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Price Discovery on Bitcoin Markets

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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 markets 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.

Keywords: price discovery; Bitcoin; Hasbrouck information shares;

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1 Introduction

The XXI century gave birth to the new concept of cryptocurrency, a decentralized peer-to-peer digital currency that uses cryptography in order to ensure that payments are received and sent in a safe manner. While there are a plenty of 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, just 4 cryptocurrencies out of the 1128 existing hold about 78.4% of the total cryptocurrency market capitalization: Bitcoin represents the highest share (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 online in 2009 and - thereafter - the usage and interest in this new digital currency uncontrollably took root all over the world. 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, sensationally 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.

Academic studies regarding Bitcoin have been carried out alongside with the booming attention it aroused over the last years. Given the innovative nature of the phenomenon in question, studies cover a broad range of issues when it comes to Bitcoin. Many researchers focus on the fundamental aspects as well as on the mechanisms behind the functioning of the cryptocurrency (see, for instance, Segendorf, 2014; Dwyer, 2015). Also, central banks conducted analyses regarding Bitcoin, e.g. ECB (2012), Velde et al. (2013) and ECB (2015). A detailed description of the Bitcoin mining process is provided by Kroll, Davey, and Felten (2013). Some researchers like Doguet (2012) or Murphy, Murphy, and Seitzinger (2015) discuss the legal status of Bitcoin and the legal issues linked to its utilization. Other studies focus on the potentiality of Bitcoin to constitute not only a proper alternative medium of exchange (Rogojanu and Badea, 2014), but also a real monetary standard, analysing the related advantages and drawbacks (Weber, 2014). An interesting research is the one conducted by Trimborn and Härdle (2016) proposing a method to create an index for the cryptocurrency market, referred to as CRIX, which shows among its main features to quickly react to market changes.

A considerable section of the literature seeks the answer to the question whether Bitcoin should be conceived as a currency or as a speculative asset. Yermack (2013) defends the speculative nature of Bitcoin since its features - like the huge volatility and the scarce correlation with gold and other widely spread currencies - do not meet the ones typical of an authentic fiat currency. The analysis of Bouoiyour and Selmi (2015) confirms the speculative behaviour of Bitcoin and its limited usefulness as a medium of exchange. Also Baur, Lee, and Hong (2015) draw the same conclusion by analysing transaction data regarding the cryptocurrency. A more recent analysis of Bitcoin realized volatility carried out by Baur and Dimpfl (2017) further supports that Bitcoin cannot serve as a currency, provided the enormous magnitude of its fluctuations in comparison to the primary traditional currencies - up to as much as 30 times more.

A key element regarding Bitcoin is that it is traded against various currencies, as well as on multiple venues. More importantly, as already noticed by Brière, Oosterlinck, and Szafarz

(2015), prices vary among the platforms in which the cryptocurrency is traded. Notwithstanding this, the literature trying to address the question where price discovery takes place related to Bitcoin markets is surprisingly underdeveloped. Brandvold, Molnár, Vagstad, and Valstad (2015) analyse the contributions to price discovery related to a representative set of Bitcoin exchanges. They select Bitcoin platforms according to trading volumes, including five big exchanges - Bitfinex, Bitstamp, BTC-e, BTC China (Btcn) and Mt.Gox - as well as two smaller ones - Bitcurex and Canadian Virtual Exchange (Virtex) - in order to additionally capture eventual differences in the behaviour of the two categories. These exchanges - put together - cover a proportion amounting to approximately 90% of Bitcoins publicly traded at that time. They conclude that the leadership of price discovery can be attributed to Mt.Gox and BTC-e during the investigated period, which ranges from 1 April 2013 to 25 February 2014. Moreover, they argue that the information shares linked to Bitcoin exchanges are dynamic and they significantly evolve 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. As a matter of fact, further research going in the same direction should provide new insights and useful information with reference to the recent developments of price discovery on Bitcoin markets.

Price discovery is a widely studied topic in finance. The financial literature contains numerous examples of price discovery related studies, from security to commodity markets, among others. There is no lack of price discovery analyses on foreign exchange markets, too. As an example, Andersen, Bollerslev, Diebold, and Vega (2003) characterise the conditional means of the US dollar spot exchange rate through real-time exchange-rate quotations, macroeconomic expectations, and macroeconomic realizations; again Andersen, Bollerslev, Diebold, and Vega (2007) characterize the response of US, German and British stock, bond and foreign exchange markets to real-time US macroeconomic news. One of the core approaches employed in the price discovery framework is the information share methodology proposed by Hasbrouck (1995). This technique allows to derive, in the context of one security traded on multiple markets, upper and lower bounds for each market's contribution to the total variance of the informationally efficient price which is taken as the respective market's contribution to price discovery. Despite empirical studies involving Hasbrouck's approach mostly covering the stock market sphere - see, for instance Hasbrouck (2003) and Dimpfl, Flad, and Jung (2017)-, some studies like Covrig and Melvin (2002) and Chen and Gau (2010) extend its domain of application also to the foreign exchange market.

Another methodological pillar in the price discovery context consists of the common factor weights outlined by Gonzalo and Granger (1995) - also known under the name of adjustment coefficient ratios. These measures are generally used in the context of one security traded on two markets. In contrast to Hasbrouck's information shares, though, these ratios can be uniquely identified and they evaluate the relative size of the adjustment of each market price to the common stochastic 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, Lopez, Ubide, and Cervero (1999) and Maeso-Fernandez, Osbat, and Schnatz (2002). Besides, price discovery literature on exchange rates also contains several studies which make use of both the forementioned techniques (see Tse, Xiang, and Fung, 2006; Cabrera, Wang, and Yang, 2009; Rosenberg and Traub, 2009).

In many contexts, the same security is not only traded on the home, but also on the foreign markets. Hence, an investigation of price discovery should also account for exchange rate impacts. Grammig, Melvin, and Schlag (2005) apply the Hasbrouck (1995) information share approach to cross-listed stocks on the New York Stock Exchange and 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. More precisely, the greater the exchange rate volatility, the greater will be the bias. This finding highlights the relevance of estimating trivariate systems modelling the exchange rate explicitly rather than only bivariate ones where prices are converted into one common currency.

The aim of the current article is to make a contribution to the literature concerning price discovery analysis on Bitcoin markets by investigating where the price formation mechanism predominantly took place over the recent past. In other words, this is equivalent to determine which Bitcoin trading platforms react most rapidly to the occurrence of new information about the price and, hence, reflect the Bitcoin fundamental value in the most accurate way. In addition, by modelling the exchange rate it is possible to assess whether it affects the Bitcoin price formation process as well as the size of such an impact. These are highly relevant topics, especially for investors and traders, over whichever time horizon - long, medium, short or high frequency - they act.

To this end, Bitcoin price series are analysed over the period ranging from 2 January 2014 to 6 March 2017. Specifically, prices from six among the most important Bitcoin trading platforms according to trading volumes - namely Bitfinex, Bitstamp, BTC-e, Kraken, OKCoin and Btcn - are sampled at a five minute interval along with their associated exchange rates. Then 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 at a time related to exchanges trading in the same currency, whereas the trivariate ones investigate the relationships between prices of exchanges trading against different currencies and include also the exchange rate between them, as in the study of Grammig et al. (2005). Indeed, modelling the exchange rates we are able to assess their contribution to price discovery.

The main results achieved can be summed up as follows. We find a clear ranking with regards 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 Btcn, 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 - leaded by Bitfinex - overpower 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 analysed - 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. Another salient conclusion pertains to the very weak effect of the exchange rate in the discovery of the informationally efficient Bitcoin price. Indeed, only a really modest contribution to price discovery regarding Bitcoin exchanges is exerted by the exchange rates.

The remainder of this article proceeds as follows. Section 2 outlines the methodology employed. Section 3 provides a description of the data involved in the study, preliminary analyses as well as the VECM estimation results. Section 4 presents the estimated information share results. In Section 5 a dynamic analysis based on impulse response functions is performed. Section 6 derives and exposes an overall ranking of the exchanges in terms of their contributions to price discovery and Section 7 concludes.

