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Bitcoin arbitrage and exchange default risk

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ABSTRACT

We investigate how exchange default risk and liquidity affect Bitcoin cross-exchange arbitrage opportunities. Analysing minute-level data from 16 cryptocurrency exchanges (April 2013–April 2024), we find arbitrage opportunities last longer when higher-risk exchanges have higher prices, as traders are cautious of default risks. There is a strong positive relation between capital flows from high-risk to low-risk exchanges and arbitrage opportunities, showing a preference for safer exchanges. Liquidity accelerates arbitrage by enabling faster execution, but high transaction fees and blockchain congestion slow capital transfers. The paper highlights exchange risk, liquidity, and transaction costs as key factors in Bitcoin market efficiency.

1. Introduction

In an efficient market, price discrepancies are quickly eliminated through arbitrage, resulting in consistent pricing for identical assets across different markets (Fama, 1970, and Isard, 1977). Bitcoin is traded in various cryptocurrency exchanges, and studies have shown varying behaviours of Bitcoin prices across different exchanges. From price efficiency perspective, Urquhart (2016) finds Bitcoin is inefficient during 2010 to 2016, however, the price efficiency improves as Bitcoin matures. From arbitrage perspective, Pieters and Vivanco (2017) and Makarov and Schoar (2020) find recurring cross-exchange arbitrage opportunities for Bitcoin between different exchanges before 2018, which violates the law of one price. Crépellière et al. (2023) and Shynkevich (2023) show that arbitrage opportunity reduces substantially after 2018.

A common cross-exchange arbitrage strategy is buying Bitcoin on a lower-priced exchange and transferring it via blockchain to a higher-priced exchange to sell (Hautsch et al., 2024) (henceforth on-chain arbitrage). While risk-neutral arbitrageurs are expected to exploit price misalignment in arbitrage, regardless of the exchange or geographical location, as long as profitable price discrepancies exist (Shleifer and Vishny, 1997), empirical evidence suggests otherwise. In equity markets, Hirshleifer et al. (2011) find more pronounced arbitrage opportunities on NASDAQ, where firm valuations are more uncertain and, thus, riskier compared to those on the NYSE. Similarly, in Bitcoin market, Hautsch et al. (2024) observe fewer arbitrage opportunities across low-risk exchanges compared to high-risk ones.[1] These indicate that arbitrage behaviour can be influenced by the level of risk associated with the market. Hautsch et al. (2024) explain this with an inventory arbitrage strategy, where arbitrageurs deposit asset in multi exchanges, and then buy and sell simultaneously in exchanges with different prices.

Nevertheless, Hautsch et al. (2024) do not investigate how the perceived exchange default risk affects on-chain arbitrage strategy. On-chain arbitrage strategy drives cross-exchange asset flows to follow arbitrage opportunities, as arbitrageurs buy on high-price

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[1] They define the risk as “default risk, which manifests in the risk of thefts, hacks, or exit scams”.

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exchanges and sell on low-price exchanges with latency (Hautsch et al., 2024). However, arbitrageurs' behaviour is not solely driven by price differentials, but also by the risk of the exchanges involved in arbitrage transactions (Hirshleifer et al., 2011; Hautsch et al., 2024), and they are hesitant to trade on riskier exchanges (Gromb and Vayanos, 2002). Therefore, arbitrageurs, who move assets from low-price to high-price exchanges in on-chain arbitrage, hesitate to transfer assets from low default risk to high default risk exchanges. As a result, they are more likely to complete transactions when the assets are being moved from high-risk, low-price exchanges to low-risk, high-price ones, leading to a positive relationship between net flow to these exchanges and arbitrage opportunities.

To address the gap in the literature regarding the perceived exchange default risk in on-chain arbitrage strategies, we propose two alternative hypotheses suggesting that on-chain arbitrage is also influenced by the default risk of cryptocurrency exchanges. Specifically, we hypothesize that:

Hypothesis 1. The percentage of high-price exchange with higher risk has a positive relationship with an arbitrage opportunity.

Hypothesis 2. Net flow to the low-risk exchange has a positive association with Bitcoin cross-exchange arbitrage opportunities.

