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Master Thesis:

Analyzing cross-regional cryptocurrency price differences – What factors contribute to arbitrage opportunities?

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Statement of Originality

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Abstract

This thesis examines cross-regional Bitcoin price differences to assess whether they create arbitrage opportunities and how institutional frictions shape these opportunities. Using high-frequency order book data from Kraken and nine regional exchanges across different regulatory environments, the study constructs arbitrage spreads and tests their persistence through panel regressions, beta estimations, and profitability measures. Results show that liquidity and latency risks are significant drivers of spreads, while restrictive capital environments and high transaction fees amplify inefficiencies, particularly during volatile periods. Although many markets display returns to baselines similar to the global exchanges, exchanges in South Africa and South Korea exhibit systematic and profitable arbitrage opportunities, highlighting the consistent impact of capital controls and institutional frictions on cryptocurrency market integration.

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1. Introduction

Bitcoin is a decentralized digital currency. The concept was first proposed in 2008 by the anonymous developer Satoshi Nakamoto in the paper "Bitcoin: A Peer-to-Peer Electronic Cash System" (Nakamoto, 2008). It was created to allow peer-to-peer transactions without needing trusted third-parties, such as banks. Since then, the technology has had a meteoric rise in adoption.

The cryptocurrency market operates continuously across many exchanges, but despite its decentralized and digital nature, which implies global ease of access, notable price differences exist across regions. These differences suggest barriers to entry at the market level, driven by heterogeneous actors and frictions. In this sense, price differences could be considered a feature rather than a bug, as arbitraging agents provide a service to compress spreads for those with limited market access (O'Flynn, 2025).

Cryptocurrency price differences present potential arbitrage opportunities, situations where traders can buy an asset on one exchange and simultaneously sell it on another for profit.

The focus of this thesis is to investigate the role of capital controls and institutional frictions in shaping Bitcoin arbitrage spreads across countries. Arbitrage spreads represent one of the best measures of integration, if markets are frictionless and capital is easily moveable, prices should converge quickly across exchanges, with only minimal deviations. However, evidence and prior studies suggest that significant and persistent spreads have existed in certain environments, particularly where cross-border flows are restricted. The research therefore asks whether these deviations are systematic, how long they persist, and whether they generate meaningful arbitrage opportunities after transaction costs. The central research question is whether Bitcoin behaves like a global, unified asset or whether capital controls give rise to stale, segmented markets.

This question is important for several reasons. It challenges the perception of Bitcoin as a borderless form of money immune to traditional regulation. If spreads remain wider and more persistent in countries with stronger restrictions, this suggests that even decentralised assets are effected by the regulations of national institutions. It contributes to the broader literature on financial integration. Much of this literature

has focused on equities, bonds, and foreign exchange, showing that capital controls can segment markets and slow the transmission of global shocks. Extending this logic to cryptocurrencies not only tests the robustness of these findings but also provides new insight into whether controls remain effective in a world of decentralised finance. Finally, the topic has practical relevance. For traders, persistent spreads represent opportunities to earn profits by buying low in one market and selling high in another. For regulators, they raise questions about the effectiveness and unintended consequences of restrictions. For exchanges, they highlight where integration is weakest and where liquidity provision is most critical.

The contribution of this thesis lies in combining institutional measures of financial openness with high-frequency data on Bitcoin arbitrage spreads. While existing studies have documented short-lived price discrepancies across exchanges, few have systematically linked the persistence of these spreads to capital controls. By focusing on the rate of spread closure and the conditions under which spreads remain profitable, this research adds a new dimension to the literature. It shows not only whether spreads exist, but also whether they are arbitrated away quickly in open markets and whether they linger in closed ones. This perspective helps distinguish between temporary inefficiencies due to liquidity shortages and more structural inefficiencies created by institutional frictions.

To address the research question, a dataset of minute-level prices and order book data across a global reference exchange (Kraken) and a set of regional exchanges located in both open and closed financial systems. The sample includes exchanges in South Korea (Upbit, Bithumb), South Africa (Luno), Latin America (Bitso, Novadax), Japan (Bitflyer), Turkey (Btcturk), and the United States (BinanceUS). This dataset allows for the construction of arbitrage spreads and the estimation of their persistence over multiple time horizons. By linking these spreads to the Chinn-Ito index of financial openness and to alternative institutional measures, it can directly be tested whether more restricted markets are characterised by slower spread convergence.

With regards to Methodology, descriptive statistics document the distribution of spreads across exchanges and highlight differences in their magnitude and volatility. This step provides a first indication of heterogeneity across countries and suggests

which markets may be more segmented. Panel regressions are used to examine spreads, interacting lagged spreads with measures of openness and volatility. This design allows testing of how spreads react in different market conditions, and gauging of the influence of capital controls. Finally, hypothetical arbitrage profits are computed after accounting for transaction fees, withdrawal costs, and FX conversion rates. This step ensures that the results are not only statistically but also economically meaningful, by showing whether persistent spreads translate into real trading opportunities.

2. Literature Review

The literature on cryptocurrency markets has grown in recent years, in line with its growth of use and institutional adoption. Past studies draw on cryptocurrency economics, international finance, and market microstructure. This literature review captures key ideas most relevant to the study of cross-regional Bitcoin price differences and arbitrage opportunities. The review covers market efficiency and price discovery, arbitrage opportunities and persistence, the role of capital controls and market regulation, microstructure and order flow models, and approaches using econometrics.

2.1 Market Efficiency and Price Discovery

A key question in existing literature is that of the Efficient Market Hypothesis, and whether cryptocurrency markets display efficiency in line with this hypothesis. Early studies have shown significant deviations from efficiency due to the youth and fragmentation of the market. Brauneis and Mestel (2018) find evidence of persistent inefficiencies in Bitcoin trading across multiple exchanges, suggesting that price discovery is uneven, and arbitrage opportunities occur due to information asymmetries. Similarly, Baur and Dimpfl (2019) show that while large and globalized exchanges such as Coinbase and Kraken often display efficient price discovery, smaller regional exchanges often show price deviations driven by liquidity constraints, limited depth, and regulatory frictions.

The research implies that cryptocurrencies do not operate as a unified global market, but rather as a cluster of exchanges with varying levels of integration, where prices often diverge. This paints a contrast to traditional equity and FX markets, where strong infrastructure and arbitrage capital mean that the law of one price is adhered to more strictly. The persistence of these inefficiencies in the cryptocurrency market raises questions regarding the nature of the barriers that prevent complete arbitrage.

2.2 Arbitrage Opportunities and Persistence

Other closely related studies examine arbitrage in cryptocurrency markets in great depth. Makarov and Schoar (2020) provide one of the most in depth analyses, documenting large and systematic price differences across multiple exchanges worldwide. They show that arbitrage opportunities persist for extended periods of time, and do not converge nearly as quickly as expected. Their study shows that arbitrageurs face multiple significant frictions such as withdrawal limits, capital controls, and transfer delays.

Shin, Liu, and Anwar (2020) investigate triangular arbitrage strategies within cryptocurrency markets. They demonstrate that profitable trades can be executed by cycling through three currency pairs. However, once transaction costs and latency are included, profit shrinks substantially. Their findings reinforce the idea that frictions, rather than lack of arbitrage awareness, explain persistent opportunities.

Other studies highlight the decomposition of arbitrage spreads into different components. Some portion reflects true arbitrage opportunities, while other portions are representations of compensation for risk and costs. For example, spreads often include a latency risk premium, the expected cost of price movement during the time it takes to transfer assets across exchanges. Recognizing these decompositions is important, as arbitrage can be seen not only as correcting market inefficiencies, but also as a service provided by agents who bridge fragmented markets. This service compensates for barriers to entry and allows for financial integration where access is usually limited.

2.3 Capital Controls, Regulation, and Market Segmentation

A strong driver of persistent price differences across markets is the presence of capital controls and regulatory restrictions. Auer and Claessens (2018) argue that regulation plays a dual role in cryptocurrency markets. They suggest it can improve market stability but also segment markets by restricting cross-border flow of capital. Their study shows that in emerging economies, capital controls and exchange rate management often create significant price premiums in regional cryptocurrency markets.

Liu and Tsyvinski (2021) extend this view by explicitly linking cryptocurrency price differences to capital control restrictions, global risk factors, and foreign exchange constraints. They show that restrictive environments tend to have systematically higher Bitcoin prices, which is consistent with the idea that cryptocurrencies serve as an alternate way of circumventing strict financial control. Similarly, Pieters and Vivanco (2017) show that countries with strict capital restrictions and limited USD liquidity show larger and more persistent arbitrage spreads.

This literature shows that macro-level institutions, capital openness, financial freedom, and regulatory environments are key to explaining cross-regional price differences. However, existing empirical studies often stop short of how these factors interact with microstructural dynamics. This thesis contributes by bridging these two factors by modelling spreads as a function of capital control indices and market variables such as volatility.

2.4 Microstructure and Order Flow Models

In addition to macro-level frictions, the literature also shows that market microstructure, trading processes, and order flows, play a role in price formation. Kyle (1985) presents information showing that prices adjust according to the order imbalance created by informed versus uninformed traders. Hasbrouck (1991) extends this by developing tools to measure the information content of trades, demonstrating that signed trading volume, which is buy pressure versus sell pressure, can predict short-term price movements.

In the context of cryptocurrencies, order flow may drive local deviations from global reference prices. A surge of buy orders in a regional exchange with low liquidity can temporarily elevate local prices above global benchmarks, creating arbitrage spreads.

2.5 Addition to Literature

Existing research uses a mix of econometric models and predictive algorithms. On the econometric side, studies such as Makarov and Schoar (2020) use panel regressions to identify causes of spreads across various exchanges, while Liu and

Tsyvinski (2021) use capital control indices as explanatory variables. Standard time series tools like autocorrelation, unit root testing, and vector autoregression have also been applied to test spread persistence and co-movement.