2 Methodology

The core issue addressed by the current study is to determine where price discovery takes place on Bitcoin markets. To answer such a question, the starting point consists of a fundamental microstructural model involving market prices and exchange rates. In particular, bivariate and trivariate models involving two market prices at a time and the corresponding exchange rate - when the two exchanges considered trade in different currencies - are built. In order to determine the contribution of each exchange to price discovery, it is then possible to rely on the Hasbrouck (1995) information share approach, accounting for the potential influence of the exchange rates as in Grammig et al. (2005), as well as on the Gonzalo and Granger (1995) common factor weights. In the end, a comprehensive analysis of the results will reveal an ordering of the exchanges concerning their importance in the price discovery mechanism.

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

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

where $P_t^{i,x}$ and $P_t^{j,y}$ denote the prices at time t of the Bitcoin exchanges i and j 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 the logarithm on both sides of the equation, 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. Note that even though the two relationships illustrated in Equations 1 and 2 do not necessarily hold for every point in time t, when the Bitcoin prices are expressed into a common unit of measure it is true that they should not deviate too much one from the other over time.

It is plausible to assume that the log of the exchange rate follows a random walk, that is

$$r_t^{x/y} = r_{t-1}^{x/y} + \epsilon_t \tag{3}$$

where ϵ_t is an exchange rate specific i.i.d. innovation. Furthermore, the exchange rate is assumed to be exogenous.

Log prices related to the exchanges x and y are also assumed to evolve as random walks

$$p_t^{i,x} = p_{t-1}^{i,x} + u_t \tag{4}$$

$$p_t^{j,y} = p_{t-1}^{j,y} + v_t \tag{5}$$

where u_t and v_t represent the specific innovations linked to the Bitcoin exchanges i and j, respectively.In this framework ϵ_t, u_t and v_t are supposed to be zero-mean random variables with no serial correlation. ϵ_t and u_t and v_t are also contemporaneously uncorrelated, while this is not necessarily true for u_t and v_t.

From Equation 2 it can be seen that

$$r_t^{x/y} + p_t^{i,x} - p_t^{j,y} = r_{t-1}^{x/y} + \epsilon_t + p_{t-1}^{i,x} + u_t - (p_{t-1}^{i,x} + r_{t-1}^{x/y} + v_t) = \epsilon_t + u_t - v_t = \eta_t \qquad (6)$$

i.e. the linear combination of the log exchange rate and the log prices related to the Bitcoin exchanges i and j yields a stationary process, denoted as η_t. As a consequence, the three variables $r_t^{x/y}$, $p_t^{i,x}$, and $p_t^{j,y}$ are cointegrated with a cointegrating vector of the form $(1, 1, -1)$.

Given the cointegration structure existing among the fore-mentioned variables, the Granger representation theorem (Engle and Granger, 1987) offers a proper model to study their dynamics: the VECM. Collecting the first differences of the variables into the vector $\Delta p_t = (\Delta r_t^{x/y}, \Delta p_t^{i,x}, \Delta p_t^{j,y})'$, the model is of the form

$$\Delta p_t = \alpha\beta' p_{t-1} + \sum_{i=1}^{k-1} \zeta_i \Delta p_{t-i} + \varepsilon_t \qquad (7)$$

with α being 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 Equation 7 in its corresponding vector moving average (VMA) representation, that is

$$\Delta p_t = \varepsilon_t + \Psi_1\varepsilon_{t-1} + \Psi_2\varepsilon_{t-2} + ... = \Psi(L)\varepsilon_t \qquad (8)$$

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

The presence of cointegration among the three variables of interest implies that

$$\alpha'\Psi(1) = 0 \qquad (9)$$

where $\Psi(1)$ is the matrix polynomial in the lag operator evaluated at $L = 1$, that is $\Psi(1) = I_3 + \Psi_1 + \Psi_2 + ...$.

It is worth noting the importance of the $\Psi(1)$ matrix 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 $\varepsilon = (\varepsilon_t, \varepsilon_{t-1}, ...)$ innovations, on the long run evolution of Bitcoin prices (and exchange rates). In the present context, the $\Psi(1)$ matrix is obtained through the VECM parameters as follows:

$$\Psi(1) = \beta_\perp[\alpha'_\perp(I_3 - \sum_{i=1}^{k-1}\zeta_i)\beta_\perp]^{-1}\alpha'_\perp. \qquad (10)$$

$\alpha_\perp$ and $\beta_\perp$ denote the orthogonal complement of α and β, respectively - see Johansen (1995) for a detailed explanation of the aforementioned expression.

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

$$\Psi(1)\varepsilon_t = \begin{bmatrix} \psi_{1,1} & \psi_{1,2} & \psi_{1,3} \\ \psi_{2,1} & \psi_{2,2} & \psi_{2,3} \\ \psi_{3,1} & \psi_{3,2} & \psi_{3,3} \end{bmatrix} \cdot \begin{bmatrix} \varepsilon_t^r \\ \varepsilon_t^i \\ \varepsilon_t^j \end{bmatrix}. \qquad (11)$$

The generic element $\psi_{i,j}$ captures the long run impact of a unit composite shock in the j^{th} market price on the i^{th} market. Taking a look at the i^{th} 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 i^{th} market price.

As far as the elements of the $\Psi(1)$ matrix are concerned, there are some theoretical considerations which are worth to be mentioned. First of all, the exchange rate should not be affected by a shock in the price of a generic Bitcoin exchange, given the relatively low market volume of the cryptocurrency compared to the traditional currencies' volumes. Thus, it is reasonable to expect that $\psi_{1,2} = \psi_{1,3} = 0$. Another consideration stems from the restrictions that cointegration entails, in particular the one contained in Equation 9 and the specific form of the theoretical cointegrating vector, i.e. $(1, 1, -1)$. Indeed, these constraints imply that the Bitcoin price related to a generic exchange, say i, should equally adjust to innovations coming from the same exchange i or from the other exchange involved in the same model, say j. This is reflected into the equalities $\psi_{2,2} = \psi_{3,2}$ and $\psi_{2,3} = \psi_{3,3}$.

After the $\Psi(1)$ matrix is computed, the long run impact variances must be decomposed in order 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. Given that, it is then possible to derive the market j information share towards the price series of market i in the Hasbrouck sense as:

$$IS_{i,j} = \frac{([\psi' F]_{i,j})^2}{[\psi\Sigma_\varepsilon\psi']_{i,i}}. \tag{12}$$

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

Nonetheless, in most of the empirical applications, there is a problem that needs to be addressed when the innovations are contemporaneously correlated: the information shares cannot be identified without imposing some restrictions. One commonly employed technique to overcome this issue is the Cholesky decomposition of the composite innovation variance-covariance matrix Σ_ε. The matrix Σ_ε can be decomposed as $\Sigma_\varepsilon = FF'$, where F is lower triangular.

It must be stressed that in the context of the 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 takes into account the exchange rate effects. As a consequence, Hasbrouck's technique is based on the core assumption that just one common trend exists - i.e. the common efficient stock price -, whereas in the present context the number of common trends is two, one for the efficient stock price and another one for the efficient exchange rate. The latter consideration implies the presence of $n - 2 = 1$ cointegrating relation - that means one cointegrating vector - in the current trivariate setup, as opposed to the $n - 1$ cointegrating relations of the Hasbrouck framework (i.e. our bivariate analysis), where n represents the number of markets considered.

Even though the use of the Cholesky factorization overcomes the issue of identification, this method brings with it 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. However, it frequently happens that no theoretical justifications are available to provide an exact order of variables to be imposed. In the present case, an important economic consideration allows to determine at least the variable which should be ordered first: the exchange rate. Indeed, 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 for that is again the relatively small-sized market volume of the cryptocurrency with respect to the one related to the traditional currencies. As no prior expectations are inferable when it comes to the second and third places in the scheme, the order of those variables 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. In order 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 weights approach. The theoretical consideration behind this decision is that exogenous exchange rates should not adjust to disequilibrium, which implies the first element of the adjustment coefficient vector $\alpha_1 = 0$, if the exchange rate is ordered first in Δp_t. Provided the fore-mentioned constraint, the adjustment share related to the Bitcoin exchange i is computed as

$$AS_i = \frac{\alpha_{i,\perp}}{\alpha_{i,\perp} + \alpha_{j,\perp}} \tag{13}$$

where $\alpha_{i,\perp}$ and $\alpha_{j,\perp}$ indicate the orthogonal complements of the adjustment coefficients associated to the Bitcoin exchanges i and j, respectively. This measure, in contrast to Hasbrouck's information shares, encompasses the advantage of a unique identification without imposing any further restriction. Nevertheless, the two measures should be differently interpreted: 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.