Meanwhile, Makarov and Schoar (2020) find smaller arbitrage opportunities within than across countries, and Hautsch et al. (2024) find settlement latency impedes arbitrage. This emphasizes the importance of capital movement in cross-exchange arbitrage. Therefore, we control for the congestion level and transaction fees in Bitcoin blockchain since they impedes capital movement. On the contrast, liquidity has long been recognized as a key factor that facilitates arbitrage activities. For instance, Chordia et al. (2008) provide supporting evidence from the U.S. stock market. Based on this, we propose

Hypothesis 3. Increase in liquidity is associated with increases in cross-exchange netflow and therefore arbitrage opportunities between exchanges.

We study 16 exchanges' between April 1st 2013 and April 30th, 2024 and find that arbitrage is influenced not only by price differences but also by the risk and liquidity of exchanges. These findings support the hypothesized relationships and contributes to the understanding of Bitcoin cross-exchange arbitrage by highlighting the role of exchange risk in arbitrageur behaviour. Arbitrageurs prefer to sell in lower risk exchanges due to the potential for holding losses. Additionally, we show that liquidity enhances arbitrage opportunities, while factors like transaction congestion can hinder capital movement. By focusing on exchange risk, this study provides a better understanding of the determinants of Bitcoin arbitrage and its impact on market efficiency.

2. Data

Following Makarov and Schoar (2020), we collect minute level Bitcoin price information via application programming interfaces (APIs)[2] of sixteen exchanges with different default risks. In line with their approach, we calculate the arbitrage index by dividing the maximum price by the minimum price for each minute and pair, and averaging it at the daily level to mitigate the effects of intra-day volatility. The exchanges are AscendEX (42.8), Binance (75), Bitfinex (72.6), BitMart (61.2), Bitstamp (83), Bybit (75), Coinbase (84), Crypto.com (70), DigiFinex (55.7), Gate.io (65.2), HitBTC (42.6), Kraken (79.6), KuCoin (54.4), OKX (74.9), Poloniex (45.2), WhiteBIT (63.8). The ratings in the parentheses are sourced from CCdata.io to estimate the default risk. The exchange rating points are calculated using a range of metrics, each weighted differently: market quality (20%), security (17.5%), legal and regulation (17.5%), KYC and transaction risk (15%), data provision (15%), exchange team (10%), asset quality and diversity (5%), and negative events (5%).[3]

We obtain Bitcoin blockchain data, including on-chain Bitcoin flows between exchanges, number of transactions, transaction fees paid by exchanges, and average transaction fees per weight in each block from Cardiff University Database (CUBiD), which covers January 3, 2009 - April 30, 2024. After combining all the datasets, our final sample period covers from April 1st, 2013, to April 30th, 2024.[4]

Table 1 reports the summary statistics for the variables we used in our regressions. It shows that the arbitrage index (AI) has a maximum value of 1.353, indicating that the highest price on a high-price exchange can be up to 35.3% higher than the lowest price on a low-price exchange. This highlights significant price discrepancies across exchanges, creating potential arbitrage opportunities. High-risk exchanges have higher prices about 43.5% of the time (pct_hh). Net flows from high-risk to low-risk exchanges are measured in millions and range from −0.361 to 0.615, indicating that flows occur in both directions. Liquidity is negative because we multiplied the Corwin and Schultz (2012) estimator by -1, ensuring that larger values represent higher liquidity. While negative it is close to zero showing these exchanges on average have adequate liquidity.

[2] See Appendix B for detailed information on the APIs.
[3] For the complete list of ranked exchanges, see CCdata.io. The benchmark calculation methodology is available on CCdata.io.
[4] See Jahanshahloo et al. (2023) for further details on CUBiD.

Table 1
Summary statistics.