While the existing literature has made important analysis in documenting price deviations, efficiency dynamics, and the role of regulation in shaping cryptocurrency markets, there are still gaps. Most prior work either focuses on short lived inefficiencies that vanish quickly, or focuses on broad measures of return predictability and volatility effects across assets. Fewer studies directly test whether institutional restrictions, such as capital controls, systematically influence the persistence of arbitrage spreads across exchanges. The majority of empirical evidence relies on daily or lower frequency data, which limits the ability to observe how spreads open and close within intraday periods.

This thesis contributes by filling these gaps. It uses high frequency data on multiple global and regional exchanges, it provides a direct test of whether capital controls translate into slower spread convergence and persistent arbitrage opportunities, linking the literatures on financial openness and cryptocurrency efficiency. Additionally, the analysis focuses explicitly on the interaction between institutional measures and spread dynamics, offering evidence on whether restrictions designed for fiat capital flows effect digital asset markets. In doing so, the thesis bridges theories of international financial with the unique microstructure of cryptocurrency markets.

3. Methodology

The dataset that is examined in this thesis consists of:

- Exchange-level order book data (prices, volumes, bid/ask spreads) across 22,570 observations and 140 features from various exchanges.
- Arbitrage spreads between Kraken (reference) and regional exchanges, with multiple lag structures.
- Macroeconomic indicators merged from external sources.
- Derived features such as rolling volatility and global buying pressure

This section outlines the methodological framework adopted to analyze cross-regional Bitcoin price differences. The approach uses descriptive statistics and econometric models

3.1 The Law of One Price

In frictionless markets, the same asset should trade for the same price across locations. In the context of Bitcoin, the asset should trade at the same price when converted into the same currency:

$$P_{i,t}^{USD} = P_{j,t}^{USD}$$

Where:

- $P_{i,t}^{USD}$ = Price of Bitcoin on exchange i at time t
- $P_{j,t}^{USD}$ = Price of Bitcoin on exchange j at time t

This often does not hold, creating arbitrage opportunities. The causes of these price discrepancies shall be investigated.

3.2 Arbitrage Spreads

The first step is to measure arbitrage spreads consistently across exchanges. The spread is defined as:

$$Spread_{i,j,t-k} = \frac{P_{i,t-k}^{exchange} \cdot FX_{i,t} - P_{j,t}^{USD}}{P_{j,t}^{USD}}$$

Where:

- $FX_{i,t}$ = Exchange rate from local currency to USD
- $P_{i,t-k}^{exchange}$ = The price of Bitcoin on a local exchange lagged by a time of k
- $P_{j,t}^{USD}$ = The price of Bitcoin on the reference exchange (Kraken)

To ensure spreads represent true arbitrage opportunities, spreads will be computed with lag structures corresponding to blockchain transfer times and exchange settlement delays. This adjustment avoids showing opportunities that cannot be realized immediately without inventory on both exchanges.

3.3 Panel Regressions

To analyze the causes of cross-exchange arbitrage spreads in cryptocurrency markets, a panel regression framework with exchange fixed effects and time fixed effects is used. This allows for the separation of idiosyncratic frictions at the exchange level from global shocks common to all exchanges.

Baseline Model:

The baseline regression focuses on two fundamental frictions, latency risk, and liquidity risk.

$$Spread_{i,j,t} = \alpha_i + \gamma_t + \beta_1 Latency_t + \beta_2 Liquidity_{i,t} + \epsilon_{i,t}$$

Where:

- Latency risk captures the expected cost of settlement delay, calculated using rolling Bitcoin volatility and expected settlement time.
- Liquidity risk measures the bid-ask spread on each exchange.

Augmented Model:

$$Spread_{i,j,t} = \alpha_i + \gamma_t + \beta_1 Latency_t + \beta_2 Liquidity_{i,t} + \beta_3 (KAOPEN_i \times Vol_t) + \beta_4 (Fees_{i,j} \times Vol_t) + \epsilon_{i,t}$$

Where:

- Capital openness ($KAOPEN_i$) is derived from the Chinn-Ito Index (Chinn & Ito, 2006)
- Capital openness x BTC Volatility interaction ($KAOPEN_i \times Vol_t$) captures whether restrictive capital regulation deepens arbitrage spreads during volatile periods.
- Fees interaction ($Fees_{i,j} \times Vol_t$) tests whether high exchange fees amplify arbitrage frictions when volatility is high.

By interacting structural characteristics with volatility, the model identifies how institutional frictions condition market dynamics.

3.4 Bitcoin Beta Estimation

In order to test whether global demand shocks transmit into regional spreads, a measure of buying pressure is created. To extract short-term demand shocks from the U.S. Bitcoin price series, the Hodrick-Prescott filter is used. This technique decomposes the log price into a smooth long-term trend and a cyclical component. The cyclical deviations are interpreted as buying pressure, reflecting temporary shifts from equilibrium prices driven by shifts in global demand.

$$BuyingPressure_t = \log(P_{US,t}) - Trend_{US,t}$$

Estimate country specific beta using regression:

$$Spread_{c,t} = \alpha_c + \beta_c BuyingPressure_{t-k} + \epsilon_t$$

Where:

- β_c = Bitcoin beta, sensitivity of country c spread to global demand shocks

Note the inclusion of k lags. Without lags, the same U.S. price could be influencing both the spread and the explanatory variable at time. Lags also capture delays in asset transfer, regulatory barriers, and information diffusion. Testing multiple lags will show whether some markets are systematically slower to incorporate global shocks, particularly those with tighter capital controls.

3.5 Correlation of Arbitrage Spreads and Capital Controls

The co-movement of spreads across countries is studied using correlations. The baseline specification is:

$$\rho_{i,j} = \text{Corr}(\text{Spread}_{i,t}, \text{Spread}_{j,t})$$

Use capital control index:

$$\text{Capital Openness}_{i,j} = CCI_i \cdot CCI_j$$

Where:

- CCI_i = capital control index for country i

Regress correlation of arbitrage spreads on capital openness:

$$\rho_{i,j} = \alpha + \beta(CCI_i \cdot CCI_j) + \epsilon$$

3.6 Measuring Arbitrage Profits

Determine whether arbitrage still exists after accounting for costs.

$$\text{Net Profit}_{i,j,t} = P_{\text{sell}} - P_{\text{buy}} - C_t$$

Where C_t includes:

- Trading, withdrawal, network fees
- Blockchain confirmation delays
- FX conversion slippage or cost of hedging

4. Data and Descriptive Statistics

4.1 Data Sources

The dataset combines real-time order book and price data from Kraken and a range of regional exchanges as shown in Table 1 below.

Table 1: Exchange and Country

Exchange	Country
Kraken	United States
Binance	United States
Luno	South Africa
Upbit	South Korea
Novadax	Brazil
Bitflyer	Japan
BtcTurk	Turkey
Bitso	Mexico
Coins.ph	Phillipines
Bithumb	South Korea

Data was collected at minute frequency over the sample period (approx. 22,570 rows, spanning July 2025). This high-frequency structure allows for the computation of arbitrage spreads between Kraken (as a global reference) and local exchanges.

Alongside spreads, Indicators of capital openness and other institutional characteristics were collected, which serve as independent variables in later regressions. The data file contains 155 variables, including raw exchange prices (open, high, low, close), bid-ask quotes, traded volumes, and multiple lagged spread measures. A full breakdown of the dataset statistics can be found in the Appendix.

4.2 Summary Statistics

The table located in the Appendix shows key descriptive statistics for the main variables.

The average Kraken close price is 118,210 USD with a tight distribution (standard deviation of 890). Prices range between 114,758 and 120,994 USD, consistent with

relatively stable BTC/USD trading over the short sample. Spread distributions vary strongly by exchange, but most exchanges cluster around 0 to $\pm 1\%$.