However, the methodology illustrated so far is only capable to provide results across exchanges trading in different currencies. Indeed, as models are built taking into account the exchange rate effect, it is possible to determine which are the leader and follower exchanges among the ones trading against different currencies, but not among the ones denominated in the same currency. That is the reason why, in order to establish a comprehensive ranking, it is necessary to slightly modify the model specified in Equation 7. In particular, bivariate models including the Bitcoin exchanges trading in the same currencies will be considered. To this end Δp_t in Eq. (7) is modified as $\Delta p_t = (\Delta p_t^{i,x}, \Delta p_t^{j,y})'$. Strictly speaking, in the bivariate framework the VECM in Equation 7 reduces to:

$$\Delta p_t = \alpha\beta' p_{t-1} + \sum_{i=1}^{k-1} \zeta_i \Delta p_{t-i} + \varepsilon_t \tag{14}$$

with Δp_t being the vector $(\Delta p_t^i, \Delta p_t^j)'$, α the (2×1) vector containing the adjustment coefficients, β the (2×1) cointegrating vector, ζ_i the (2×2) parameter matrices and k the autoregressive order. p_t^i and p_t^j refer to the Bitcoin prices related to the exchanges i and j, respectively.[1]

[1]Currencies are omitted in the present notation since the exchanges taking part in the pairwise models are denominated in the same currency.

As a consequence, the variance covariance matrix of the VECM innovations, together with the $\Psi(1)$ and the F matrices are (2×2). As before, the Cholesky decomposition of the composite innovation variance-covariance matrix Σ_ε allows to determine upper and lower bounds of the Hasbrouck (1995) information shares. Furthermore, we derive the Gonzalo and Granger (1995) common factor weights as additional price discovery measure.

In addition, a dynamic analysis will be performed in Section 5. In other words, orthogonalized impulse response functions will be derived - along with their associated confidence bounds - in order to assess the dynamic impact of an innovation in the exchange rate and exchange prices on the system variables themselves.

As far as the estimation precision is concerned, the parametric bootstrap method proposed by Li and Maddala (1997) will be employed. This technique allows to determine standard errors of the parameters in case they cannot be derived analytically. Strictly speaking, the estimated VECM innovations in Equation 7 are randomly re-sampled with replacement in order to get a different residual vector from the original one. After that, by means of the new residual vector and the original VECM parameter estimates, bootstrap time series are generated. These artificial data are then used to re-estimate the VECM parameters. [2] This procedure is repeated 1000 times in order to get an empirical distribution for each parameter of interest. The very last step consists of computing the standard errors of the previously derived empirical distributions of the parameters. Hence, one is able to produce bootstrap standard errors for all the parameters of interest, like the elements of the long run impact matrix $\Psi(1)$. Moreover, empirical quantiles related to the bootstrap distribution of the impulse response functions are also obtained in this way, with the aim of providing confidence bounds for the responses.

3 Data description, analysis and estimations

The present section provides at first a description of the data, then a preliminary analysis which comprises stationarity as well as cointegration tests and finally presents the VECM estimation results. All the analyses and estimations are performed using Matlab version R2016b.

The dataset is composed of six Bitcoin price series belonging to the most important platforms in terms of trading volumes and without major gaps during the analysed period, and the exchange rates related to the currencies in which Bitcoin is traded, all sampled at a five minute interval. In particular, three exchanges trade Bitcoin against the US dollar (Bitfinex, Bitstamp, BTC-e), two against the Chinese Renminbi (Btcn, OKCoin) and one against the euro (Kraken). Therefore, also the USD/CNY, EUR/USD and EUR/CNY exchange rates are collected over the same time-frame. To derive the information shares, we rely on bivariate and trivariate VECMs. After combining in pairs the price series linked to the various exchanges along with the corresponding exchange rate - if they trade in different currencies - a total of four bivariate and eleven trivariate models are estimated. The different model combinations obtained in this way are shown in Table 1.

Contributions to price discovery are studied over the period ranging from 2 January 2014 to 6 March 2017. To illustrate the price dynamics of Bitcoin during the considered period, a plot

[2] Before the estimations are performed, the first 200 observations of each bootstrap time series are cut off (this is a good practice known in literature as "burn in").

showing the Bitstamp price series is reported in Figure 1. Unfortunately, the sample contains some missing data during this time-frame. Moreover, each series contains its own specific missing values. The solution employed in order to deal with this issue consists of dropping from the analyses and estimations the data from all the series taking part in the model related to the point in time in which at least one of the series' value lacks. This is done for each of the fifteen models considered. Table 1 reports the resulting number of observations linked to the models here studied.

As far as the preliminary analysis of the data is concerned, prices and exchange rates are firstly tested for (non-)stationarity. It has to be pointed out that it is not sufficient to confine the stationarity check exclusively to the six price series and the three exchange rate ones. As a matter of fact, the dropping scheme adopted above leads to new series whose sample sizes diverge from the original ones, as well as from the size of the same price series taking part into other models. For example, the original sample size of the OKCoin price series is different from the one related to the OKCoin series involved in the first model, as well as both of them diverge from the OKCoin sample size related to the second model, etcetera. Thus it is essential to examine whether all of the series taking part in each model are non-stationary, instead of conducting the tests only on the original ones. To this end, Augmented Dickey-Fuller (ADF) and Kwiatkowsky, Phillips, Schmidt and Shin (KPSS) tests are conducted. Results are shown in 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. Indeed, as an example, while the ADF test just weakly indicates the non-stationarity of the EUR/CNY exchange rate in levels involved in models 10 and 11 - being the p-values associated to the test only slightly above 5% -, the KPSS test solidly points to its non-stationary behaviour. The latter consideration allows to proceed with the analysis, provided that non-stationarity of the series in levels - and stationarity of their first differences - is required from a theoretical point of view.

Another cardinal point for the current methodology to be employed is the presence of cointegration among data. For this purpose, 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 $r = 1$, that is $g = n - r = 2$ common stochastic trends, being n the number of variables involved in each model. Indeed, the tests should indicate the presence of one trend associated to the efficient exchange rate and another one for the common efficient Bitcoin price. Results are illustrated in Table 2. Overall, both tests point to the same conclusion for almost all of the models: a cointegrating rank $r = 1$, in other words $g = 3 - 1 = 2$ common stochastic trends. The only model for which the two tests report conflicting outcomes is the first one - i.e. the one involving Bitfinex, OKCoin and the USD/CNY exchange rate. However, the p-value of the Trace test for $r = 1$ is still close to the conventional significance level of 5% and the one related to the Max Eigenvalue test is even above 10%, as well as both the other results and theory amply support a cointegrating rank of 1. Therefore, it is sensible to conclude that the cointegrating rank r is 1 and, thus, the number of common trends is 2 for all of the models.

The next step consists of estimating the cointegrating vectors for all of the models. Right after that they are normalized, i.e. they are written in the form $(1, -\hat{\gamma}_2, -\hat{\gamma}_3)$. Provided that the cointegrating vector prescribed by economic theory is $(1, 1, -1)$, the estimated cointegrating vectors obtained as above are subjected to the Johansen constraint test in order to check whether they meet that specific form. Results are reported in Table 2. The test rejects the null hypothesis that the true cointegrating vector is $(1, 1, -1)$ for eight out of eleven models on a 5% significance level. Notwithstanding this, the theoretical model implies a cointegrating vector of the form $(1, 1, -1)$, as well as estimates are extremely close to the theoretical counterparts. Furthermore, using the estimated cointegrating vector rather than the theoretical one for the information share estimation does not dramatically affect the quality of the interpretations.[3] Hence, the VECM parameter estimations will be performed using the theoretical cointegrating vector rather than the estimated one. This specific form of the cointegrating vector leads to the fact that prices adjust with equal weights to the common stochastic trend.

Subsequently, the VECM specified in Equation 7 is estimated through full information maximum likelihood. 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. The main outcomes achieved from the estimations are contained in Table 3.