	N	Min	Mean	Max	S.D
AI	185,460	1	1.002	1.352	0.009
pct_hh		0	0.435	1	0.306
NetFlow		−0.361	0.008	0.615	0.1
Liquidity		−0.009	−0.002	−0.0003	0.002
fee_h_usd		0	4096.054	106 195.9	14 013.93
fee_l_usd		0	14 473.67	319 703.5	43 508.45
FpW	4048	10^{-5}	0.002	0.155	0.004
#Transactions		30,356	242,593	927,010	119,532.2
Risk Diff	119	0.100	16.079	41.400	11.063

This table reports number of observations, minimum value, mean, maximum value, and standard deviation of the variables, winsorized at 1%. All the variables are in daily frequency. AI is the Arbitrage index , pct_hh is the percentage of the minutes that the high-risk exchange has a higher price in a day, $NetFlow_t$ is the bitcoin on-chain net flow from high-risk exchange to low-risk exchange in the units of billions of dollars, $Liquidity$ is the liquidity of higher-risk exchange, and fee_h_usd and fee_l_usd are transaction fees paid by the high- and low-risk exchanges, respectively, for the 119 exchange pairs. $\#Transactions$ and FpW are the number of transactions and average fee per weight (in USD) per day. Risk Diff is the difference between each exchange pair risk score. There are 119 exchanges in rather than 120 in our sample because there is no on-chain flow between Poloniex and OKX and thus this pair is excluded from the sample. The sample spans from April 1st, 2013 to April 30th, 2024.

3. Methodology

We introduce the following regression model to analyse the effect of exchange default risk on arbitrage activities:

$$\begin{aligned} AI_t = \beta_0 + \beta_1 pct\_hh_t + \beta_3 Liquidity_t + \beta_4 NetFlow_t * Liquiidty_t \\ + \sum Controls + Pari\_FE + Year\_FE + \epsilon_t \end{aligned} \tag{1}$$

where AI_t is the arbitrage index at time *t*. Following Makarov and Schoar (2020), arbitrage index is calculated by taking the ratio of the maximum to minimum price of each exchange pair and averaging it over the day. pct_hh_t is the percentage of the minutes that the high-risk exchange has a higher price in a day, $NetFlow_t$ is the Bitcoin on-chain net flow from high-risk exchange to low-risk exchange, $Liquidity_t$ is the liquidity of the high-risk exchange, and $Controls_t$ are control variables. As arbitrage via on-chain transaction is affected by transaction fees and congestion (Hautsch et al., 2024), we control for the transaction fees paid by the exchanges, and congestion estimators including average fee per weight per day and number of transactions per day. In our sample period, there are three Bitcoin halving. We include dummy variables corresponding to the three most recent intervals defined by these halving events, which occurred on July 9th, 2016, May 11th, 2020, and April 19th, 2024 to capture the temporal shifts associated with the halving events.

To further test if the effect of net flow on arbitrage opportunity is affected by liquidity, we include an interaction term between $NetFlow_t$ and $Liquidity_t$ to capture the impact of liquidity on the relationship between arbitrage opportunity and net flow.

The liquidity in regression (1) is estimated with Corwin and Schultz (2012) bid–ask spread estimator (CS) as it more effectively captures the time-series variability of liquidity in the cryptocurrency market compared to other commonly used stock market liquidity estimators, such as the Amihud illiquidity ratio (Brauneis et al., 2021). Following Corwin and Schultz (2012) and Brauneis et al. (2021), we set the negative values of $CS_{i,i+1}$ to zero, and liquidity for day t is calculated as the opposite of the average of $CS_{i,i+1}$ within that day. To enhance interpretability, we multiply the liquidity estimate by -1, so that higher values now indicate a more liquid market. Similar to Brauneis et al. (2021), we do not adjust the estimator for the overnight trading halt because Bitcoin is traded continuously, 24 h a day, seven days a week.[5]

4. Results and discussion

Table 2 presents the regression results of model (1). We separate FpW and fee_h_usd and fee_l_usd to two regressions to avoid multi-collinearity as they have high correlations.[6] In regressions (1) and (2), we apply pair fixed effects following Hautsch et al. (2024). Meanwhile, Makarov and Schoar (2020) highlight the importance of geographical location since arbitrage opportunities are much larger across countries than within them. Therefore, in regressions (3) and (4), we control for the geographical location and risk difference of the exchange.[7] Among the 119 exchange pairs, there are 11 in the same country and 109 in different countries.[8]

Table 2 shows that the percentage of high-price exchange with higher risk has a significant and positive relationship with arbitrage opportunity. In other words, high-risk exchanges tend to have lower selling pressure because fewer participants are willing to sell. This creates a positive relationship with arbitrage opportunities because arbitrageurs hesitate to act due to perceived risks,

[5] See Jahanshahloo et al. (2022) for further detail on the around the clock activity of the Bitcoin blockchain.