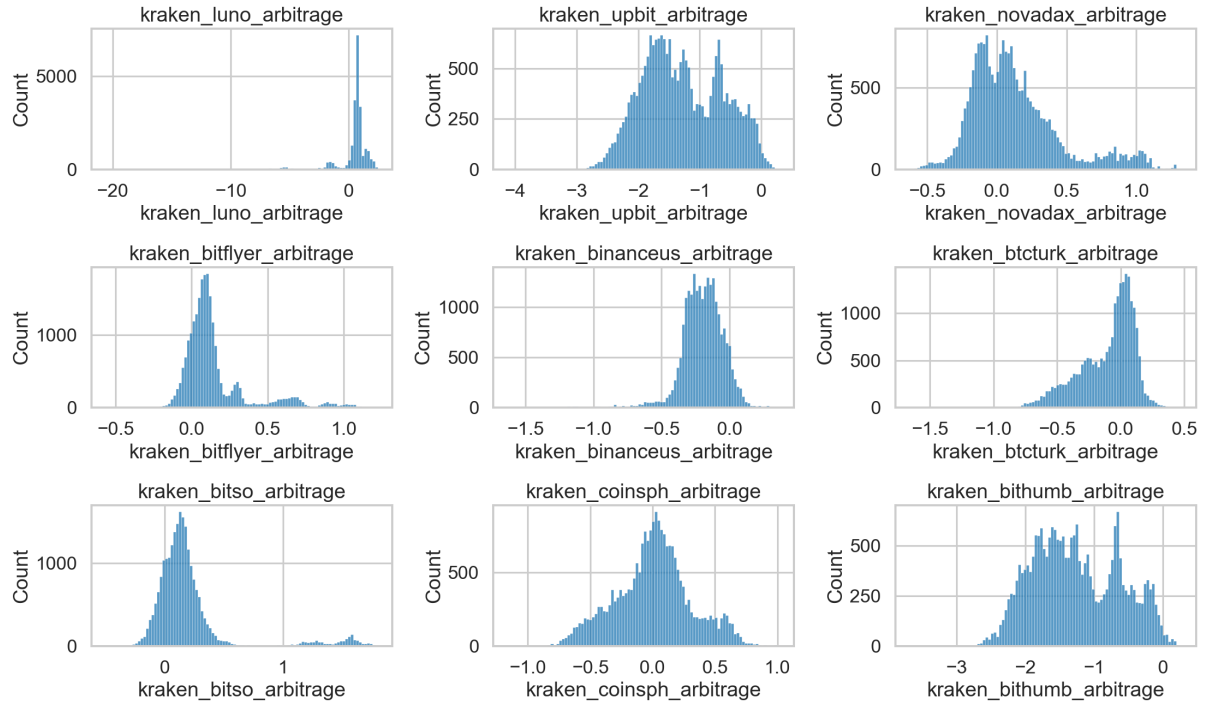
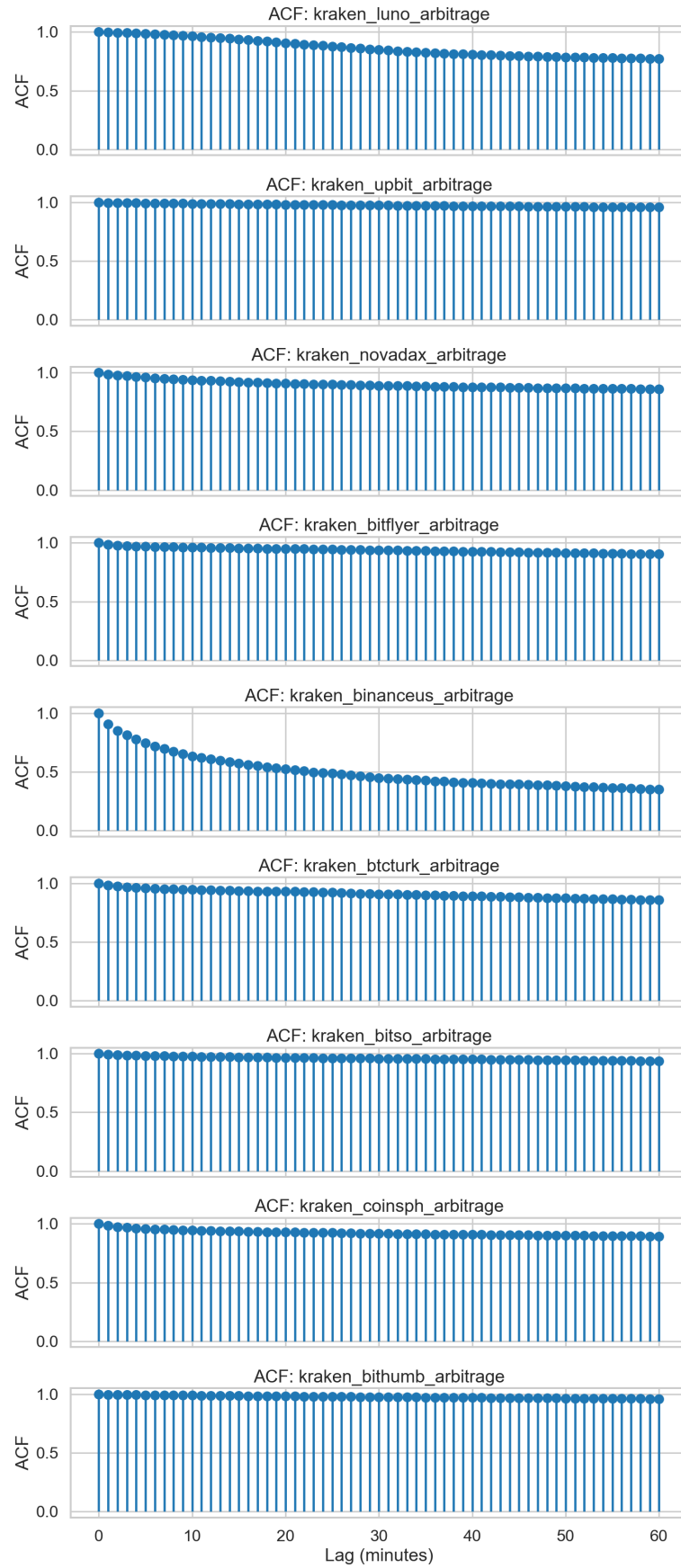


Figure 1: Spread Histograms for Exchanges

The spread histograms in Figure 1 above illustrate spread differences. Some markets (Bitflyer, Bitso, BinanceUS) show narrow, near normal distributions around zero, reflecting small and short lived arbitrage deviations. Others (Luno, Upbit, Bithumb) display wide or skewed distributions, suggesting more persistent or asymmetric frictions.

The autocorrelation functions in Figure 2 below highlight persistence. Most exchanges, with the exception of the other U.S. exchange Binance, show autocorrelations close to 1 even at long lags, indicating spreads decay very slowly.

Figure 2: ACF for Different Exchanges



The correlation heatmap in Figure 3 presents co-movements across exchanges.

High correlations (0.5-0.6): Novadax (Brazil), Bitflyer (Japan), and Bitso (Mexico) are strongly linked, showing they are more integrated with global flow.

Moderate correlations (0.3-0.5): Upbit and Bithumb (Korea) correlate strongly with each other and moderately with other markets, suggesting partial segmentation.

Weak correlations (<0.2): Luno (South Africa) and BtcTurk (Turkey) exhibit weak co-movements, consistent with their more restrictive environments.

This heterogeneity indicates the presence of institutional frictions.

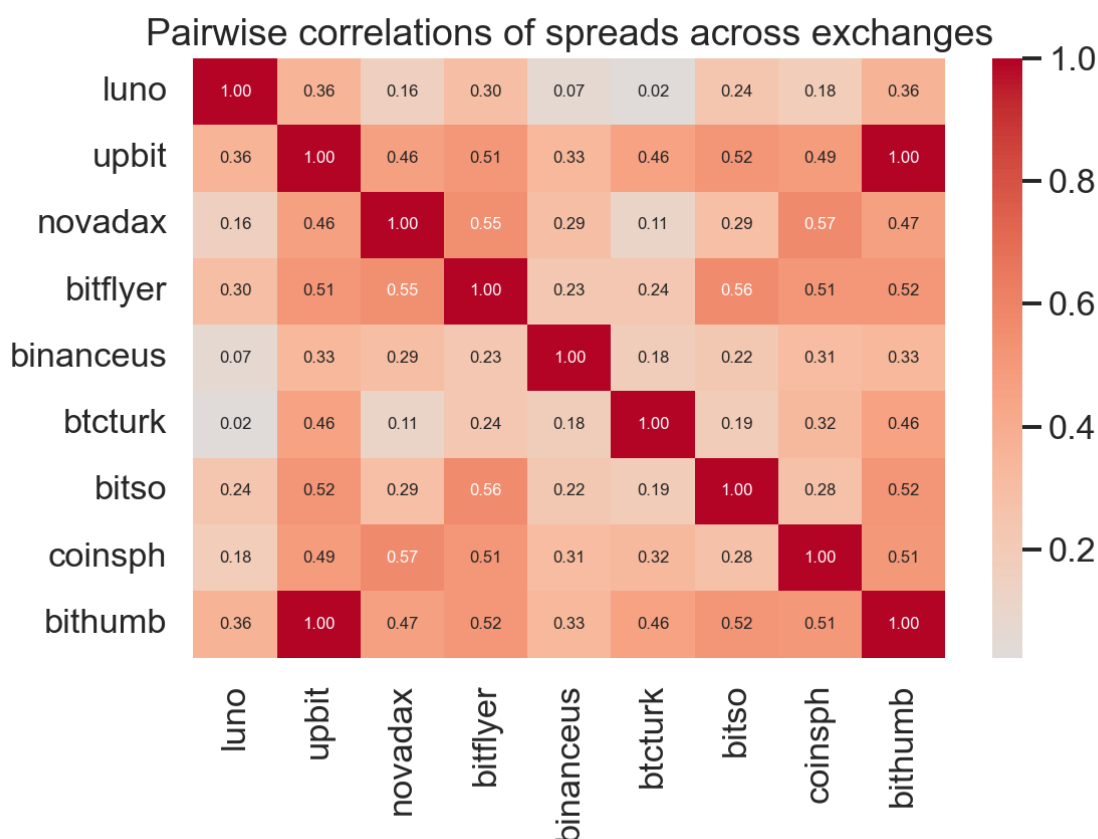


Figure 3: Correlations between Exchanges

Figure 4 shows the evolution spreads over time. Most markets fluctuate around zero. Luno exhibits extreme, short-lived negative spreads (up to -20%), this is a result of a period of low trading volume and a liquidity shortage. Upbit consistently trades below

Kraken by 1-2%, suggesting structural price discounting. BtcTurk and Bitso track Kraken more closely, with deviations typically <1%. These time series patterns reinforce the view that certain exchanges are structurally segmented, while others remain closely integrated with global prices.

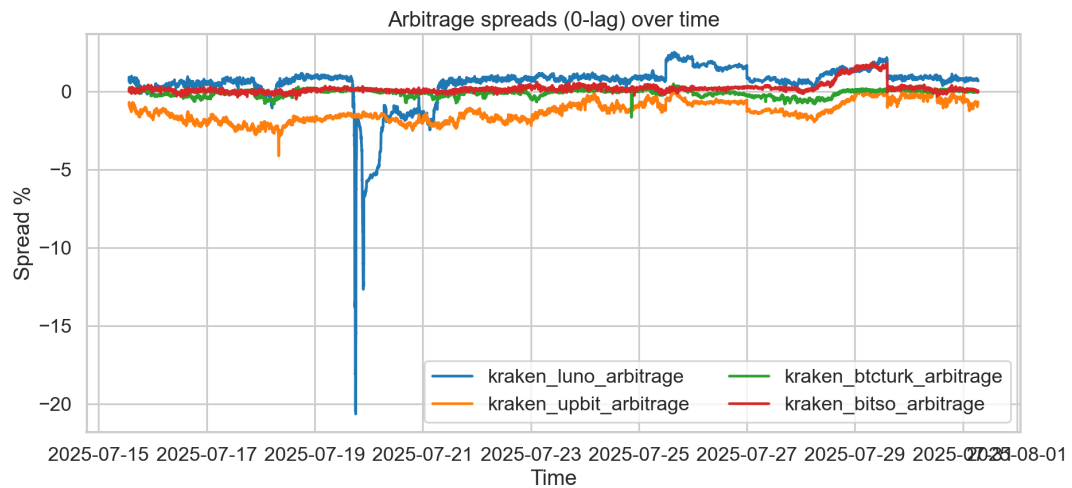


Figure 4: Arbitrage Spreads Over Time

5. Results

5.1 Panel Regressions

The regressions were estimated on 203040 observations covering 9 exchanges.