After the VECM parameters are estimated, one is able to obtain the long run impact matrix $\Psi(1)$ through the analytical formula reported in Equation 10. The $\Psi(1)$ matrix estimates are shown in Table 3. Firstly, 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 related to the last six models considered, though, the magnitude of the VMA coefficients is considerably higher than the one linked to the first five models. However, it is clearly noticeable that - for each model - these two coefficients are still low if compared to the other ones belonging to the same long run impact matrix. Secondly, the size of $\psi_{2,1}$ and $\psi_{3,1}$ reveal that the exchange rate has a certain effect on the long run evolution of the Bitcoin exchange prices. This is sensible, provided that we have in hand the same asset traded in different currencies and - as a consequence - the exchange rate needs to influence the Bitcoin exchange prices in the long run. Thirdly, in any case an innovation in the exchange price ordered first (second) always exerts a larger long run impact towards the exchange ordered first (second) itself, rather than on the exchange price ordered second (first). However, despite this difference being subtle for the first five models, it gains a certain importance from the sixth model onwards. In particular, the spread grows when considering the exchanges trading against US dollar and euro and it further surges for the models involving exchanges which trade against the euro and the Chinese Renminbi.

4 Price discovery analysis

As far as the information shares are concerned, the order chosen in order to decompose the innovation variance-covariance matrix through the Cholesky decomposition matters. Therefore, in the bivariate setup the order of variables is switched in order to get upper and lower bounds of the information shares and, similarly, in the triviariate case the exchange rate is always placed first and the order of the exchanges at second and third place is swapped. The issue of ordering does not occur in the adjustment and Gonzalo and Granger (1995) information share context, given their uniqueness regardless to the order of variables imposed.

Results related to the Hasbrouck (1995) information shares are reported in Table 4, while the ones linked to the adjustment shares are illustrated in Table 5. The bounds of the informa-

[3]Repeating the analysis using the estimated cointegrating vector yields almost identical conclusions with respect to the identification of the leadership. Indeed, leadership results are identical when considering the Hasbrouck (1995) information shares, whereas the Gonzalo and Granger (1995) common factor weights reveal that there is one model in which the dominant platform switches when using the estimated cointegrating vector, i.e. the one involving Kraken and Btcn (model 11). This could mean that Kraken and Btcn behave not that much dissimilarly one towards the other when it comes to price discovery contributions.

tion shares are found to be wide. In particular, the greatest spread between upper and lower bounds regards the contribution of an innovation in the Bitfinex price on itself in model 1: the lower bound touches 7.79%, whereas the upper bound reaches 91.04% - showing, then, a range of as much as 83.35%. The main reason behind the huge difference between the bounds is the high contemporaneous correlation among the VECM innovations. The estimated information shares may therefore appear 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 Btcn dominate - from a price discovery perspective - all the other platforms considered in the analysis which trade against currencies different from the Chinese Renminbi. Indeed, their information shares always report greater values than the ones belonging to the platforms to which they are compared. Secondly, 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 to the latter ones being greater in both cases. Thirdly, the American BTC-e does not show the same behaviour as the other two exchanges trading against US dollar. Indeed, it is not only overtaken by the exchanges trading in Chinese Renminbi, but also by the one trading in euro, that is Kraken.

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 for sure 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. Another remarkable insight is that the American market is not generally more informative than the European one from a price discovery point of view. In point of fact, the predominance of the European exchange Kraken towards the American BTC-e does not allow to attest a general supremacy of the American market with respect to the European one over the considered time-frame.

Another crucial finding regards the magnitude of the exchange rates' contributions to price discovery towards the Bitcoin price series, measured through the Hasbrouck (1995) information shares. 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 analysed 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.

Unexpected results are then achieved taking a look at the contributions of the Bitcoin exchanges with respect to the exchange rates. Indeed, models 3 as well as 6 to 11 reveal a quite intense relative importance of the fore-mentioned shocks on the exchange rate evolution. These outcomes, in part already anticipated from the long run impact matrix estimates, are confirmed here. The latter fact is in contrast with the theoretical considerations stating that the exchange rate evolution should not be affected by shocks in the Bitcoin exchange prices. At the moment, we cannot provide an explanation regarding this incongruous outcome. This phenomenon is worthy of further investigation which is, however, beyond the scope of the present article.

Finally, despite some noteworthy conclusions have been drawn from the analysis, a proper overall ranking is still missing. As a matter of fact, provided that only exchanges trading against different currencies are analysed in this context, one is not currently able to determine an inner ranking among exchanges denominated in the same currency. That is the reason why - in Section 6 - pairwise models between exchanges trading against the same currencies will be studied in order to fill in the blanks left by the present trivariate setup.

5 Dynamic analysis

In this section the variables' responses to shocks are investigated through impulse response function analysis. The primary aim of such an analysis is to see how Bitcoin exchange prices dynamically react to an idiosyncratic innovation in themselves, as well as in the exchange rate or in the price of the other platform involved in the same VECM.

It has to be highlighted that studying the generalized impulse response functions would mean investigating the responses of the system variables to composite shocks, given that the contemporaneous correlation among the VECM innovations does not allow to derive the pure impacts of a single specific innovation, i.e. a shock occurring only in one variable at a time. This is the reason why it has been chosen - as often performed in literature - to base the current dynamic analysis on the orthogonalized impulse response functions, which enable to disentangle this problem by relying one more time on the Cholesky factorization of the innovation variance-covariance matrix. As a consequence, the order of variables imposed to derive the decomposed innovation variance-covariance matrix is again influential on the impulse response function outcomes. Therefore, as before, the exchange rate will be always placed first, while the positions of the two Bitcoin exchange prices will be switched for the sake of providing the responses for both possible orders of the variables in each model.

As far as the estimation accuracy is concerned, the bootstrap method described in Section 2 allows to determine confidence bounds for the impulse response function. In other words, for each forward step considered, the bootstrap distribution of the impulse response function is derived by means of 1000 bootstrap replications from the artificial data, which are in turn obtained by re-sampling the VECM innovations with replacement and plugging them into the VECM. One may then find the bootstrap upper and lower bounds for the responses at each point in time, which are computed in the present case as the empirical 5% and 95% quantiles of the above mentioned distribution. These are important tools to investigate whether a response to a shock could be conceived as significant or not.

Graphs showing the impulse response functions and their bounds are illustrated in Figure 2, i.e. the plots related to the first type of ordering in the Cholesky decomposition, as well as in Figure 3, which contains the ones related to the second Cholesky ordering scheme. The number of forward steps for which the orthogonalized impulse response functions are derived - along with their bootstrap confidence bounds - is 288. This value has been chosen since, dealing with data sampled at 5 minute intervals, the number of steps amounts to $288 \cdot 5$ minutes $= 24$ hours, thus a daily response is investigated. Moreover, this time-frame is not only short enough to have at least a clue about the immediate response of the variable to a shock, but also long enough to get a glimpse of the variables' convergence towards the new equilibrium.

As clearly noticeable, shocks in the Bitcoin exchange prices always exert a positive and significant dynamic impact on the Bitcoin trading platforms themselves. Moreover, an innovation in a generic platform is always perceived by the platform itself first, rather than by the other exchange involved in the model, which instead tends only to rapidly adjust to the external price shock. Besides, the magnitude of the impact is greater on the exchange to which the shock belongs, although after a certain amount of steps this difference generally vanishes. It can be undoubtedly claimed, then, that all of these conclusions are well grounded from a theoretical point of view.

A remarkable insight regards the dynamic impact of an exchange rate innovation on the Bitcoin exchange prices. Indeed, the responses of Bitcoin prices to a unit (as well as one standard deviation) shock in the exchange rate are in general not significantly different from zero, except for the slightly positive ones related to the EUR/USD exchange rate impact on Kraken. Hence, it is not possible to argue that an exchange rate shock generates any kind of significant - positive or negative - response of Bitcoin prices. However, platforms often react differently to an exchange rate innovation, which shows that each Bitcoin exchange assimilates the impact of such a shock in its own way. Despite that, it can be noticed that magnitudes of the responses are still quite comparable among them.

6 Identification of the leadership

The aim of the present section is to build a comprehensive exchange ranking by merging the results achieved through the trivariate framework with the ones provided by the bivariate models. As a matter of fact, it is not possible to construct a hierarchical structure of the exchanges in terms of their contributions to price discovery by solely relying on the outcomes described in Section 4. This is because the trivariate models already employed do not compare the exchanges trading in the same currency. To cope with this, it seems natural to setup bivariate models involving the exchanges which trade against the same currency and enrich the results from above. Consequently, having in hand three exchanges trading against the US dollar, two against the Chinese Renminbi and just one against the euro, the total number of pairs to be analysed is four.