[6] See correlation matrix in Appendix A.

[7] We exclude exchange pair fixed effect in regressions (3) and (4) it absorbs information on geographical and risk differences, as there is no variation in an exchange pair's location or risk score difference.

[8] The headquarters locations for each exchange and exchanges' risk scores are listed in Appendix C.

Table 2
Regression results.

	(1) AI	(2) AI	(3) AI	(4) AI
pct_hh	0.222***	0.222***	0.175***	0.180***
	(0.005)	(0.005)	(0.004)	(0.004)
NetFlow	0.164***	0.161***	0.184***	0.153***
	(0.025)	(0.025)	(0.024)	(0.025)
Liquidity	−48.103***	−47.657***	−51.110***	−51.501***
	(1.173)	(1.160)	(1.208)	(1.192)
NetFlow * Liquidity		21.396**	18.764**	17.615**
	(8.541)	(8.549)	(8.588)	(8.569)
#Transactions	8.189***	9.664***	9.205***	12.920***
	(1.205)	(0.972)	(1.220)	(0.972)
FpW	1.711***		1.233***	
	(0.316)		(0.315)	
fee_h_usd		54.917***		82.727***
		(11.759)		(7.505)
fee_l_usd		22.141***		−24.984***
		(2.523)		(1.892)
2nd Halving	−0.476***	−0.477***	−0.475***	−0.475***
	(0.022)	(0.022)	(0.023)	(0.023)
3rd Halving	−0.484***	−0.485***	−0.479***	−0.477***
	(0.022)	(0.022)	(0.023)	(0.023)
4th Halving	−0.515***	−0.508***	−0.506***	−0.495***
	(0.023)	(0.023)	(0.024)	(0.024)
Risk Diff			0.005***	0.006***
			(0.000)	(0.000)
Same Country			−0.080***	−0.079***
			(0.002)	(0.002)
Constant	100.420***	100.417***	100.343***	100.328***
	(0.022)	(0.022)	(0.023)	(0.023)
Observations	185,460	185,460	185,460	185,460
R-squared	0.446	0.446	0.414	0.415
Year FE	Yes	Yes	Yes	Yes
Pair FE	Yes	Yes	No	No

This table reports the OLS regression results using daily data, in which the dependent variable is cross-exchange arbitrage opportunity. The key independent variables are the percentage of the minutes that the high-risk exchange has a higher price in a day (pct_hh), Bitcoin on-chain net flow from high-risk exchange to low-risk exchange ($NetFlow_t$), and liquidity of higher-risk exchange ($Liquidity$). We control for on-chain transaction costs, including number of transactions ($\#Transactions$), average fee per weight (FpW), transaction fees paid by the high- and low-risk exchanges (fee_h_usd and fee_l_usd), and Bitcoin halving events. $Risk\ Diff$ is the difference between each exchange pair risk score. $SameCountry$ is a binary variable equal to 1 when both exchanges in an exchange pair are located in the same country and zero otherwise. AI_t is multiplied by 100 and $NetFlow_t$ is divided by 1000 for the ease of interpretation. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels and t-statistics are reported in parentheses.

as a result, price differences persist because the arbitrage opportunity is not utilized. This indicates that price difference is higher and more persistent when riskier exchanges have higher price, which is consistent with Hautsch et al. (2024) and supports the view that the exchange's risk level affects arbitrageurs' trading (Hirshleifer et al., 2011).