Table 2: Baseline Model and Augmented Model Regression Results

Robust t-statistics are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Variable	Baseline Model	Augmented Model
Latency premium	2.9201** (1.2517)	29.0832*** (1.7048)
Liquidity premium	-136.7081*** (1.1913)	-136.9844*** (1.1894)
KAOPENxVol	N/A N/A	-115.6871*** (4.4695)
FeesxVol	N/A N/A	-991.0288*** (51.8873)
Exchange Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
N	203040	203040
Adj. R-sq	0.659	0.660

Baseline Model:

The baseline regression included both exchange fixed effects and time fixed effects, alongside two explanatory variables, a latency premium, representing transfer and settlement risk and a liquidity premium, capturing depth and tightness of order books.

The model achieved an R-squared of 0.6595, suggesting that approximately 66% of the variation in arbitrage spreads is explained by the included regressors and fixed effects. The adjusted R-squared, 0.6589, is nearly identical, implying a robust fit without overfitting.

The latency premium has a positive and statistically significant coefficient of 2.92 ($p = 0.0197$). This indicates that spreads widen as latency increases, consistent with theory. Arbitrageurs facing longer transfer or confirmation times require additional compensation for risk exposure during volatile periods. Even a slight increase in expected latency translates into higher spreads.

The liquidity premium is negative and highly significant (-136.71 , $p < 0.0001$). This strong effect confirms that higher liquidity reduces arbitrage frictions. Exchanges with greater market depth exhibit lower arbitrage spreads relative to those with thinner liquidity.

The baseline regression shows that latency and liquidity are two key influencers of cross-exchange arbitrage spreads, with liquidity having a particularly strong influence.

Augmented Model:

To capture the role of structural, time invariant frictions, those being capital openness and fee structures, the regression was augmented with interaction terms between volatility and these exchange specific characteristics. Because fees and capital openness are constant within exchanges, they are absorbed by exchange fixed effects in their raw form. However, by interacting them with time varying volatility, we test whether these characteristics condition how spreads respond under stressed market conditions.

The augmented regression gives an R-squared of 0.6606, slightly higher than the baseline.

Latency premium = 29.08 ($p < 0.0001$)

The effect of latency increases strongly relative to the baseline. This shows that once volatility interactions are accounted for, latency risk becomes a strong driver of spreads. Arbitrageurs thus seem to penalize latency heavily in volatile periods, where the risk of unfavourable price movement during transactions is greatest.

Liquidity premium = -136.99 ($p < 0.0001$)

The liquidity effect remains the same and strongly negative. This confirms that liquidity consistently narrows spreads.

KAOPEN x Volatility = -115.69 ($p < 0.0001$)

Negative and highly significant. Therefore higher KAOPEN values (more capital openness) reduces spread widening during volatility spikes. Restrictive capital environments create greater spread persistence in volatile periods. This shows evidence that capital controls act as a constraint on arbitrage efficiency when it matters most.

Fees x Volatility = -991.03 ($p < 0.0001$)

Also negative and highly significant. High-fee exchanges suffer more during volatile periods, as arbitrageurs cannot absorb costs quickly enough. Spreads widen more strongly on exchanges with high transaction costs when volatility rises.

Table 3: Augmented and Baseline Model Fixed Effects

Exchange	Fixed Effects (Baseline)	Fixed Effects (Augmented)
Bitflyer	0.036	0.081
Bithumb	-1.40	-1.37
Bitso	0.13	0.11
Btcturk	-0.21	-0.31
Coinsph	0.05	0.007
Luno	0.43	0.39
Novadax	0.42	0.45
Upbit	-1.41	-1.35

Exchange Fixed Effects:

The exchange fixed effects capture time invariant, structural differences in arbitrage spreads across exchanges. Fixed effects for South Korea (Bithumb and Upbit) are strongly negative across both models. This suggests that Korean exchanges systematically trade at discounts relative to Kraken. This is surprising considering that Korea is well known for trading at prices significantly higher than global exchanges, hence the term “Kimchi Premium”. The discount shows the segmentation in the Korean market, and is contributed to due to weak investor sentiment in South Korea, as well as a growth in demand for assets on foreign platforms. South Africa (Luno) and Brazil’s (Novadax) fixed effects are significantly positive. These markets show systematically higher spreads. Mexico (Bitso) and Phillipines (Coins.ph) have small but positive fixed effects. These exchanges experience slightly higher spreads, but not as extreme as South Africa or Brazil. Turkey (BtcTurk) is slightly negative. This suggests that Turkish markets trade at slightly narrower spreads. Japan (Bitflyer) is close to zero in both models. Japanese markets appear tightly integrated, with spreads close to the global baseline.

5.2 Bitcoin Beta

Table 4: Regression Results for Bitcoin Beta

Robust t-statistics are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Variable	BR	JP	KR	MX	PH	TR	US	ZA
Constant	0.1293*** (0.0021)	0.1517*** (0.0015)	-1.2674*** (0.0030)	0.2023*** (0.0023)	0.0061*** (0.0020)	-0.1022*** (0.0014)	-0.2009*** (0.0011)	0.5031*** (0.0095)
Beta	-30.537*** (2.1659)	-10.118*** (1.5216)	-34.545*** (3.0322)	-17.891*** (2.3362)	-24.801*** (2.0393)	-12.631*** (1.4539)	-38.594*** (1.0782)	-26.004*** (9.6576)
N	22570	22570	45140	22570	22570	22570	22570	22570

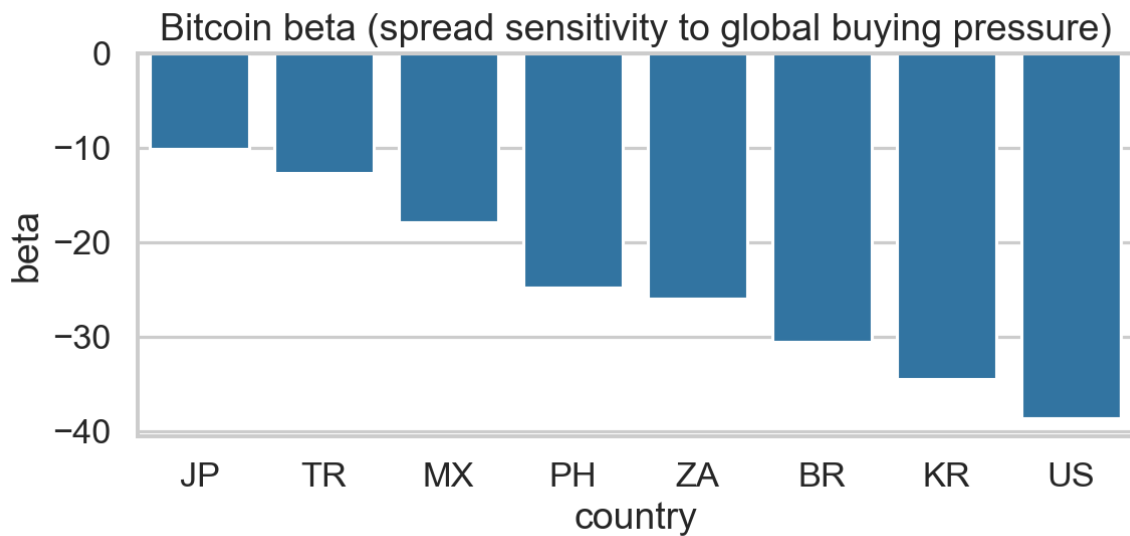


Figure 5: Bitcoin Beta per Country

Across all countries, the estimated betas are negative. This indicates that when U.S. prices rise above trend, foreign spreads compress relative to the U.S. benchmark exchange (Kraken). In other words, U.S. demand shocks push U.S. prices upward first, and foreign markets subsequently adjust, narrowing the measured spread. The negative sign is thus consistent with arbitrage dynamics. U.S. shocks flow through outward, and local markets catch up with some delay.

The magnitudes of the betas, which range from roughly -10 (Japan) to -38 (U.S.), are largely negative. This partly reflects the construction of the buying pressure measure, it also reflects the strong co-movement of Bitcoin markets, where even small U.S. deviations are mirrored abroad. The relative sizes of the betas are meaningful. Countries with smaller betas (Japan, Turkey) are more tightly integrated with U.S. markets, while those with larger betas (South Africa, Brazil, Korea) display heightened sensitivity.

Comparing these estimates to the Chinn-Ito index of capital account openness is useful. Countries with low openness (South Africa, Brazil, Philippines) exhibit large betas, while Japan and Mexico, with more open capital accounts, show smaller betas. Korea is an outlier, despite being classified as highly open, it shows one of the largest betas, reflecting the possibility of other restrictions and cryptocurrency specific frictions perhaps not accounted for in the index. The U.S. beta, estimated

using Binance vs. Kraken, is the most negative by construction, since the buying pressure measure itself is U.S. defined.

The Bitcoin beta measure reflects the effective segmentation in crypto markets. Larger betas in restricted markets suggest that institutional frictions amplify the impact of global shocks.