Applying the same logic described in Section 2 one is able to determine both the Hasbrouck (1995) information shares and the adjustment shares which - in this case - coincide with the Gonzalo and Granger (1995) common factor weights, provided that in the bivariate context only exchange prices are modelled.[4]

Results are contained 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 if compared to the one obtained in the trivariate models. For example, the model involving the two Chinese platforms - namely, 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 anew due to the existence of a noticeable contemporaneous correlation in the VECM innovation already discussed in Section 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 points one more time to the same conclusions.

At an exchange level, the pairwise approach clearly provides the price discovery leaders between the two platforms involved in each model. As a matter of fact, Bitfinex holds the

[4] As a consequence, these measures will be referred to as Gonzalo and Granger common factor weights, rather than adjustment shares as before.

dominion of the American Bitcoin market with respect to the other exchanges analysed, as suggested by the results of models 1 and 2. The second place on the American podium goes to Bitstamp, whose informativeness in the price discovery context overwhelms the one of BTC-e, which instead turns out to be the least informative among the American platforms taken into account in the study. Evidence also suggests that the supremacy in the Chinese market in the price formation mechanism belongs to OKCoin, provided that it contributes more to price discovery than Btcn.

A comprehensive analysis of the results which have just been illustrated along with the ones contained in Section 4 present the opportunity to form a clear hierarchical structure of the exchanges in terms of their contribution to price discovery. The information share ranking obtained in this way is illustrated in Table 7. The Outcome asserts the primacy of the Chinese platform OKCoin, as both the information shares and the common factor components prone to qualify this exchange as the most informative one. Indeed, whenever it is compared to any of the other considered exchanges, OKCoin indisputably shows higher values of contribution to price discovery. The second place belongs to the other Chinese market included in the study, Btcn, which is defeated only by OKCoin on the price discovery field. Bitfinex holds the third place in the overall ranking, being still more informative than the other platforms trading in USD or EUR. The fourth place belongs again to an exchange trading against the US dollar: Bitstamp. However, the American market - as already stated in Section 4 - does not wholly subdue the European one in terms of price discovery. Indeed, the exchange emerging as fifth in the ranking is Kraken, whose price discovery contributions point to the fact that it is more informative than the American BTC-e, which is the sixth and last on the list.

It is particularly edifying to relate the results of the present research to the ones obtained by Brandvold et al. (2015). The authors find that Mt.Gox and BTC-e are the market leaders during their analysed 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 excluded from the current analysis because of its bankruptcy on 28 February 2014. However, also BTC-e's dominance is not confirmed in the present context. Moreover, among the trading platforms considered in this study, BTC-e is even the one with the weakest contribution to price discovery. Therefore, on the one hand the present outcomes are in contrast with the ones achieved by Brandvold et al. (2015) as far as the leader exchanges are concerned. On the other hand, results are in line with their claim stating that the information shares are dynamic and they considerably evolve over time.

7 Conclusion

Bitcoin's increasing success over the last years stimulated the likewise growing interest of researchers in studying this phenomenon from a quite broad range of viewpoints. Notwithstanding this, price discovery on Bitcoin markets is still a surprisingly under examined topic in the literature, which surely deserves more attention than the one it currently draws. This article analyses six main Bitcoin trading platforms - in terms of trading volumes - in order to determine in which exchanges price discovery primarily occurs and, hence, which of these reflect the Bitcoin fundamental value with the highest degree of accuracy. To this extent, the commonly accepted Hasbrouck (1995) information share and Gonzalo and Granger (1995) common factor weight approaches are employed in order to determine the leader and follower exchanges in the price discovery mechanism, accounting for the potential effect of the exchange rate.

Outcomes reveal the presence of a solid ranking in terms of price discovery contribution among the exchanges taking part in the study. In particular, OKCoin is the leader of price discovery over the examined period, followed by Btcn (second) and then Bitfinex (third), Bitstamp (fourth), Kraken (fifth) and BTC-e (sixth). Therefore, it can be concluded that the two Chinese exchanges exert a larger contribution to price discovery than the American and European ones. However, it cannot be stated that the American market actors play in general a bigger role than the European one, being BTC-e overwhelmed by the European Kraken as far as contributions to price discovery are concerned. Furthermore, it is interesting to link the conclusions drawn from the current research with the ones achieved by Brandvold et al. (2015). Indeed, they find that BTC-e is one of the most informative exchange from a price discovery point of view - unlike in the present case - during their studied time-frame. Nevertheless, the change in the leadership should not be read as a particularly surprising result. As a matter of fact, as already pointed out again by Brandvold et al. (2015), the information shares linked to Bitcoin exchanges are dynamic and they are inclined to witness substantial changes over time. Indeed, during the preparation of this manuscript the Chinese government decided to shut down platforms on mainland China by 30 September 2017 which of course affects our analysis.

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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Table 1: Number of observations and stationarity

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
	Btcn		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
	Btcn		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
	Btcn		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
	Btcn		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)	Btcn	235626	0.8650	<0.001	<0.01	>0.1
	OKCoin		0.8511	<0.001	<0.01	>0.1

Note. The first and second columns show the label of the models along with their related series. The third column illustrates 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 executed including a constant but no time trend, as well as the KPSS ones do not include trends. Both tests are conducted using an optimal lag length determined according to the Bayes-Schwarz information criterion, as well as on a 5% significance level. The minimum p-value reported by MATLAB is 0.001 for the ADF and 0.01 KPSS tests, while the maximum p-value reported for the KPSS test is 0.1.

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

Note. 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 to 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 a cointegrating rank 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.

Table 3: Adjustment and vector moving average (VMA) coefficients

	Model	α	VMA coefficients		
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)
	Btcn	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)
	Btcn	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)
	Btcn	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)
	Btcn	0.0020 (0.00062)	0.3548 (0.1397)	0.4198 (0.1131)	0.5587 (0.1287)

Note. The third column illustrates the adjustment coefficients related to the VECM estimation using the fixed cointegrating vector $(1, 1, -1)$. Columns 4 to 6 present the estimates of the long impact matrices linked to the VMA coefficients:

$$\Psi(1) = \begin{bmatrix} \psi_{1,1} & \psi_{1,2} & \psi_{1,3} \\ \psi_{2,1} & \psi_{2,2} & \psi_{2,3} \\ \psi_{3,1} & \psi_{3,2} & \psi_{3,3} \end{bmatrix}.$$

The specific order of variables considered is reported in column 2. Bootstrap standard errors based on a sample of 1000 bootstrap replications are reported in parentheses. For the sake of brevity, the remaining VECM parameters are omitted.

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
	Btcn	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
	Btcn	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
	Btcn	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
	Btcn	p_j	1.12	9.42 - 80.91	17.98 - 89.46

Note. The table above 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
	Btcn	54.70
5)	Bitstamp	40.73
	Btcn	59.27
6)	BTC-e	22.57
	Btcn	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
	Btcn	51.75

Note. 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.

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

Model		IS low	IS up	GG
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)	Btcn	1.24	85.44	23.26
	OKCoin	14.56	98.76	76.74

Note. 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.

Table 7: Information share ranking

Variable	Innovation					
	OKCoin	Btcn	Bitfinex	Bitstamp	Kraken	BTC-e
OKCoin	-	43.44	48.87	47.11	44.48	44.90
Btcn	56.66	-	48.98	46.85	45.16	38.87
Bitfinex	50.25	50.63	-	23.30	21.58	13.88
Bitstamp	52.28	52.87	76.70	-	33.19	28.42
Kraken	51.32	49.16	73.81	61.24	-	38.02
BTC-e	54.29	60.57	86.12	71.58	55.55	-

Note. The table shows the contributions to price discovery of the variables reported in columns towards the ones contained in the rows, measured through the Hasbrouck (1995) information share midpoints. Variables are ordered with respect to their ranking position in price discovery inferred by the information share results. Midpoints related to the same exchanges sum up to 100 if they trade in the same currency, while this may not be the case for the platforms denominated in different currencies, provided that also the exchange rate contribution is taken into account. Values are illustrated in percentage terms.