The relationship between arbitrage opportunity and net flow from high-risk to low-risk exchange is significant and positive. According to Fama (1970) and Ross (2013), arbitrageurs are risk-neutral and the arbitrage opportunity should primarily be driven by net flow between exchanges with different prices, regardless of the risk associated with the exchanges. However, our empirical evidence suggests that net flows between exchanges with different levels of risk also significantly affect arbitrage opportunities. This indicates that arbitrageurs are not entirely indifferent to the risks posed by exchanges. This is also evidenced by the positive signs of $Risk\ Diff$, which means the arbitrage opportunities are larger when the risk differences between the exchanges are higher. Our finding via on-chain transaction analysis is in line with Hautsch et al. (2024)'s finding on off-chain inventory arbitrage strategy that exchanges with lower default risk attract more arbitrage capital.

Similar to Hautsch et al. (2024), we use net flow to the low-risk exchange as a proxy for buying in high-risk exchange with lower price and selling in low-risk exchange with higher price. The positive relationship between arbitrage opportunity and net flow suggests that asset flows tend to chase arbitrage opportunities (Hautsch et al., 2024), particularly those involving selling on low-risk exchanges with higher prices. This makes sense because arbitrage via on-chain transaction involves buying in high-price exchange first, and then selling in low-price exchange with a latency (Hautsch et al., 2024). If the low-price exchange is riskier, arbitrageurs are more likely to face the risk of being stuck with a holding (Gromb and Vayanos, 2002). The settlement process may take up to two days following an arbitrage opportunity, as the lagged terms remain significant through the second lag. This delay could be a result of margin trading (Strych, 2022).

Furthermore, we include liquidity and its interaction with net flows from high-risk to low-risk exchanges. We find a negative relationship between arbitrage opportunities and liquidity on the exchange, which aligns with the theory that increased liquidity facilitates arbitrage (Chordia et al., 2008, and Rösch et al., 2017). The interaction term is positive and significant, suggesting that the relationship between arbitrage opportunity and the net flows from high-risk to low-risk exchanges is influenced by the level of exchange liquidity. More specifically, the positive interaction means that as liquidity increases, the influence of net flows on arbitrage opportunities grows stronger. This implies that in more liquid exchanges, the movement of funds (net flows) from high-risk to low-risk exchanges has a greater effect on the arbitrage opportunities. When liquidity is high, it is easier to conduct arbitrage, because trades can happen more quickly and with less price disruption.

In addition, an increase in the average fee per weight, the number of transactions, and the fees paid by exchanges is associated with greater arbitrage opportunities. This is due to increased cost restricts capital movement. On one hand, higher fees per weight directly increase the cost of arbitrage, which aligns with the observed positive relationship between arbitrage opportunities and fees paid by exchanges. On the other hand, an increase in the fee per weight and the number of transactions signals higher congestion on the Bitcoin blockchain (Easley et al., 2019, and Huberman et al., 2021). This congestion raises the likelihood of delays in transaction processing, thereby exposing arbitrageurs to greater risks of adverse price movements. As a result, increased blockchain congestion hampers the efficiency of cross-exchange arbitrage (Hautsch et al., 2024).

The negative and increasing in magnitude of each halving is similar to Crépellière et al. (2023) who find arbitrage opportunities decrease over time. The negative signs of *Same Country* indicate the arbitrage opportunities are smaller if the two exchanges are in the same country than in different countries, which is consistent with Makarov and Schoar (2020).

The rating data from CCdata.io is only available from 2022 to 2024.[9] According to the available data, the rating points vary slightly over time, however, the rankings of the exchanges mainly do not change. As not all 16 exchanges are listed in the ranking before 2024, we use the ranking for 2024 in our main analysis. For robustness, we also use the available rankings for 2022 and 2023, and the results are qualitatively identical.[10]

5. Conclusion

This study examines the influence of exchange risk and liquidity on Bitcoin cross-exchange arbitrage opportunities. We find that arbitrage opportunities persist longer when higher-risk exchanges have higher prices, as arbitrageurs hesitate due to perceived risks. Additionally, net flows from high-risk to low-risk exchanges positively affect arbitrage opportunities, as arbitrageurs prefer selling on safer exchanges. Liquidity enhances the impact of these flows, making arbitrage easier in more liquid markets. Higher transaction fees and blockchain congestion also hinder capital movement and slow down arbitrage execution. Overall, this research highlights the importance of exchange risk, liquidity, and costs in shaping Bitcoin arbitrage behaviour.