5.3 Correlation of Arbitrage Spreads and Capital Controls

Table 5: Regression Results of Capital Controls and Arbitrage Spreads

Robust t-statistics are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Variable	Coefficient
Constant	0.3614*** (11.807)
Capital Openness (CCI_i × CCI_j)	0.0148 (1.388)
N	36
R-squared	0.0536
Adj. R-squared	0.0258
F-statistic	1.9263
Prob(F-statistic)	0.1742

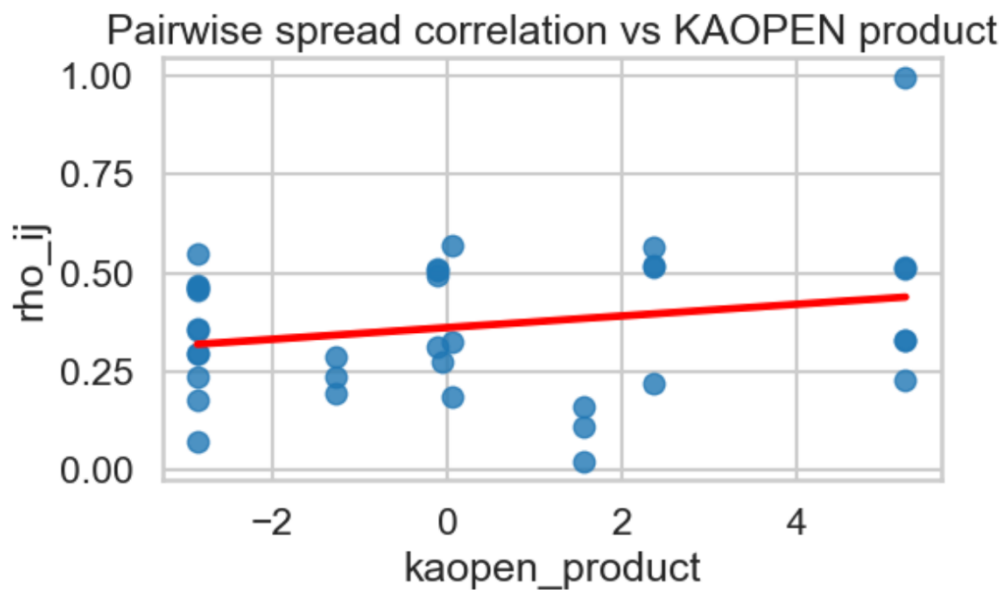


Figure 6: Spread Correlation and Capital Controls

With regards to the regression show in Table 4, the constant is highly significant and implies a baseline pairwise correlation of approximately 0.36, even when both markets are highly closed. This indicates that Bitcoin markets display a degree of co-movement across borders irrespective of institutional restrictions.

The coefficient on the KAOPEN product is positive (0.0148) but statistically insignificant ($p = 0.174$). The direction of the effect is consistent with theoretical predictions, greater openness is associated with somewhat higher spread correlations. However, the lack of statistical significance suggests that this relationship is weak and not robust across the sample. The model explains only 5.3% of the variation in spread correlations highlighting that capital openness alone is not sufficient to capture the drivers of international co-movement in arbitrage spreads.

The relationship is visualised in Figure 6. The regression line slopes upward, consistent with the positive coefficient, but the scatter of points reveals substantial dispersion. Some highly open market pairs still exhibit weak correlations, while some relatively closed market pairs display moderate or high correlations. A small number of outliers with very high correlations appear to drive the slope

5.4 Measuring Arbitrage Profits

Table 6: Profitable Arbitrage Scenarios

Exchange	Mean Profit	Standard Profit	Profit Rate	P95 Profit	Max Profit	Average Cost	Average Spread
Bitflyer	-0.21	0.23	15.6	0.33	0.82	0.41	0.2
Bithumb	-0.29	0.06	0.0	-0.17	-0.12	0.36	0.07
Bithumb	0.99	0.65	91.76	1.98	3.81	0.36	1.35
(Reverse)							
Bitso	-0.09	0.37	13.49	0.97	1.44	0.36	0.26
Btcturk	-0.3	0.06	0.05	-0.17	0.1	0.38	0.08
Coinsph	-0.18	0.19	22.36	0.19	0.53	0.41	0.23
Luno	0.26	0.46	72.49	1.23	1.95	0.56	0.82
Novadax	-0.46	0.29	13.78	0.18	0.47	0.76	0.3
Upbit	-0.39	0.06	0.0	-0.26	-0.15	0.46	0.07
Upbit	0.91	0.66	89.33	1.93	4.18	0.46	1.37
(Reverse)							

Table 6 summarises estimated arbitrage profitability across exchanges. The table reports mean profit per trade, profit variability, profit rates (the proportion of trades yielding positive returns), the 95th percentile of profits (P95), the maximum observed profit, as well as average trading costs and average spreads. These indicators provide an overview of whether arbitrage opportunities exist, whether they are systematic or merely occasional, and whether they survive once transaction costs are taken into account. Note that for the South Korean exchanges, Upbit and

Bithumb, reverse direction trades where taken into account (from local exchange to Kraken) due to the systemic discounting shown in the data of the Korean markets.

For several exchanges, the results suggest that arbitrage is largely unprofitable. This is the case for Bithumb, Btcturk, Novadax, Coins.ph, and Upbit, all of which record negative mean profits ranging from -0.18% to -0.46%. Profit rates in these markets are negligible. Btcturk's profit rate is only 0.05%, while both Bithumb and Upbit (in the forward direction) register virtually zero profitable trades. This implies that, once transaction costs are incorporated, these markets do not support sustainable arbitrage.

A second group of exchanges shows slightly better performance but still falls short of consistent profitability. Bitflyer records a mean profit of -0.21%, but with a profit rate of 15.6% and occasional large trades yielding up to 0.82%. Bitso follows a similar pattern, with a mean profit of -0.09%, a profit rate of 13.5%, and a 95th percentile profit of 0.97%. In both cases, profitable opportunities exist but are infrequent and generally small in magnitude. These findings are consistent with more integrated markets where spreads are rapidly arbitrated away.

The most striking evidence of profitable arbitrage appears in the reverse direction for Bithumb and Upbit, both located in South Korea. In these cases, mean profits are high (0.99% for Bithumb and 0.91% for Upbit), and profit rates exceed 89%.

Maximum profits are substantial, reaching 3.81% and 4.18% respectively, with 95th percentile profits close to 2%. These results indicate that arbitrage opportunities are not only frequent but also systematic.

Another exchange where arbitrage appears consistently profitable is Luno (South Africa). Here, mean profits are positive (0.26%) and the profit rate is very high at 72.5%. Maximum profits reach 1.95%, and even the 95th percentile of profits is comfortably above 1%. At the same time, Luno faces high costs (0.56%) and spreads (0.82%), suggesting that local frictions are severe. The persistence of profits despite these costs reinforces the interpretation that institutional and liquidity constraints prevent arbitrageurs from fully exploiting these opportunities.

6. Robustness Checks

6.1 Lag Implementation

As a robustness check, both the baseline and augmented regression models were run, lagging the arbitrage values by 15, 30, 45, 60, 90, and 120 minute intervals.

Table 7: Baseline Model and Augmented Model Lagged Regression Results

Robust t-statistics are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Model	Latency Premium	Liquidity Premium	R-squared	N
Baseline (15min)	2.0315** (2.307)	-136.6920*** (-114.754)	0.660	203040
Augmented (15min)	18.9746*** (15.119)	-136.9779*** (-115.155)	0.661	203040
Baseline (30min)	2.9201** (2.333)	-136.7081*** (-114.752)	0.660	203040
Augmented (30min)	29.0832*** (17.060)	-136.9844*** (-115.171)	0.661	203040
Baseline (45min)	1.9390 (1.196)	-136.6648*** (-114.725)	0.660	203040

Augmented (45min)	25.8915*** (13.048)	-136.7769*** (-114.988)	0.661	203040
Baseline (60min)	1.7566 (0.899)	-136.6499*** (-114.727)	0.660	203040
Augmented (60min)	24.4558*** (10.841)	-136.7045*** (-114.933)	0.660	203040
Baseline (90min)	5.9412** (2.215)	-136.6805*** (-114.752)	0.660	203040
Augmented (90min)	29.0628*** (9.953)	-136.7348*** (-114.954)	0.660	203040
Baseline (120min)	4.4303 (1.355)	-136.6559*** (-114.737)	0.660	203040
Augmented (120min)	27.5953*** (7.939)	-136.6216*** (-114.852)	0.660	203040

In the baseline model, the latency premium is small in magnitude and is only sometimes significant. This suggests that when latency is modelled alone, its estimated effect is weak and unstable across lag choices.

Once the regression is augmented with the additional factors, the premium jumps substantially (19-29) and is highly significant (t-stats > 15 for all). This indicates that when institutional frictions are included, the role of latency becomes stronger and more robust.

For the liquidity premium, both baseline and augmented models show a large, negative coefficient that is highly significant. The stability of this coefficient across lag structures and model specifications suggests that liquidity consistently drives spreads lower and deeper markets converge more quickly, regardless of lags or controls.

R-squared is stable around 0.660-0.661 across all lag structures and specifications. This indicates that adding lags or augmenting the model with controls does not change explanatory power much overall, but it redistributes the power of the variables.

6.2 Leave-one-out

As a robustness check, both the baseline and augmented regression models were run multiple times, with each iteration excluding a specific exchange to analyze the effects of its removal.

Table 8: Baseline and Augmented Leave-one-out

Robust t-statistics are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1%, respectively.

Excluded Exchange	Model	Latency Premium	Latency t-stat	R-squared	N
luno	Baseline	1.6021***	(182.348)	0.688	60160
luno	Augmented	1.6021***	(182.348)	0.688	60160
upbit	Baseline	0.0825***	(7.155)	0.442	60160

upbit	Augmented	0.0825***	(7.155)	0.442	60160
novadax	Baseline	-1.8800***	(-186.635)	0.528	60160
novadax	Augmented	-1.8800***	(-186.635)	0.528	60160
bitflyer	Baseline	-1.8581***	(-182.539)	0.517	60160
bitflyer	Augmented	-1.8581***	(-182.539)	0.517	60160
binanceus	Baseline	-1.8651***	(-182.025)	0.525	60160
binanceus	Augmented	-1.8651***	(-182.025)	0.525	60160
btcturk	Baseline	-1.8504***	(-181.177)	0.524	60160
btcturk	Augmented	-1.8504***	(-181.177)	0.524	60160
bitso	Baseline	-1.8512***	(-183.380)	0.516	60160
bitso	Augmented	-1.8512***	(-183.380)	0.516	60160
coinsph	Baseline	-1.8547***	(-182.900)	0.525	60160
coinsph	Augmented	-1.8547***	(-182.900)	0.525	60160
bithumb	Baseline	-1.8510***	(-192.333)	0.441	60160

bithumb	Augmented	-1.8510***	(-192.333)	0.441	60160
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When exchanges are excluded one by one, the latency premium remains consistently significant, though its size and sign vary depending on the market removed. For example, when Luno is excluded, the coefficient is positive and very large (1.60 with a t-stat above 180), while excluding Novadax yields a strongly negative coefficient (-1.88, t-stat 186). Excluding Upbit produces a much smaller positive coefficient (0.08), but still statistically significant. These patterns suggest that the magnitude of the latency premium is heavily influenced by which market is in the sample, but the fact that it never becomes insignificant indicates that latency is a systematic determinant of spreads across all markets.