Figure 1: Bitstamp price series (USD)

The graph from above shows the dynamics of the Bitstamp price series - expressed in US dollars - during the analysed period 2 January 2014 - 6 March 2017. Prices are sampled at a 5 minute interval.

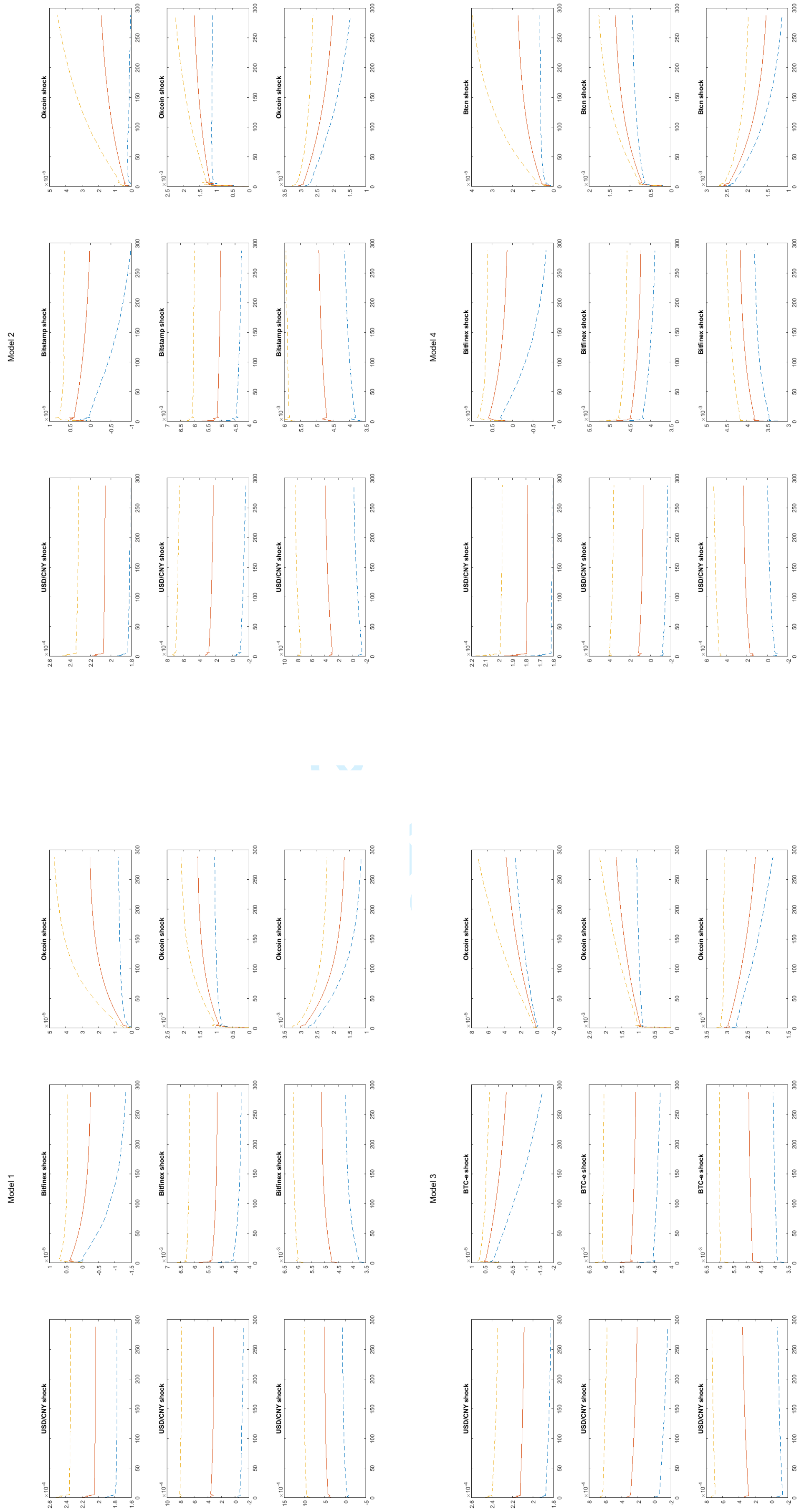
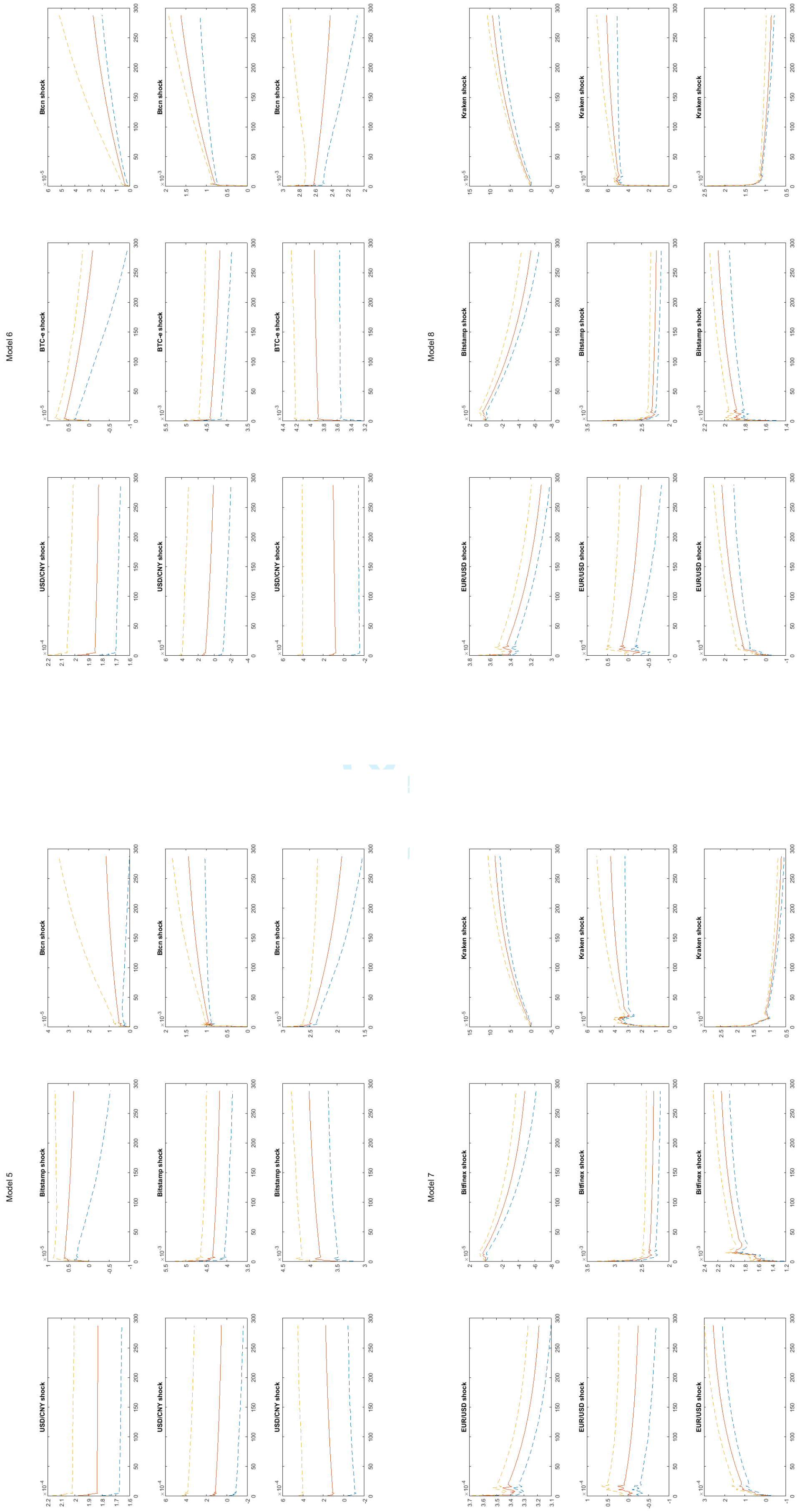
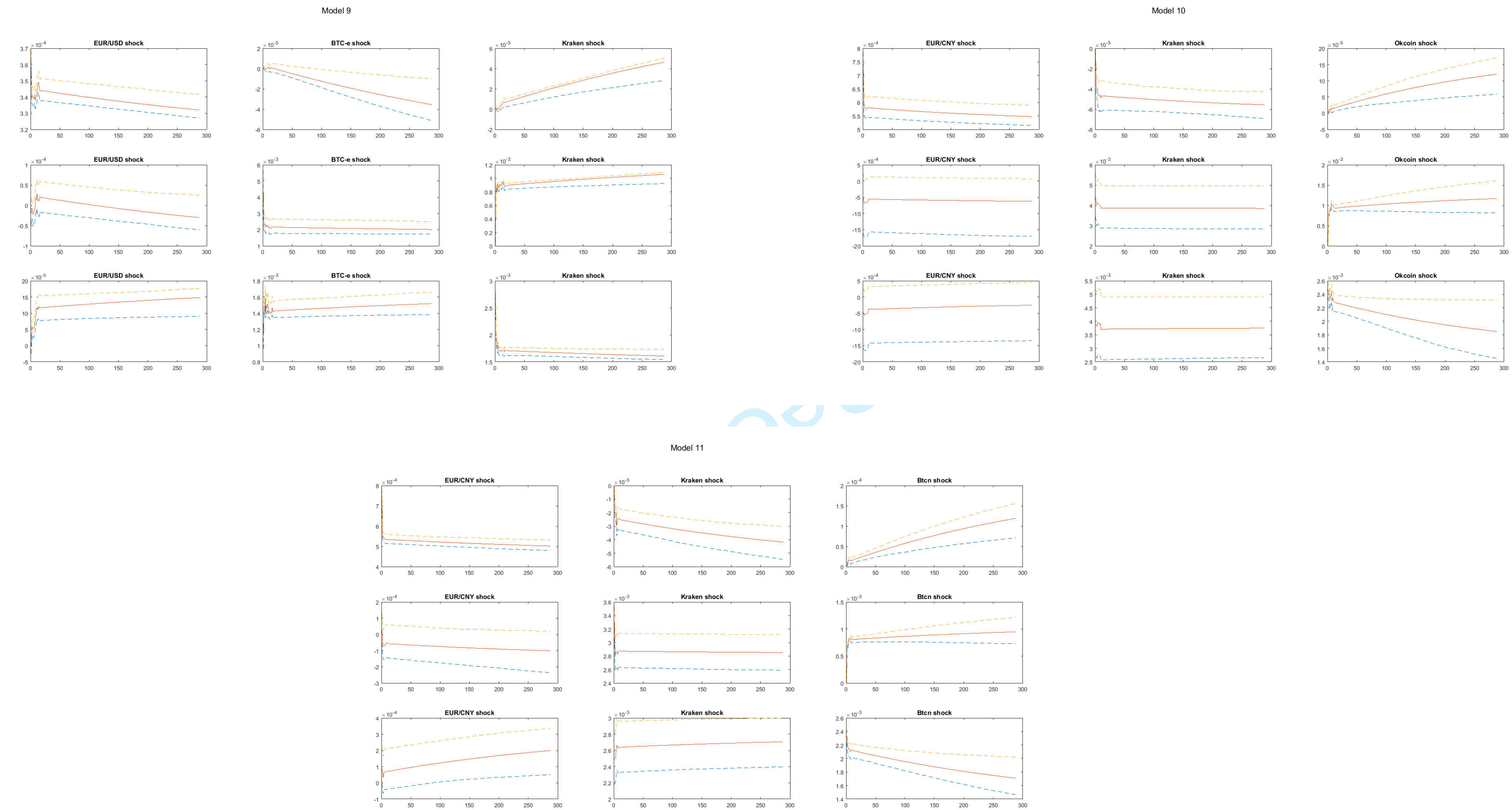