CRediT authorship contribution statement

Weiwei Guo: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Silvia Intini:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Conceptualization. **Hossein Jahanshahloo:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Appendix A

Correlation matrix of variables used in the regression model.
This table reports the pairwise correlation coefficients between the variables in the regression model (1) and their significance. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels.

	AI	pct_hh	NetFlow	Liquidity	#Transactions	FpW	fee_usd_h_w	fee_usd_l_w	Risk Diff
AI	1								
pct_hh	0.166***	1							
NetFlow	−0.001	−0.081***	1						
Liquidity	−0.239***	0.035***	−0.013***	1					
#Transactions	−0.204***	−0.054***	0.020***	0.205***	1				
FpW	−0.058***	−0.083***	0.014***	−0.186***	0.440***	1			
fee_h_usd	0.010***	−0.075***	0.252***	−0.166***	0.056***	0.258***	1		
fee_l_usd	−0.027***	0.028***	−0.017***	−0.141***	0.130***	0.403***	0.137***	1	
Risk Diff	0.152***	−0.109***	−0.074***	−0.032***	−0.008***	−0.017***	−0.177***	0.014***	1

[9] See 2022 exchange benchmark report at CCdata.io and the 2023 exchange benchmark report at CCdata.io

[10] Regression results based on rankings for 2022 and 2023 are available from the authors upon request.

Appendix B

This appendix provides the links to the Application Programming Interfaces (APIs) utilized for collecting price data from the exchanges referenced in this study.

AscendEX: https://ascendex.github.io/ascendex-pro-api/#historical-bar-data
Binance: https://binance-docs.github.io/apidocs/spot/en/#kline-candlestick-data
Bitfinex: https://docs.bitfinex.com/reference/rest-public-candles
BitMart: https://developer-pro.bitmart.com/en/spot/#get-history-k-line-v3
Bitstamp: https://www.bitstamp.net/api/#tag/Market-info/operation/GetOHLCData
Bybit: https://bybit-exchange.github.io/docs/v5/market/kline
Coinbase: https://docs.cdp.coinbase.com/advanced-trade/reference/retailbrokerageapi_getpubliccandles
Crypto.com: https://exchange-docs.crypto.com/exchange/v1/rest-ws/index.html#public-get-candlestick
DigiFinex: https://docs.digifinex.com/en-ww/spot/v3/rest.html#get-candles-data
Gate.io: https://www.gate.io/developer/historical_quotes
HitBTC: https://api.hitbtc.com/#candles
Kraken: https://support.kraken.com/hc/en-us/articles/360047124832-Downloadable-historical-OHLCVT-Open-High-Low-Close-Volume-Trades-data
Kucoin: https://www.kucoin.com/docs/rest/spot-trading/market-data/get-klines
OKX: https://www.okx.com/docs-v5/en/#rest-api-market-data-get-candlesticks-history
Poloniex: https://api-docs.poloniex.com/spot/api/public/market-data#candles
Whitebit: https://docs.whitebit.com/public/http-v1/#kline

Appendix C

Exchanges information.
This table shows the locations (country) of the headquarters for each exchange, and the risk scores sourced from CCdata.io between 2022 and 2024.

Exchange name	Country	Risk score 2024
Ascendex	Singapore	42.8
Binance	N.A.	75
BitFinex	Taiwan	72.6
Bitmart	Cayman Islands	61.2
Bitstamp	Luxembourg	83
Bybit	Singapore	75.1
Coinbase	US	84
Crypto.com	Singapore	70
Digifinex	Singapore	55.7
Gate.io	Cayman Islands	65.2
Hitbtc	UK	42.6
Kraken	US	79.6
Kucoin	Seychelles	54.4
OKX	Seychelles	74.9
Poloniex	US	45.2
Whitebit	Lithuania	63.8

Data availability

The authors do not have permission to share data.

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