with rather large bounds is—at least partly—overcome by relying on an additional price discovery measure, the Gonzalo and Granger (1995) common factor component, which is presented in the last column of Table 6.

At an exchange level, the pairwise approach clearly indicates a leader in price discovery in each model. In sum, it turns out that Bitfinex has the highest information share when compared to Bitstamp or BTC-e which suggests that it is the leading platform for price discovery in trading Bitcoin against the US Dollar. Model 14 then suggests that Bitstamp is more important than BTC-e for the price discovery process which establishes a clear ranking within these platforms. With respect to the markets trading Bitcoin against the Renminbi, OKCoin turns out to be the leader in price discovery as can be seen from model 15.

A comprehensive analysis of these results coupled with the ones contained in Sect. 4 provides the possibility to derive a hierarchical structure of the exchanges in terms of their contribution to price discovery. The results assert the supremacy of the Chinese platform OKCoin in terms of price discovery, highlighted by both the Hasbrouck information shares as well as the common factor components. Indeed, whenever OKCoin is compared to any of the other considered exchanges, it indisputably shows higher values of contribution to price discovery. The second important platform is the other Chinese market included in the study, BTC China. This result is in line with the trading intensity measures presented in Figs. 2 and 3. In the absence of a fundamental value of Bitcoin (there are no future dividends or market information like in the case of stocks), only trading itself can reveal how much traders value one Bitcoin. As the figures illustrate, trading was heavily concentrated on OKCoin and BTC China during our sample period which supports the notion that these platforms lead the price discovery process.

The two exchanges Bitfinex and Bitstamp are ranked third and fourth. This indicates that during the investigated period trading Bitcoin against the US Dollar was more informative than trading against the Euro as Kraken emerges on rank five in our analysis. This ranking is again in line with the distribution of trading volume in Fig. 2 or the number of trades in Fig. 3. Lastly, trading on Kraken also turns out more informative than trading on BTC-e which there is considered the least informative market in our sample.

To gain further insight into how price discovery shifts over time between exchanges, we can relate our results to the study of Brandvold et al. (2015). The authors find that Mt.Gox and BTC-e are the market leaders during their analyzed time frame which ranges from 1 April 2013 to 25 February 2014. Of course, the supremacy of Mt.Gox cannot be reconfirmed here, as it is not included in the current analysis because of its bankruptcy on 28 February 2014. It should be noted that the steps that led to its shutdown are not related to price discovery rather than security breaches, hacker attacks, and fraud by employees. Still, price discovery had to shift away from Mt.Gox and one might have assumed that BTC-e which is identified as the second most important market takes its place. However, we cannot confirm BTC-e's dominance in our time period. On the contrary, among the considered trading platforms, BTC-e is even the one with the lowest contribution to price discovery. Therefore, our results are in line with the conclusion of Brandvold et al. (2015) who state that information shares are "dynamic and evolve significantly over time" (p. 18). We suggest that this evolution is to the greatest extent related to a shift of trading volume from one market to another. In our sample period, trading of Bitcoin was hyped in China for various reasons and, therefore, price discovery also followed to these markets.

6 Conclusion

Bitcoin's increasing success over the last years stimulated research to study different aspects of this still rather new cryptocurrency. This article analyses six main Bitcoin trading platforms which together account for more than 50% of overall trading volume, to determine on which exchange price discovery primarily occurs and, hence, which of these reflect the value of Bitcoin with the highest degree of accuracy. To this end, we use Hasbrouck (1995) information shares and the Gonzalo and Granger (1995) common factor weight approach to determine the leader and follower exchanges in the price discovery mechanism, accounting for the potential effect of the exchange rate.

The results suggest a solid ranking in terms of price discovery contribution among the exchanges considered in the study. In particular, OKCoin is the leader of price discovery over the examined period, followed by BTC China and then Bitfinex, Bitstamp, Kraken, and BTC-e. Therefore, it can be concluded that trading Bitcoin against the Renminbi exerts a larger contribution to price discovery than trading against the US Dollar or the Euro. However, it cannot be stated that the American platforms play, in general, a bigger role than the European ones as BTC-e has a lower information share than Kraken. Comparing our results to Brandvold et al. (2015), we find indeed that price discovery shifts across exchanges over time. We suggest that this is due to trading volume shifts because Bitcoin attracts different levels of attraction in different currency zones over time. In fact, while preparing this article, the Chinese government decided to shut down trading platforms on mainland China by 30 September 2017. Hence, the supremacy of OKCoin will not hold any longer. However, the new leader is most definitely to be found amongst the most trading-intensive Bitcoin exchanges.

Another crucial finding concerns the magnitude of the contributions to price discovery of the exchange rates towards Bitcoin prices. Indeed, even though contributions of the exchange rate to Bitcoin price discovery vary across models, their sizes are all relatively modest. This suggests that the Bitcoin and forex markets are informationally detached. Information that is important for exchange rates does not move BTC prices. This is a hint that BTC does not (yet) belong to the global forex market.

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