Figure 2: Impulse response functions (Cholesky order I)


Model 6
Btcn shock
BTC-e shock
USD/CNY shock
Model 8
Kraken shock
Bitstamp shock
EUR/USD shock
Model 5
Btcn shock
Bitstamp shock
USD/CNY shock
Model 7
Kraken shock
Bitfinex shock
EUR/USD shock



Note. The plots from above show the orthogonalized impulse response functions associated to unit (as well as one standard deviation) shocks in the VECM innovations, using the first variable ordering scheme in the Cholesky factorization of the innovation variance-covariance matrix. The position of each variable in the Cholesky ordering is the same as the number of the column in which the effects of its shock are illustrated. Solid lines represent the impulse response functions, whereas dashed lines indicate the confidence bounds, i.e. the 5% and 95% empirical quantiles of the bootstrap distribution based on a sample of 1000 bootstrap replications.

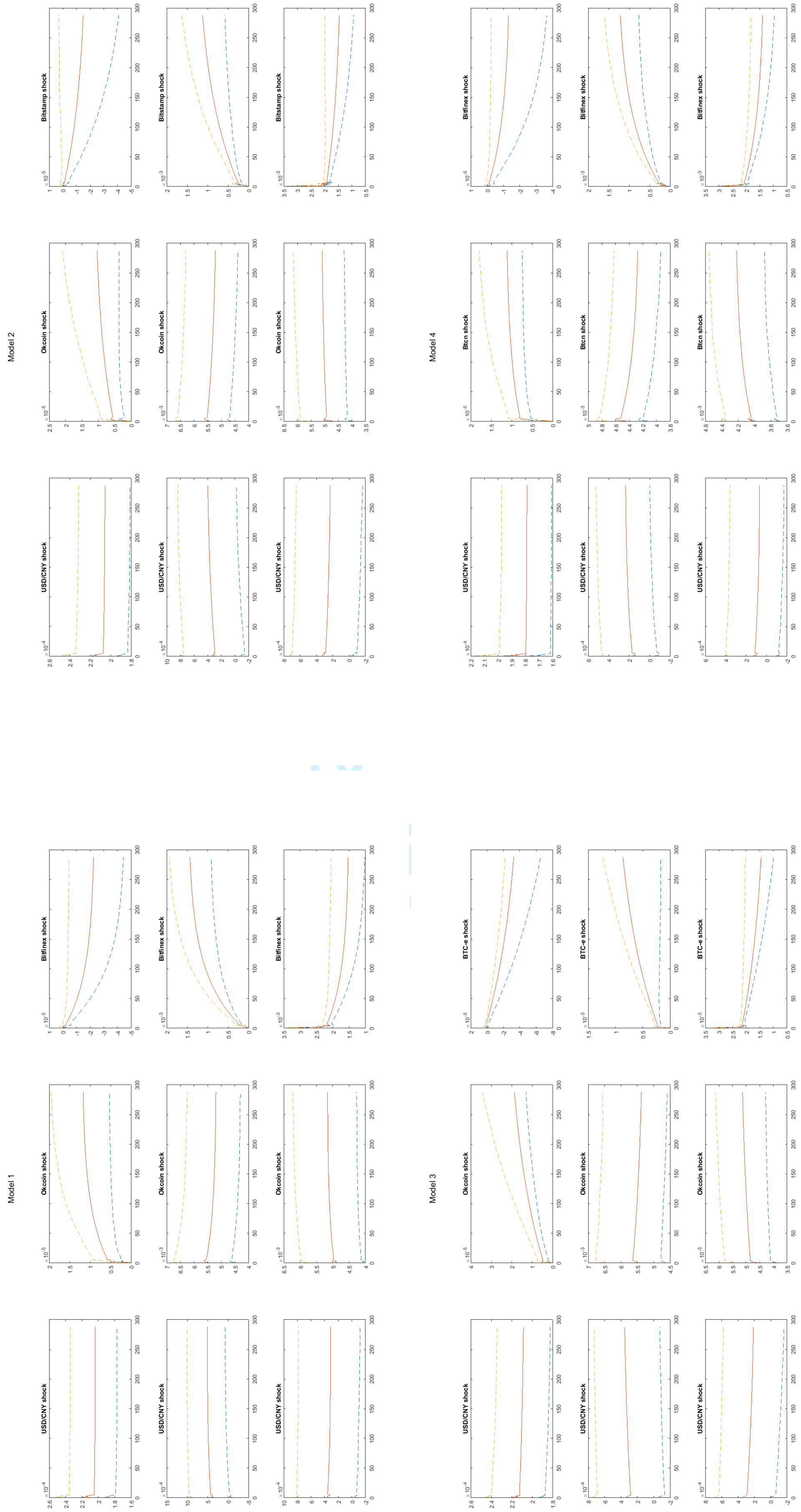
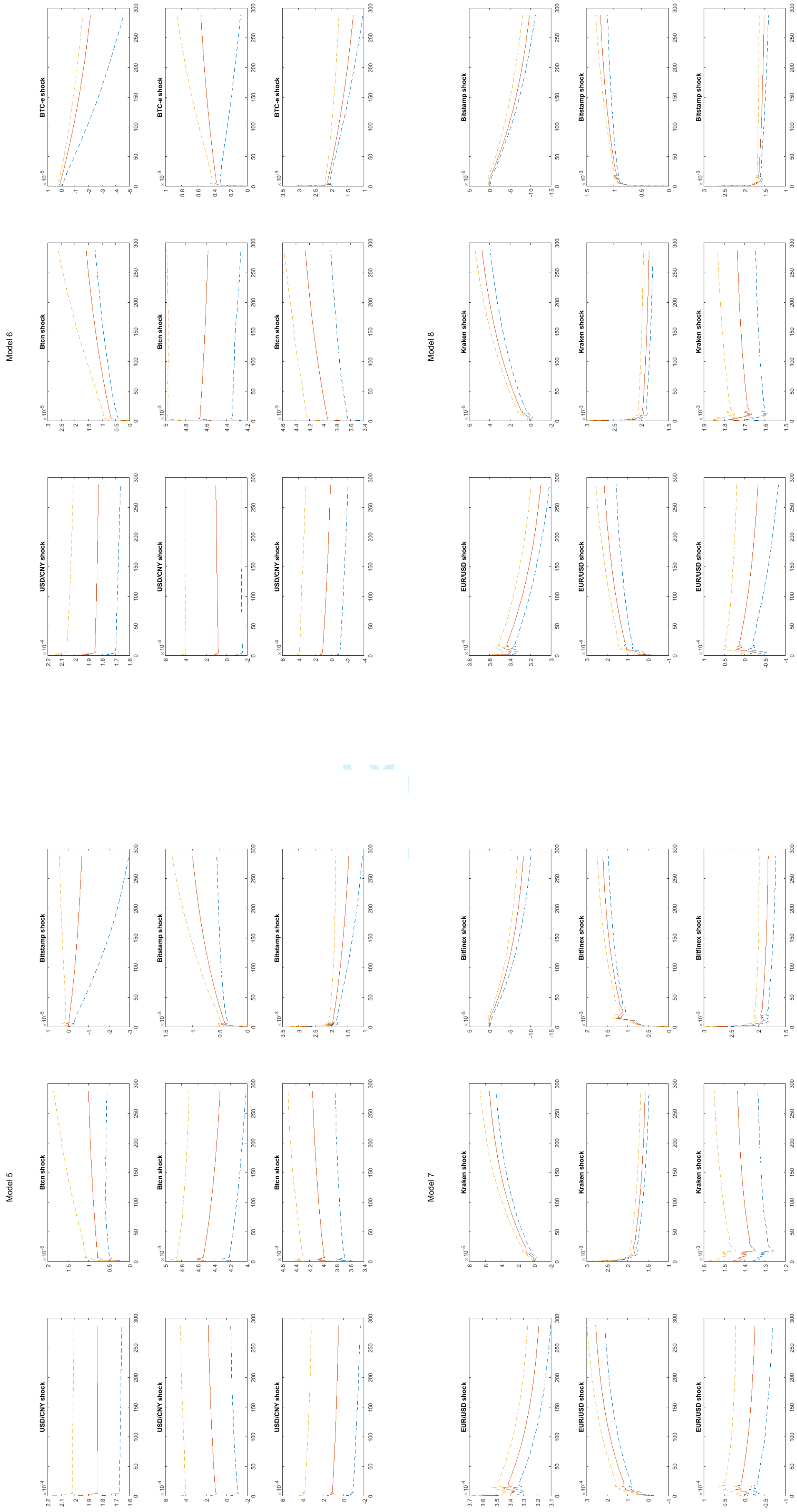
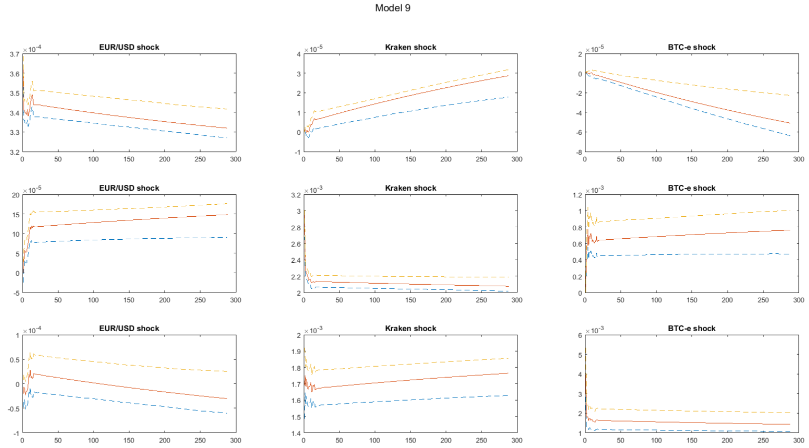
