Finance Research Letters 51 (2023) 103332

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Exploring sources of statistical arbitrage opportunities among Bitcoin exchanges

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A R T I C L E I N F O

JEL classification:
G14
G15
G23

Keywords:
Cryptocurrencies
Cryptoassets
Bitcoin
Arbitrage
Exchanges

A B S T R A C T

We investigate potential sources of emerging statistical arbitrage opportunities in the Bitcoin market across five exchanges – Binance, Bitfinex, Bitstamp, Coinbase, and Kraken – via the instrumental variables approach to control for apparent endogeneity. We show that arbitrage opportunities arise when the network is congested and Bitcoin prices are volatile. Increased exchanges volume and on-chain activity increase the correlation between exchanges and thus reduce the arbitrage opportunities. These outcomes are intuitive and economically valid which supports the notion that Bitcoin market is highly volatile and risky but its behavior follows standard economic and financial intuition.

1. Introduction

Dual and multiple listings[1] are common in the stock markets, mostly to enlarge the capital base, spread the trading time, and access higher liquidity. For cryptoassets, multiple listings are practically automatic with the exception of very new and illiquid assets that are often self-listed on an automated market maker decentralized exchange (AMM DEX) like UniSwap, Sushiswap, PancakeSwap or Trader Joe. This is the case due to the mostly unregulated market entry and the crypto-exchanges specifics – anyone can create a pair (i.e., list a token) on a decentralized exchange, and there exist many medium-to-small size centralized exchanges that self-list tokens and coins without any effort from the team behind a coin or a token.[2] The large number of exchanges trading a cryptoasset hypothetically creates higher possibilities for arbitrage. However, one must keep in mind the specifics of cryptoassets, blockchain and crypto-exchanges that may go against these, making them rather statistical than real profitable avenues.

Investigating arbitrage opportunities across Bitcoin exchanges is not new. Network structures among Bitcoin exchanges are studied by Ji et al. (2021) and Bruzge and Sapkauskiene (2022) pointing at lead–lag relationships. Kruckeberg and Scholz (2020), in their analysis between 2013 and 2018, argue that Bitcoin market inefficiency with respect to arbitrage opportunities increases over time. Shynkevich (2021) uncovers arbitrage opportunities but shows that they mostly disappear after 2018. Makarov and Schoar (2020) explain that the opportunities occur mostly during Bitcoin fast appreciation. Bistarelli et al. (2019) develop Black–Scholes-based and attention-based models to profit from the cross-exchange arbitrage while Duan et al. (2021) argue that the Bitcoin markets

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[1] I.e., an asset being listed and traded on two or more exchanges simultaneously.

[2] Of course, more standard approaches are often taken by larger exchanges but they still do not resemble the initial public offerings (IPOs) in the stock markets much and most tokens now start with initial decentralized exchange offerings (IDOs) often with some form of a pre-sale, or a more historically standard initial coin offerings (ICOs), mostly in the case of coins building their new network and blockchain.

https://doi.org/10.1016/j.frl.2022.103332
Received 26 July 2022; Received in revised form 8 September 2022; Accepted 11 September 2022
Available online 20 September 2022
1544-6123/

are mostly efficient with respect to the no-arbitrage condition on their dataset up to 2020. Most studies thus test or look for the arbitrage opportunities but do not explain their emergence. The current study contributes to the existing literature by exploring the sources of such arbitrage opportunities when they occur.

Here we focus on examining possible sources of emergence of statistical arbitrage opportunities in Bitcoin markets. As a measure of such opportunities, we utilize conditional correlations between Binance as the number one centralized crypto-exchange and four other crypto-exchanges. Notably, the perfect unity correlation would reflect no arbitrage opportunities. We stress the "statistical" there as the existence of statistical opportunities does not necessarily imply real profitable strategies. As this is the first such study into the causes and sources, we focus on Bitcoin as the dominant cryptoasset. Also, Bitcoin allows for a more straightforward approach as most of its trading takes place on the centralized exchanges (it needs to be wrapped for the decentralized exchanges). In the instrumental variables models, we show that the arbitrage opportunities occur mostly during the periods of network congestion and high volatility. Therefore, actually realizing such arbitrage opportunities into profits might be challenging.