R-squared ranges between 0.44 (when Upbit is excluded) and 0.69 (when Luno is excluded), showing that explanatory power depends on which exchange is dropped. However, the fit remains solid across all scenarios, confirming robustness.

These results demonstrate that the main findings are robust to leave-one-out analysis. The variation across exclusions also highlights that certain markets, such as Korea (Upbit) or South Africa (Luno), carry strong weight in determining the size of the effect.

7. Conclusion

This thesis set out to investigate whether Bitcoin behaves as a unified global asset or whether institutional frictions and capital controls create persistent arbitrage opportunities across regions. Using high-frequency order book data from Kraken and nine regional exchanges, arbitrage spreads were constructed, their persistence modeled through panel regressions, and their profitability assessed after costs. The main findings can be summarized as follows.

Liquidity and latency risks emerged as consistent drivers of spreads, with thin order books and settlement delays widening gaps across exchanges. Capital controls and fee structures significantly amplify inefficiencies, particularly during periods of volatility, confirming the importance of institutional frictions in market segmentation. While most exchanges displayed rapid convergence to global benchmarks, systematic and profitable arbitrage opportunities were found in South Korea and South Africa, highlighting the role of restrictive financial environments in sustaining segmentation.

These findings extend the existing literature. Prior studies such as Makarov and Schoar (2020) documented persistent arbitrage spreads, attributing them largely to withdrawal frictions and latency. This thesis supports their conclusions by finding that latency premiums are significant, but it goes further by showing that the effect is conditional on institutional characteristics. Similarly, the observation that higher liquidity narrows spreads is consistent with Baur and Dimpfl (2019), who emphasized the role of depth in reducing inefficiencies.

Most importantly, this work links spread persistence directly to measures of capital account openness, extending the insights of Pieters and Vivanco (2017) and Liu and Tsyvinski (2021). While previous studies have suggested that restrictive regimes inflate regional Bitcoin prices, the present analysis shows that such restrictions not only raise levels but also slow the speed of convergence, particularly under volatility.

Several limitations must be acknowledged. The dataset, though high-frequency, covers only a one month sample period. Market conditions in July 2025 may not

reflect broader cycles of liquidity, sentiment, or regulatory shocks. A longer horizon could capture structural changes and changing patterns over time. Additionally, the analysis is limited to a set of nine exchanges. While diverse, they do not exhaust the global universe of crypto markets. Additional exchanges, particularly in regions with informal markets or stronger enforcement, might alter the findings. Furthermore, the Chinn-Ito index, while widely used, may not fully capture cryptocurrency specific restrictions such as domestic banking prohibitions or outright bans. Finally, the profitability analysis is based on simulated trades net of transaction costs, but does not account for balance sheet constraints of arbitrageurs, limits to ability to move capital, or risks associated with sudden regulatory changes.

The results have several implications. For traders, the persistence of profitable opportunities in South Africa and South Korea indicates that arbitrage can be profitable, but only in environments where institutional constraints limit competition. However, such opportunities may be difficult to exploit due to capital restrictions, suggesting that profits are more theoretical than practical for many global traders.

For regulators, the findings are interesting. Capital controls and exchange restrictions are often justified as stabilizing measures, but in cryptocurrency markets they appear to create segmentation and inefficiencies, which may encourage different channels of moving capital. This highlights the need for regulators to consider unintended consequences when designing restrictions in a world where digital assets provide alternative channels for cross-border capital flow.

For exchanges, the evidence suggests that liquidity provision remains a critical factor for integration. Exchanges with deep order books are more tightly linked to global benchmarks, while those with shallow markets display persistent deviations. This emphasizes the importance of developing robust market-making infrastructure in emerging regions.

Finally, for the broader financial system, the results caution against assuming that cryptocurrencies automatically constitute a “borderless” form of money. Institutional realities remain central. Even decentralized technologies are not entirely insulated

from national regulations, and their integration with traditional financial infrastructure subjects them to similar frictions observed in equity, bond, and FX markets.

Future research could extend this study in several ways. Expanding the dataset across multiple years would allow for testing the stability of results during bull and bear cycles, as well as in response to regulatory shocks. Incorporating additional institutional measures could provide a richer account of why spreads persist. An important extension would be to consider other cryptocurrency assets.

In conclusion, this thesis demonstrates that while Bitcoin is globally traded, its market is not frictionless. Liquidity, latency, and particularly capital controls continue to generate segmentation and arbitrage opportunities, limiting its integration as a unified global asset. These findings not only deepen the understanding of cryptocurrency market structure but also touch on broader themes in international finance, institutions still matter, even in decentralized systems.

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9. Appendix

Table 9: Summary Statistics for Dataset

	count	mean	median	std	var	min	25%	50%	75%	max
id	225	1128	1128	6515,	4,2E		5643,	1128	1692	2257
	70	5,5	5,5	54	+07	1	25	5,5	7,8	0
kraken_open	225	1182	1182	889,9	7919	1147	1177	1182	1187	1209
	70	10	00	18	53	58	88	00	50	95
kraken_high	225	1182	1182	889,4	7911	1147	1177	1182	1187	1209
	70	15	02	48	18	58	91	02	56	95
kraken_low	225	1182	1182	890,4	7928	1147	1177	1182	1187	1209
	70	05	00	07	24	33	84	00	50	95
kraken_close	225	1182	1182	889,8	7917	1147	1177	1182	1187	1209
	70	10	00	15	70	58	88	00	50	95
kraken_volume	225	0,272		1,655	2,739				0,046	61,73
	70	23	0	17	58	0	0	0	06	47
kraken_ask	225	1182	1182	889,7	7917	1147	1177	1182	1187	1209
	70	10	00	78	05	59	88	00	50	95
kraken_bid	225	1182	1182	889,8	7917	1147	1177	1182	1187	1209
	70	10	00	15	71	58	88	00	50	95
kraken_ask_volume	225	23,00	22,72	11,23	126,1		15,80	22,72	30,50	
	70	93	35	25	69	0,046	28	35	35	77,03
kraken_bid_volume	225	21,52		10,91	119,1		14,47		28,38	77,46
	70	5	21,84	71	83	0,057	73	21,84	78	2
kraken_volume_24h	225	997,4	1023,	411,7	1695	260,6	705,9	1023,	1210,	2340,
	70	47	73	41	31	16	22	73	19	79
kraken_spread_pct	225	0,000	8,5E-	0,000	6,5E-	8,3E-	8,4E-	8,5E-	8,5E-	0,037
	70	12	05	81	07	05	05	05	05	92
luno_open	225	2107	2113	3445	1,2E	1659	2097	2113	2127	2166
	70	116	576	8	+09	999	664	576	086	002
luno_high	225	2107	2113	3381	1,1E	1730	2098	2113	2127	2166
	70	439	637	0,6	+09	000	141	637	325	003
luno_low	225	2106	2113	3531	1,2E	1656	2097	2113	2126	2166
	70	696	369	8,7	+09	328	310	369	959	002
luno_close	225	2107	2113	3442	1,2E	1660	2097	2113	2127	2166
	70	103	579	6,7	+09	000	847	579	103	003
luno_volume	225	0,035	0,003	0,109	0,012		0,000	0,003	0,024	3,665
	70	3	04	62	02	0	23	04	16	2
luno_ask	225	2107	2113	3411	1,2E	1660	2098	2113	2127	2166
	70	675	812	5,9	+09	000	716	812	425	002
luno_bid	225	2106	2113	3511	1,2E	1658	2097	2113	2126	2165
	70	326	277	8,9	+09	469	021	277	704	541
luno_ask_volume	225	1,331	1,259	0,490	0,240	0,149	1,015	1,259	1,547	9,719
	70	25	19	59	68	26	16	19	72	84
luno_bid_volume	225	1,000	0,876	0,558	0,311	0,097	0,691	0,876	1,138	7,327
	70	05	46	01	38	65	73	46	77	96
luno_volume_24h	225	52,59	46,28	22,74	517,1	11,12	39,62	46,28	64,42	108,7
	70	3	16	01	14	6	28	16	06	1
luno_spread_pct	225	0,064	0,023		0,023	4,6E-	4,7E-	0,023	0,090	8,189
	70	88	44	0,152	1	05	05	44	88	46
upbit_open	225	1,6E+	1,6E+	1132	1,3E	1,6E+	1,6E+	1,6E+	1,6E+	1,6E+
	70	08	08	032	+12	08	08	08	08	08
upbit_high	225	1,6E+	1,6E+	1131	1,3E	1,6E+	1,6E+	1,6E+	1,6E+	1,6E+
	70	08	08	689	+12	08	08	08	08	08
upbit_low	225	1,6E+	1,6E+	1131	1,3E	1,6E+	1,6E+	1,6E+	1,6E+	1,6E+
	70	08	08	975	+12	08	08	08	08	08
upbit_close	225	1,6E+	1,6E+	1131	1,3E	1,6E+	1,6E+	1,6E+	1,6E+	1,6E+
	70	08	08	825	+12	08	08	08	08	08
upbit_volume	225	0,172	0,051	0,427	0,182	3,1E-	0,014	0,051	0,161	13,51
	70	7	97	61	85	05	56	97	92	71
upbit_ask	225	1,6E+	1,6E+	1132	1,3E	1,6E+	1,6E+	1,6E+	1,6E+	1,6E+
	70	08	08	000	+12	08	08	08	08	08
upbit_bid	225	1,6E+	1,6E+	1131	1,3E	1,6E+	1,6E+	1,6E+	1,6E+	1,6E+
	70	08	08	167	+12	08	08	08	08	08