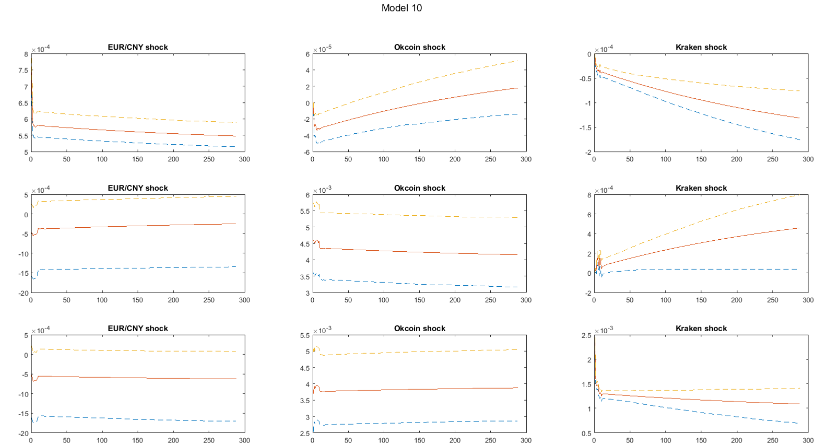
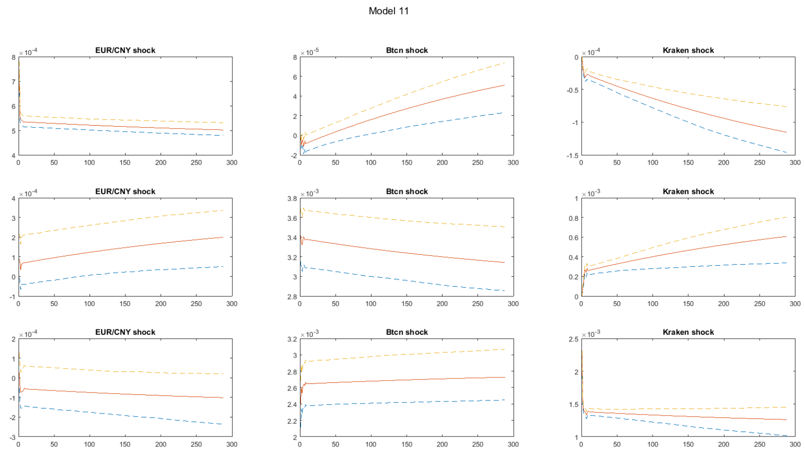


Figure 3: Impulse response functions (Cholesky order II)


Model 6
BTC-e shock
Btcn shock
USD/CNY shock
Model 8
Bitstamp shock
Kraken shock
EUR/USD shock
Model 5
Bitstamp shock
Btcn shock
USD/CNY shock
Model 7
Bitfinex shock
Kraken shock
EUR/USD shock







Note. The plots from above show the orthogonalized impulse response functions associated to unit (one standard deviation) shocks in the VECM innovations, using the second variable ordering scheme in the Cholesky decomposition of the innovation variance-covariance matrix. The position of each variable in the Cholesky ordering is the same as the number of the column in which the effects of its shock are illustrated. Solid lines represent the impulse response functions, whereas dashed lines indicate the confidence bounds, i.e. the 5% and 95% empirical quantiles of the bootstrap distribution based on a sample of 1000 bootstrap replications.

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