2. Methods and data

As a baseline metric to measure co-movement between Bitcoin returns on different exchanges, we utilize the Grey correlation. Building on the Grey system theory (Ju-Long, 1982), the Grey correlation captures non-linear connections between return series without assuming Gaussian distribution, thus providing a more robust metric than the standard Pearson correlation (Ju-Long, 2012; Yin, 2013; Wang et al., 2022). The Grey correlation $\gamma(X_0, X_i)$ between return series X_0 and X_i is defined in two steps as

$$\gamma\left(x_0(k), x_i(k)\right) = \frac{\min_i \min_k \left|x_0(k) - x_i(k)\right| + \varepsilon \max_i \max_k \left|x_0(k) - x_i(k)\right|}{\left|x_0(k) - x_i(k)\right| + \varepsilon \max_i \max_k \left|x_0(k) - x_i(k)\right|} \tag{1}$$

$$\gamma(X_0, X_i) = \frac{1}{n}\sum_{i=1}^{n} \gamma\left(x_0(k), x_i(k)\right). \tag{2}$$

Coefficient $\varepsilon \in [0,1]$ represents the adjustment parameter which is standardly set to $\varepsilon = 0.5$ (Chang and Lin, 1999) and we follow the standard.

In addition, we also utilize a DCC-GARCH(1,1) model (Engle, 2002) so that eventually, we obtain two series of conditional correlations for each analyzed pair of Bitcoin exchanges. We thus obtain series $\{\hat{\rho}_i\}_{t=1}^{T}$ where T is the number of observations and $i = 1,2$ for the Grey correlation series and DCC-GARCH series, respectively, between Bitcoin returns on two exchanges.

We strive to explain why such correlations might differ from the perfect unity correlation expected for the no arbitrage condition. As the time series of conditional correlations are practically always strongly serially correlated, we include the lagged correlation into the model. However, we are obviously more interested in the other explanatory variables that can help explain the occurrence of such arbitrage opportunities. Our baseline model is the following:

$$\begin{aligned} \hat{\rho}_{i,t} &= \beta_{i,0} + \beta_{i,1}\log(\sigma_t) + \beta_{i,2}\log(volume_t) + \beta_{i,3}\log(transfers_t) + \beta_{i,4}\log(fees_t) + \\ &\beta_{i,5} momentum_t + \beta_{i,6} searches_t + \beta_{i,7}\hat{\rho}_{i,t-1} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

We expect $volume$, $transfers$, and $fees$ to be endogenous, directing toward the instrumental variables (IV) or two-stage least squares (2SLS) estimation. For each endogenous variable, there needs to be at least one instrument, i.e., excluded exogenous variable. We use $\log(price)$, $exchange\_ratio$, and $\log(addresses)$ as instrumental variables.

We consider five major Bitcoin exchanges – Binance, Bitfinex, Bitstamp, Coinbase, and Kraken. Using CryptoDataDownload website,[3] we collect daily Bitcoin prices on each of these five exchanges over the period 20 October 2017–7 January 2022, according to their availability.[4] Based on daily prices, we compute daily log-returns (1534 observations) and use them for computing two measures of correlations. The right-hand side variables in Eq. (3) are the following:

- σ is the standard deviation of average Bitcoin return, estimated using the range-based Garman and Klass (1980) estimator; the open-close-high-low prices are obtained from the CoinMarketCap website[5];
- $volume$ is the overall exchanges traded volume (in USD) as reported on CoinMarketCap;
- $transfers$ is the overall on-chain transfers volume (in USD), i.e., without the traded volume on the centralized exchanges, obtained from the Coinmetrics website[6] as $TxTfrValAdjUSD$;
- $fees$ is the median fees for the given day (in BTC) paid to miners (in addition to the newly created BTC per block), obtained from the Coinmetrics website as $FeeMedNtv$;
- $momentum$ is a logarithm of a ratio between the current price and the average price of the previous seven days using the CoinMarketCap closing prices;

3 https://www.cryptodatadownload.com/data/

4 If Bitcoin is priced against USDT, we transform the price to USD based on the CoinMarketCap USDT/USD exchange rate for the given day.