upbit_ask_volume	225	2,721	2,299	2,098	4,404	0,012	1,313	2,299	3,624	44,16
	70	16	29	72	61	45	68	29	79	55
upbit_bid_volume	225	1,589	1,167	1,808	3,270	0,014	0,665	1,167	2,024	46,84
	70	85	46	4	3	53	73	46	28	43
upbit_volume_24h	225	1844,	1845,	714,4	5103	656,8	1211,	1845,	2473,	3365,
	70	17	96	03	71	5	56	96	85	62
upbit_spread_pct	225	0,018	0,007	0,022	0,000	0,000	0,001	0,007	0,027	0,154
	70	05	43	95	53	61	24	43	91	57
novadax_open	225	6594	6604	5232,	2,7E	6380	6569	6604	6627	6701
	70	66	07	24	+07	00	65	07	01	36
novadax_high	225	6596	6605	5184,	2,7E	6381	6572	6605	6629	6701
	70	67	48	78	+07	00	06	48	26	37
novadax_low	225	6592	6602	5287,	2,8E	6371	6567	6602	6624	6701
	70	34	00	76	+07	13	14	00	44	36
novadax_close	225	6594	6604	5232,	2,7E	6380	6569	6604	6627	6701
	70	66	18	32	+07	00	76	18	02	36
novadax_volume	225	0,654	0,024	6,906	47,69	3,8E-	0,010	0,024	0,037	95,05
	70	03	13	4	83	05	5	13	81	49
novadax_ask	225	6602	6609	5171,	2,7E	6385	6580	6609	6637	6701
	70	81	98	99	+07	61	39	98	36	37
novadax_bid	225	6580	6590	5164,	2,7E	6371	6554	6590	6612	6696
	70	72	00	46	+07	13	79	00	42	05
novadax_ask_volume	225	0,131	0,088	0,114	0,013	0,018	0,038	0,088	0,187	1,160
	70	31	4	54	12	96	21	4	61	06
novadax_bid_volume	225	0,100	0,073	0,093	0,008	0,025	0,036	0,073	0,135	0,909
	70	85	39	78	8	03	76	39	03	25
novadax_volume_24h	225	74,26	76,20	12,39	153,5	47,68	64,22	76,20	84,55	104,6
	70	38	12	06	27	96	98	12	62	72
novadax_spread_pct	225	0,335	0,374	0,151	0,022	1,5E-	0,214	0,374	0,471	0,926
	70	19	21	54	97	06	23	21	73	68
bitflyer_open	225	1,8E+	1,8E+	1514	2,3E	1,7E+	1,7E+	1,8E+	1,8E+	1,8E+
	70	07	07	03	+10	07	07	07	07	07
bitflyer_high	225	1,8E+	1,8E+	1512	2,3E	1,7E+	1,7E+	1,8E+	1,8E+	1,8E+
	70	07	07	33	+10	07	07	07	07	07
bitflyer_low	225	1,8E+	1,8E+	1515	2,3E	1,7E+	1,7E+	1,8E+	1,8E+	1,8E+
	70	07	07	80	+10	07	07	07	07	07
bitflyer_close	225	1,8E+	1,8E+	1513	2,3E	1,7E+	1,7E+	1,8E+	1,8E+	1,8E+
	70	07	07	78	+10	07	07	07	07	07
bitflyer_volume	225	31,26	0,171	131,9	1742	0,000		0,171	0,574	942,4
	70	51	81	94	2,4	8	0,061	81	84	7
bitflyer_ask	225	1,8E+	1,8E+	1517	2,3E	1,6E+	1,7E+	1,8E+	1,8E+	1,8E+
	70	07	07	76	+10	07	07	07	07	07
bitflyer_bid	225	1,8E+	1,8E+	1514	2,3E	1,7E+	1,7E+	1,8E+	1,8E+	1,8E+
	70	07	07	50	+10	07	07	07	07	07
bitflyer_ask_volume	225	2,660	2,462	1,484	2,202	0,114	1,811	2,462	3,128	20,20
	70	76	65	09	53	15	72	65	7	16
bitflyer_bid_volume	225	2,154	2,003	1,114	1,242	0,117	1,391	2,003	2,699	24,12
	70	2	59	71	58	31	03	59	51	05
bitflyer_volume_24h	225	596,9	632,6	202,4	4097	163,4	509,2	632,6	739,2	1074,
	70	7	58	2	3,9	23	32	58	76	6
bitflyer_spread_pct	225	0,034	0,032	0,054	0,002	7,701	0,022	0,032	0,044	0,142
	70	65	89	52	97	9	62	89	2	76
binanceus_open	225	1181	1181	854,2	7297	1151	1177	1181	1187	1200
	70	56	35	77	88	30	02	35	06	00
binanceus_high	225	1181	1181	854,2	7297	1151	1177	1181	1187	1200
	70	56	35	43	31	30	02	35	06	00
binanceus_low	225	1181	1181	854,1	7295	1151	1177	1181	1187	1200
	70	55	35	11	06	30	02	35	06	00
binanceus_close	225	1181	1181	854,1	7295	1151	1177	1181	1187	1200
	70	55	35	62	92	30	02	35	06	00
binanceus_volume	225	0,000		0,009	8,6E-					0,795
	70	44	0	28	05	0	0	0	0	26
binanceus_ask	225	1182	1183	848,8	7206	1151	1178	1183	1188	1200
	70	87	07	83	03	30	64	07	37	00
binanceus_bid	225	1179	1179	832,1	6924	1151	1175	1179	1185	1200
	70	72	95	16	18	30	49	95	00	00

binanceus_ask_volume	225	0,761	0,514	0,635	0,403	0,029	0,222	0,514	1,200	3,087
	70	37	51	4	73	41	62	51	39	39
binanceus_bid_volume	225	0,320	0,280	0,265	0,070	0,018	0,160	0,280	0,407	3,241
	70	44	02	22	34	41	72	02	1	92
binanceus_volume_24h	225	2,758	2,343	1,326	1,758	0,488	1,706	2,343	3,548	6,362
	70	83	5	1	54	72	8	5	76	41
binanceus_spread_pct	225	0,266	0,276	0,148	0,022	8,3E-	0,160	0,276	0,359	1,117
	70	46	89	56	07	06	44	89	5	08
btcturk_open	225	4776	4779	3250	1,1E	4654	4760	4779	4797	4870
	70	617	401	7,5	+09	818	499	401	847	179
btcturk_high	225	4776	4779	3251	1,1E	4654	4760	4779	4797	4871
	70	713	495	6,3	+09	818	610	495	937	676
btcturk_low	225	4776	4779	3257	1,1E	4650	4760	4779	4797	4870
	70	464	228	0	+09	000	330	228	739	179
btcturk_close	225	4776	4779	3257	1,1E	4650	4760	4779	4797	4871
	70	568	355	4,1	+09	000	422	355	860	676
btcturk_volume	225	21,38	22,09	19,36	375,1		0,008	22,09	40,63	64,61
	70	21	47	93	7	0	75	47	81	37
btcturk_ask	225	4777	4780	3256	1,1E	4654	4761	4780	4798	4874
	70	644	402	5	+09	817	506	402	841	899
btcturk_bid	225	4775	4778	3254	1,1E	4654	4759	4778	4796	4867
	70	602	417	2,9	+09	001	575	417	871	668
btcturk_ask_volume	225	2,633	2,324	1,616	2,614	0,104	1,538	2,324	3,414	9,009
	70	45	94	99	66	44	98	94	23	98
btcturk_bid_volume	225	1,107	0,896	0,741	0,549	0,000	0,561	0,896	1,510	5,994
	70	89	55	28	5	44	23	55	05	77
btcturk_volume_24h	225	34,85	37,82	13,55	183,6		23,98	37,82	44,85	64,61
	70	04	58	17	49	10,31	28	58	55	37
btcturk_spread_pct	225	0,042	0,040	0,027	0,000	2,1E-		0,040	0,057	0,305
	70	76	39	07	73	05	0,023	39	56	77
bitso_open	225	2211	2214	2008	4E+0	2135	2200	2214	2222	2269
	70	625	050	1,1	8	000	950	050	130	990
bitso_high	225	2211	2214	2009	4E+0	2135	2201	2214	2222	2269
	70	900	260	2,7	8	000	330	260	245	990
bitso_low	225	2211	2213	2009	4E+0	2134	2200	2213	2221	2268
	70	347	860	1,9	8	000	500	860	948	000
bitso_close	225	2211	2214	2010	4E+0	2134	2200	2214	2222	2269
	70	631	055	1	8	170	933	055	120	980
bitso_volume	225		0,004	5,209	27,14		0,000	0,004	5,103	28,75
	70	2,931	2	62	01	6E-07	4	2	69	61
bitso_ask	225	2212	2214	2009	4E+0	2135	2201	2214	2222	2269
	70	234	790	1,5	8	010	800	790	765	990
bitso_bid	225	2210	2213	2006	4E+0	2134	2200	2213	2221	2268
	70	678	100	5,4	8	010	010	100	210	770
bitso_ask_volume	225	3,140	3,077	0,818	0,669	0,059	2,680	3,077	3,623	6,953
	70	09	65	41	8	69	07	65	92	68
bitso_bid_volume	225	1,745	1,704	0,768	0,591	0,011	1,209	1,704	2,213	7,083
	70	99	54	9	2	07	95	54	25	74
bitso_volume_24h	225	10,69	9,300	5,403	29,19	2,643	6,503	9,300	14,37	28,77
	70	78	56	33	6	71	02	56	62	61
bitso_spread_pct	225	0,070	0,078	0,037	0,001	0,000	0,054	0,078	0,088	0,578
	70	35	94	72	42	44	36	94	96	98
coinsph_open	225	6751	6754	5386	2,9E	6550	6729	6754	6783	6896
	70	615	485	3,8	+09	051	123	485	827	892
coinsph_high	225	6753	6756	5386	2,9E	6550	6731	6756	6786	6897
	70	903	133	5,8	+09	051	172	133	657	422
coinsph_low	225	6749	6752	5383	2,9E	6550	6726	6752	6781	6896
	70	402	746	2	+09	051	746	746	603	201
coinsph_close	225	6751	6754	5381	2,9E	6550	6729	6754	6784	6897
	70	638	506	7,7	+09	051	001	506	230	422
coinsph_volume	225	0,374	0,000	1,172	1,375	7,4E-	0,000	0,000		7,710
	70	12	32	62	05	06	16	32	0,003	89
coinsph_ask	225	6756	6759	5401	2,9E	6551	6734	6759	6789	6897
	70	745	252	4,3	+09	384	279	252	527	421
coinsph_bid	225	6746	6750	5386	2,9E	6550	6723	6750	6779	6892
	70	417	001	7,1	+09	051	167	001	071	889