5 https://www.coinmarketcap.com

6 https://www.coinmetrics.io

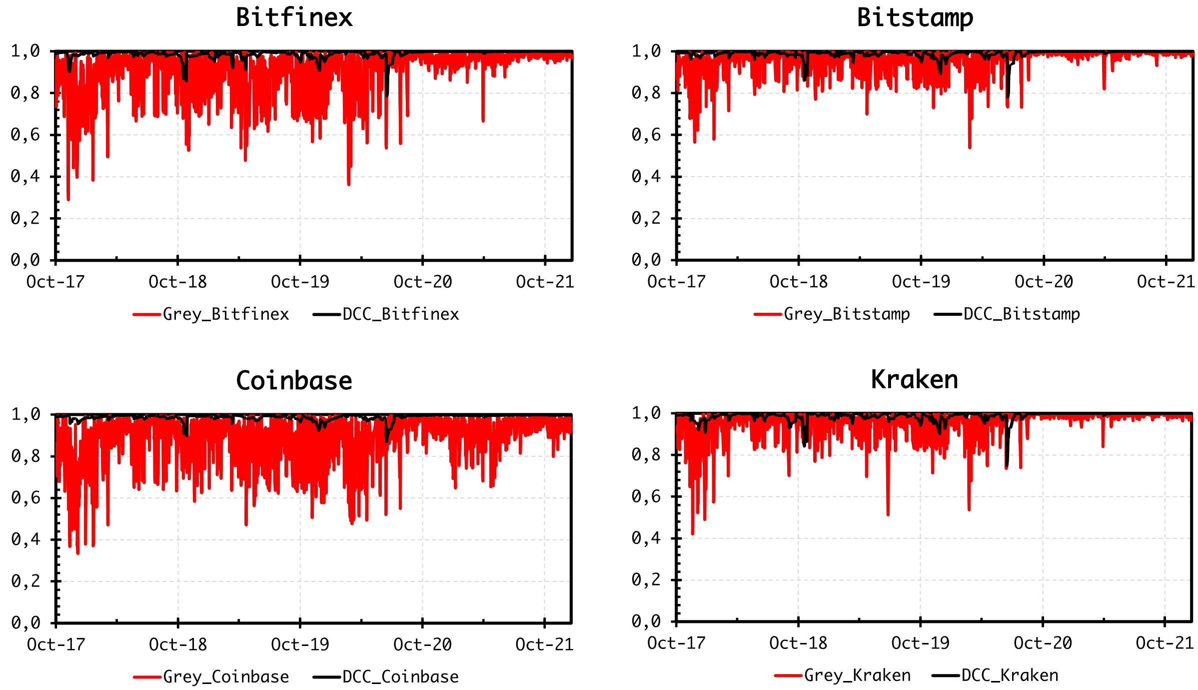

Fig. 1. Grey and DCC-GARCH correlations between exchanges. All pairs are with Binance as the baseline exchange.

Table 1
Basic descriptive statistics of Grey and DCC-GARCH correlations.

Correlation	Mean	Median	SD	Min	Max
	Grey				
Bitfinex	0.9024	0.9528	0.1152	0.2895	1.0000
Bitstamp	0.9538	0.9814	0.0624	0.5389	1.0000
Coinbase	0.8755	0.9184	0.1196	0.3333	1.0000
Kraken	0.9511	0.9800	0.0701	0.4210	1.0000
	DCC-GARCH(1,1)				
Bitfinex	0.9881	0.9940	0.0188	0.7862	0.9998
Bitstamp	0.9897	0.9949	0.0174	0.7817	0.9999
Coinbase	0.9884	0.9926	0.0141	0.8703	0.9993
Kraken	0.9875	0.9942	0.0207	0.7495	0.9999

All pairs are with Binance as the baseline exchange.

- *searches* is the Google Trends[7] searches for queries "Bitcoin" and "BTC" constructed on the daily basis (as the default for Google Trends data is monthly frequency, we download daily data for overlapping three-month periods and chain them, rescaling with respect to the overlapping month's mean search volume; in addition, we get the daily data five times for each segment, combined with a random alphanumerical string to enforce new sampling from the Google algorithm, and average them; the final value is a weighted average between "Bitcoin" and "BTC" series, weighted according to the overall searches ratio);
- *price* is the CoinMarketCap closing price;
- *exchange_ratio* is a ratio between *volume* and *transfers*;
- *addresses* is the number of active addresses for the given day, obtained from Coinmetrics as *AdrActCnt*

The two measures of correlations are plotted in Fig. 1 and their basic statistics are summarized in Table 1. The DCC-based correlations show little variability, with mean and median values around 0.99 for all four pairs. The Kraken DCC correlation is the most volatile, whereas the one of Coinbase is the least volatile. The Grey correlation shows much richer dynamics, ranging between 0.29 and 1. Coinbase Grey correlation exhibits the highest volatility, whereas the one of Bitstamp has the lowest volatility.

[7] https://trends.google.com

Table 2
First-stage equations – instrumental variables.

	$\log(fees)$	$\log(transfers)$	$\log(volume)$
Constant	-65.4500^{***}	0.1780^{***}	0.0909
	(3.0772)	(0.7858)	(1.1850)
$\log(price)$	-0.8371^{***}	0.7485^{***}	0.6878^{***}
	(0.1086)	(0.0249)	(0.0380)
$exchange\_ratio$	-0.0121	-0.0271^{***}	0.7962^{***}
	(0.0082)	(0.0027)	(0.0046)
$\log(addresses)$	4.6861^{***}	1.0903^{***}	1.2061^{***}
	(0.2748)	(0.0678)	(0.1083)
R^2	0.4570	0.9058	0.8523
$\bar{R}^2$	0.4560	0.9056	0.8520
F-test	113.92^{***}	1085.15^{***}	739.69^{***}

Estimates are reported on the first lines, standard errors in the parentheses on the second lines.
*, **, *** indicate significance at 90%, 95%, and 99% confidence level, respectively.

3. Results and discussion

We now turn to estimating the proposed model in Eq. (3) between 20 October 2017 and 7 January 2022 to see whether the dynamics of correlations can be reasonably explained by the model or whether they are simply noise superimposed on an auto-regressive process capped at 1. We investigate whether the dynamics of correlations between Binance and four other crypto-exchanges – Bitfinex, Bitstamp, Coinbase, and Kraken – can be explained by blockchain-specific as well as other economic factors. To account for potential presence of endogeneity, we utilize the instrumental variables for possibly endogenous variables $fees$, $transfers$, and $volume$. The instrumental variables parts of the first-stage regressions are summarized in Table 2, showing the instruments are indeed strong (clear rejection of weak instruments through the F-tests and medium to high adjusted coefficients of determination for the separate equations). We can thus proceed to the eventual estimation of models according to Eq. (3).

Table 3 summarizes the model setting for the determinants of the Grey correlation. We have eliminated statistically insignificant variables in a step-wise manner with the breaking point of the 90% level of confidence. Insignificant variables, apart from an insignificant constant term, are eliminated and thus not reported in Table 3. If an included exogenous variable is eliminated this way, it is included as an instrumental variable unless stated otherwise. Starting with validity of the models' specification, we see that the Hausman tests' (Hausman, 1978) null hypothesis is firmly rejected for all four models, i.e., the OLS estimates are not consistent but the IV/2SLS estimates are. The assumed endogenous variables are in fact endogenous and the instrumental variables approach is necessary. The Sargan's test (Sargan, 1958; Hansen, 1982) is passed by all four models so that the over-identifying restrictions are valid.

The Grey correlations between Binance and Bitfinex, Bitstamp, and Kraken are all highly auto-correlated with estimated auto-regressive parameters around 0.4. All four pairs share a set of significant explanatory variables with same signs of the effects – $sigma$, $transfers$, and $fees$. In addition, Kraken and Bitfinex pairs with Binance share a significant positive effect of $volume$. Let us now focus on these effects.

There is a negative effect of $sigma$ on the correlation, i.e., the higher the uncertainty in the Bitcoin market overall, the lower the correlation between the returns of Bitcoin prices on the two exchanges, and thus the higher the likelihood of statistical arbitrage opportunities. The specific effect on the correlation between Binance and Bitfinex, Bitstamp, and Kraken is between -0.037 and -0.017 which means that a 100% change in $sigma$ has an effect of between approximately 0.02 and 0.04 on the correlation. This sounds like a tiny change for such a huge shock into $sigma$. However, when we look at Fig. 2, which shows the time dynamics of the four most relevant explanatory variables, the range of $sigma$ is more than an order of magnitude. A 100% change is not unheard of in the dynamics as is evident from the graphics. Increased uncertainly of the overall Bitcoin market thus leads to higher arbitrage opportunities among the analyzed exchanges.

An effect of a lower magnitude and an opposite sign, i.e. positive, is found for $volume$. The higher the volume on exchanges, the higher the correlation between the returns of Bitcoin prices on two exchanges, and thus the lower the chance of arising arbitrage opportunities. Volume spreads over two orders of magnitude (Fig. 2) but is evidently less volatile than the previous variable. An increased trading activity thus eliminates or, maybe better, diminishes the market inefficiency. Even though it has been technically validated, the endogeneity arises from exchange divergence likely leading to increased trading activity on the exchanges as traders can spot the price on Binance and assume that the other exchange will, sooner or later, converge to the largest crypto-exchange. Note that $volume$ is significant for only two out of four of the analyzed exchange pairs with Binance, specifically for Bitfinex and Kraken, and the effect is practically lower than of $sigma$ and of the other two endogenous variables that we turn to now.

The other two endogenous variables ($transfers$ and $fees$) show similar estimates for the four exchanges, the strongest effects being found for the Coinbase and Bitfinex correlation. The on-chain activity ($transfers$), including transfers between centralized exchanges but not within them, increases the correlation and thus decreases the likelihood of arbitrage opportunities, which is expected and similar to $volume$. The endogeneity is evident as arbitrage opportunities should lead to increased between-exchanges transfers activity as investors try to monetize it. The trading fees decrease the correlation and thus increase the likelihood of arbitrage opportunities as a congested network limits investors in clearing out the exchanges divergence. The endogeneity story holds, albeit now more indirectly, as arbitrage opportunities will motivate investors to transfer between exchanges which can possibly congest

Table 3
Estimated models for Grey's correlation between Binance and the given exchange.

	Bitfinex	Bitstamp	Coinbase	Kraken
Constant	-0.5900^{***}	0.0433	-0.4026^{***}	-0.0409
	(0.1098)	(0.0585)	(0.0957)	(0.0644)
log(*sigma*)	-0.0261^{***}	-0.0174^{***}	-0.0370^{***}	-0.0166^{***}
	(0.0061)	(0.0037)	(0.0063)	(0.0040)
log(*volume*)	0.0093^{*}			0.0047^{*}
	(0.0049)			(0.0028)
log(*transfers*)	0.0302^{***}	0.0187^{***}	0.0306^{***}	0.0147^{***}
	(0.0053)	(0.0023)	(0.0037)	(0.0031)
log(*fees*)	-0.0169^{***}	-0.0075^{***}	-0.0152^{***}	-0.0095^{***}
	(0.0038)	(0.0023)	(0.0032)	(0.0026)
$\hat{\rho}_{t-1}$	0.3917^{***}	0.3825^{***}	0.3700^{***}	0.4267^{***}
	(0.0355)	(0.0321)	(0.0302)	(0.0374)
R^2	0.3104	0.2875	0.2784	0.3187
$\bar{R}^2$	0.3081	0.2857	0.2765	0.3164
Hausman	26.7675^{***}	31.0507^{***}	18.5636^{***}	22.0534^{***}
Sargan	0.0435	3.2709	5.9633	4.3437

Estimates are reported on the first lines, HAC standard errors (MacKinnon and White, 1985) in the parentheses on the second lines. *, **, *** indicate significance at 90%, 95%, and 99% confidence level, respectively. Null hypothesis for the Hausman test states that both OLS and IV/2SLS estimates are consistent and OLS is efficient, alternative states that only IV/2SLS estimates are consistent. Sargan's test null hypothesis implies validity of over-identifying restrictions.

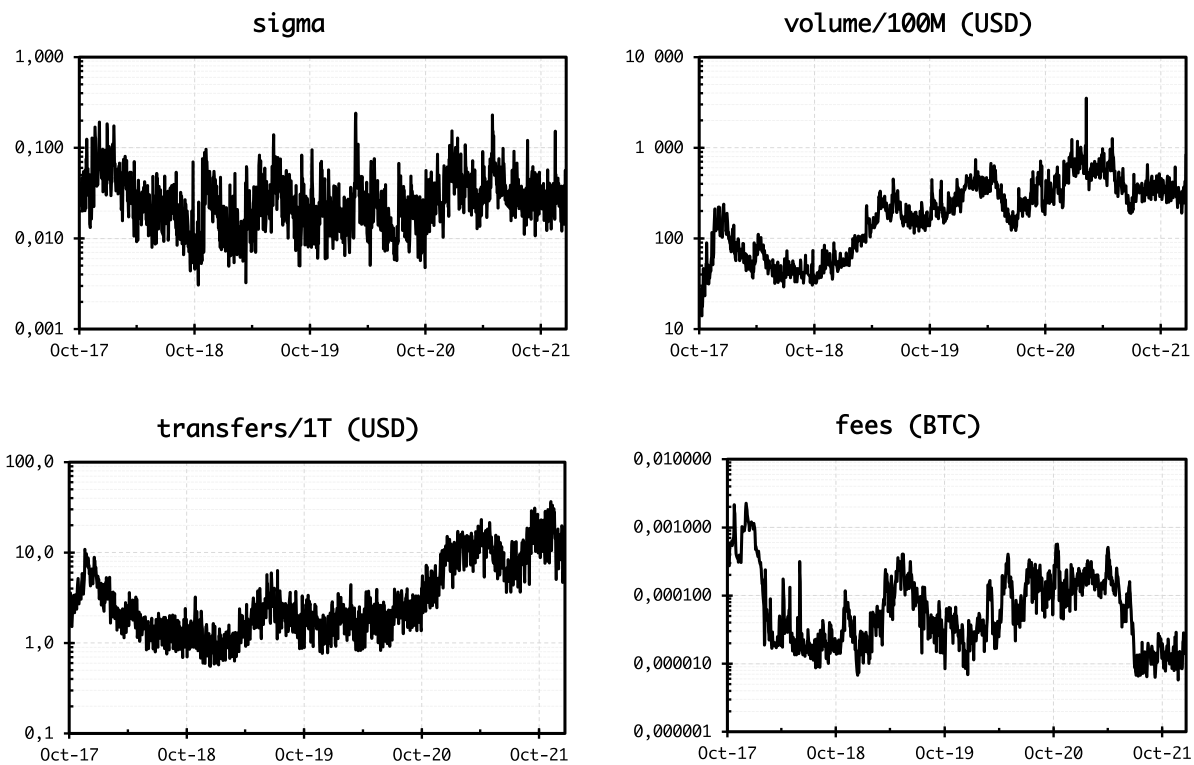

Fig. 2. Most relevant explanatory variables. Semi-logarithmic representation. Volume and transfers are rescaled for better graphical representation.

the network, i.e., increase the transfer fees considerably. These two endogenous variables – *transfers* and *fees* – thus seem rather connected but this connection does not lead to collinearity issues as their correlation remains rather low or certainly not critical (correlation of 0.20 between the levels and of 0.51 between the first differences). All four models have $\bar{R}^2$ of around 0.3 and their residuals pass the necessary stationarity and unit root tests (these are available upon request) so that we can consider the results valid.

Table 4 summarizes the results for the DCC-GARCH correlations. The whole dynamics are dominated by the auto-regressive term for all four exchange pairs. Even though *sigma* and *transfers* are significant, their effects are between one and two orders of magnitude weaker than for the Grey correlation regressions, i.e., they are practically and economically insignificant. The DCC-GARCH methodology thus seems to be unable to properly capture the dynamics between the exchanges. The Grey correlation turns

Table 4
Estimated models for DCC correlation between Binance and the given exchange.

	Bitfinex	Bitstamp	Coinbase	Kraken
Constant	0.0900***	0.0894***	0.0590**	0.0834***
	(0.0313)	(0.0322)	(0.0264)	(0.0292)
log($sigma$)	0.0011***	0.0009**	0.0006**	0.0008*
	(0.0004)	(0.0004)	(0.0003)	(0.0004)
log($transfers$)	0.0005**	0.0004**	0.0002*	0.0005**
	(0.0002)	(0.0002)	(0.0001)	(0.0002)
$\widehat{\rho}_{t-1}$	0.9022***	0.9037***	0.9386***	0.9083***
	(0.0349)	(0.0346)	(0.0273)	(0.0321)
R^2	0.8468	0.8479	0.9022	0.8453
$\bar{R}^2$	0.8465	0.8476	0.9020	0.8450
Hausman	3.8521**	7.4763***	9.2398***	7.3355***
Sargan	2.0838	0.5082	0.7588	0.2419

Notation holds from Table 4.

out to be more appropriate as it is able to reflect the non-linear connections between the exchanges as well as not relying on practical smoothing as the DCC-GARCH procedure does.

As a robustness check, we rerun the analysis for the exchange pairs with Coinbase as the main exchange in the place of Binance in the original analysis. The results are summarized in Tables A.1 and A.2. Note that the Coinbase–Binance pair is the same as the Binance–Coinbase pair so that it is not reported here. We find that the results are qualitatively very similar – the same signs and magnitudes of effects for $sigma$, $transfers$ and $fees$, and strong autoregressive components for the Grey's correlation, and weak information value in the DCC correlations.

Our results clearly show that the on-chain activity and price dynamics can explain the emergent arbitrage opportunities, corroborating the results of Makarov and Schoar (2020) and complementing various other studies showing that Bitcoin technical drivers can help explaining the dynamics of its pricing structure (Kristoufek, 2015; Phillips and Gorse, 2018; Garriga et al., 2018; Ahmed, 2022) as well as the studies arguing and showing that Bitcoin and cryptoassets markets mostly follow the standard economic and financial logic (Drozdz et al., 2018; Kristoufek, 2019; Watorek et al., 2021). Although, it needs to be noted that actually profiting from the statistical arbitrage opportunities and its proper analysis remain challenging. As Bitcoin is mostly traded on centralized exchanges, one would need to transfer between divergent exchanges to profit from it, or take a short position on one, a long position on another and wait for the price convergence. The former approach (transferring between the exchanges) faces the restrictions of the exchanges as in theory, a Bitcoin block takes around 10 min to be confirmed but nothing ensures the exchange will be able or willing to push the transfer into the nearest block. Quite the contrary, exchanges often bulk their transactions and do not overpay in order to jump the queue. And the latter strategy (short-long position) might prove challenging to be actually profitable as reported by Duan et al. (2021).

4. Conclusions

We investigate the sources of emerging statistical arbitrage opportunities in the Bitcoin market across five exchanges – Binance, Bitfinex, Bitstamp, Coinbase, and Kraken – via the instrumental variables approach to control for apparent endogeneity of some explanatory variables. We show that arbitrage opportunities arise when the network is congested and the price is volatile. Increased exchanges volume and on-chain activity push such opportunities down. These are all economically valid and logical outcomes which supports the notion that Bitcoin markets are very volatile and risky but their behavior follows standard economic and financial logic.

CRediT authorship contribution statement

Ladislav Kristoufek: Methodology, Formal analysis, Investigation, Writing – original draft. **Elie Bouri:** Conceptualization, Investigation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data sources are open and referenced in the text.

Acknowledgments

This work was supported by the Cooperatio Program at Charles University, research area Economics. Support from the Czech Science Foundation (project 20-17295S) is also highly appreciated.

Table A.1
Estimated models for Grey's correlation between Coinbase and the given exchange.

	Bitfinex	Bitstamp	Kraken
Constant	−0.1647*	0.4579***	0.3749***
	(0.0985)	(0.0617)	(0.0519)
$\log(sigma)$	−0.0359***	−0.0124***	−0.0100***
	(0.0056)	(0.0024)	(0.0021)
$\log(volume)$		−0.0053***	
		(0.0022)	
$\log(transfers)$	0.0177***	0.0053**	
	(0.0035)	(0.0023)	
$\log(fees)$	−0.0217***	−0.0046**	−0.0049***
	(0.0043)	(0.0017)	(0.0018)
$\hat{\rho}_{t-1}$	0.3699***	0.4415***	0.5224***
	(0.0343)	(0.0459)	(0.0470)
R^2	0.3222	0.3546	0.3948
$\bar{R}^2$	0.3205	0.3525	0.3936
Hausman	23.9743***	27.4670***	0.0031
Sargan	3.2320	–	–

Notation holds from Table 4. The Sargan test is not performed for Bitstamp and Kraken. For the former, only the three baseline instrumental variables are used so that there is no need to test for over-identification. And for the latter, the Hausman test prefers OLS over 2SLS.

Table A.2
Estimated models for DCC correlation between Coinbase and the given exchange.

	Bitfinex	Bitstamp	Kraken
Constant	0.0835	0.0209	0.0374**
	(0.0555)	(0.0137)	(0.0162)
$\log(sigma)$		0.0001***	
		(0.0000)	
$\log(volume)$	0.0003**	−0.00003**	
	(0.0001)	(0.00001)	
$\hat{\rho}_{t-1}$	0.9088***	0.9801***	0.9624***
	(0.0582)	(0.0135)	(0.0163)
R^2	0.8354	0.9552	0.9261
$\bar{R}^2$	0.8352	0.9551	0.9261
Hausman	1.7768	15.9153***	–
Sargan	–	0.6161	–

Notation holds from Table 4. The Sargan test is not run for Bitfinex as the null hypothesis of the Hausman test is not rejected. Neither test is performed for Kraken as there is no right-hand side endogenous variable left after the step-wise elimination.

Appendix

See Tables A.1 and A.2.

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