coinsph_ask_volume	225	0,790	0,831	0,374	0,140	0,000	0,511	0,831	1,031	1,799
	70	21	87	62	34	22	15	87	16	88
coinsph_bid_volume	225	0,309	0,275	0,179	0,032	0,000	0,183	0,275	0,393	1,328
	70	33	23	47	21	22	83	23	01	06
coinsph_volume_24h	225	3,864	3,577	1,481	2,195	1,602	2,787	3,577	4,624	7,923
	70	49	14	77	64	1	24	14	31	2
coinsph_spread_pct	225	0,152	0,147	0,085	0,007	1,5E-	0,084	0,147	0,215	0,526
	70	97	78	76	36	06	64	78	76	29
bithumb_open	225	1,6E+	1,6E+	1135	1,3E	1,6E+	1,6E+	1,6E+	1,6E+	1,6E+
	70	08	08	406	+12	08	08	08	08	08
bithumb_high	225	1,6E+	1,6E+	1131	1,3E	1,6E+	1,6E+	1,6E+	1,6E+	1,6E+
	70	08	08	984	+12	08	08	08	08	08
bithumb_low	225	1,6E+	1,6E+	1138	1,3E	1,6E+	1,6E+	1,6E+	1,6E+	1,6E+
	70	08	08	196	+12	08	08	08	08	08
bithumb_close	225	1,6E+	1,6E+	1135	1,3E	1,6E+	1,6E+	1,6E+	1,6E+	1,6E+
	70	08	08	763	+12	08	08	08	08	08
bithumb_volume	225	0,678	0,248	12,75	162,5	3,1E-	0,101	0,248	0,534	907,3
	70	16	07	06	78	05	65	07	79	65
bithumb_ask	225	1,6E+	1,6E+	1134	1,3E	1,6E+	1,6E+	1,6E+	1,6E+	1,6E+
	70	08	08	008	+12	08	08	08	08	08
bithumb_bid	225	1,6E+	1,6E+	1136	1,3E	1,6E+	1,6E+	1,6E+	1,6E+	1,6E+
	70	08	08	096	+12	08	08	08	08	08
bithumb_ask_volume	225	1,399	0,896	1,461	2,136	0,003	0,438	0,896	2,039	19,33
	70	39	6	84	97	9	43	6	48	02
bithumb_bid_volume	225	0,931	0,633	1,137	1,293	0,000	0,372	0,633	1,139	30,64
	70	4	65	53	98	3	6	65	38	18
bithumb_volume_24h	225	725,0	750,0	285,5	8151	239,1	455,2	750,0	996,2	1273,
	70	05	15	12	6,9	51	35	15	1	5
bithumb_spread_pct	225	0,014	0,008	0,016	0,000	0,000	0,001	0,008	0,023	0,122
	70	96	11	92	29	61	26	11	38	44
usd_krw_rate	225	1384,	1383,	7,142	51,00	1364,	1378,	1383,	1391,	1398,
	70	01	96	09	95	54	86	96	2	53
usd_zar_rate	225	17,72	17,71	0,122	0,014	17,50	17,62	17,71	17,82	18,02
	70	95	13	13	92	48	42	13	21	14
usd_brl_rate	225	5,559	5,564	0,022	0,000	5,515	5,549	5,564	5,576	5,628
	70	82	81	87	52	14	16	81	28	95
usd_jpy_rate	225	147,8	147,7	0,849	0,721	145,8	147,2	147,7	148,7	149,5
	70	66	81	66	92	62	17	81	19	25
usd_try_rate	225	40,44	40,45	0,109		40,16	40,37	40,45	40,55	41,21
	70	09	08	55	0,012	93	55	08	47	43
usd_mxn_rate	225	18,66	18,68		0,010	18,52	18,54	18,68	18,73	18,88
	70	36	07	0,104	82	26	45	07	7	17
usd_php_rate	225	57,06	57,06	0,278	0,077	56,60	56,87	57,06	57,14	58,46
	70	85	37	83	75	08	81	37	57	03
kraken_luno_arbitrage	225	0,503	0,762	1,432	2,050	-	0,527	0,762	0,940	2,506
	70	13	86	03	71	20,64	96	86	54	49
kraken_upbit_arbitrage		-	-			-	-	-	-	
	225	1,277	1,347	0,644	0,415	4,130	1,774	1,347	0,726	0,308
	70	9	3	41	26	2	9	3	2	78
kraken_novadax_arbitrage		-	-			-	-	-	-	
	225	0,129	0,066	0,322	0,104	0,631	-	0,066	0,265	1,331
	70	34	42	51	01	7	0,097	42	25	02
kraken_bitflyer_arbitrage		-	-			-	-	-	-	
	225	0,151	0,091	0,225	0,050	0,567	0,028	0,091	0,161	1,226
	70	72	42	81	99	4	32	42	44	39
kraken_binanceus_arbitrage		-	-			-	-	-	-	
	225	0,200	0,192	0,164		1,633	-	0,192	0,099	0,371
	70	9	3	33	0,027	1	0,287	3	9	33
kraken_btcturk_arbitrage		-	-			-	-	-	-	
	225	0,102	0,035	0,215	0,046	1,663	0,241	0,035	0,057	0,483
	70	2	8	91	62	5	7	8	11	67
kraken_bitso_arbitrage		-	-			-	-	-	-	
	225	0,202	0,131	0,346	0,120	0,505	0,034	0,131	0,227	1,808
	70	32	28	81	28	3	72	28	49	61
kraken_coinsph_arbitrage		-	-			-	-	-	-	
	225	0,006	0,015	0,303		1,165	-	0,015	0,177	1,022
	70	11	13	32	0,092	7	0,179	13	79	97

kraken_bithumb_arbitrage	225	-	-	-	-	-	-	-	-	-
	70	1,256	1,320	0,628	0,395	3,686	1,757	1,320	0,711	0,279
		9	7	69	25	8	5	7	8	66
kraken_luno_arbitrage_lag_-30	225	0,504	0,761	1,448	2,098	-	0,444	0,761	1,040	2,976
	40	54	65	72	78	20,56	94	65	98	48
kraken_luno_arbitrage_lag_-45	225	0,505	0,759	1,458	2,128	20,57	-	0,759	1,077	2,907
	25	04	32	78	05	8	0,417	32	93	37
kraken_luno_arbitrage_lag_-60	225	0,505	0,760	1,468	2,157	20,64	0,383	0,760	1,114	3,035
	10	78	69	9	65	5	61	69	51	31
kraken_upbit_arbitrage_lag_-30	225	-	-	-	-	-	-	-	-	-
	40	1,277	1,343	0,676	0,457	4,326	1,765	1,343	0,734	0,443
		2	8	62	81	2	8	8	1	77
kraken_upbit_arbitrage_lag_-45	225	-	-	-	-	-	-	-	-	-
	25	1,276	1,339	0,689	0,475	4,635	-	1,339	0,734	0,690
		9	4	86	9	7	1,764	4	3	49
kraken_upbit_arbitrage_lag_-60	225	-	-	-	-	-	-	-	-	-
	10	1,276	1,354	0,701	0,492	4,807	1,755	1,354	-	0,714
		4	5	7	39	6	8	5	0,734	09
kraken_novadax_arbitrage_lag_-30	225	0,130	0,093	0,400	0,160	1,747	0,114	0,093	0,327	1,352
	40	72	1	32	26	2	2	1	13	76
kraken_novadax_arbitrage_lag_-45	225	0,131	0,094	0,436	0,190	2,371	0,122	0,094	0,347	1,427
	25	31	89	58	6	3	6	89	11	66
kraken_novadax_arbitrage_lag_-60	225	-	-	-	-	-	-	-	-	-
	10	0,132	0,102	0,466	0,218	2,127	0,137	0,102	0,368	-
			26	99	08	1	4	26	83	1,543
kraken_bitflyer_arbitrage_lag_-30	225	0,152	0,126	0,331	0,109	1,813	-	0,126	0,318	1,652
	40	66	51	43	85	6	-0,04	51	22	73
kraken_bitflyer_arbitrage_lag_-45	225	0,152	0,134	0,367	0,135	2,008	0,062	0,134	0,344	1,718
	25	89	99	63	15	4	3	99	39	61
kraken_bitflyer_arbitrage_lag_-60	225	0,153	0,146	0,397	0,157	1,728	0,078	0,146	0,370	1,769
	10	35	16	32	87	9	6	16	07	67
kraken_btcturk_arbitrage_lag_-30	225	-	-	-	-	-	-	-	-	-
	40	0,100	0,074	0,320	0,102	1,821	0,299	0,074	0,109	1,402
		6	3	64	81	8	2	3	03	95
kraken_btcturk_arbitrage_lag_-45	225	-	-	-	-	-	-	-	-	-
	25	0,099	0,075	0,355	0,126	2,062	0,321	0,075	0,132	1,341
		9	1	87	64	2	3	1	7	16
kraken_btcturk_arbitrage_lag_-60	225	-	-	-	-	-	-	-	-	-
	10	0,099	0,082	0,385	0,148	1,887	0,338	0,082	0,153	1,610
			7	5	61	1	5	7	24	02
kraken_bitso_arbitrage_lag_-30	225	0,203	0,154	0,416	0,173	1,350	0,014	0,154	0,315	2,057
	40	81	36	41	4	4	9	36	8	04
kraken_bitso_arbitrage_lag_-45	225	0,204	0,161	0,446	0,199	1,897	0,034	0,161	0,347	2,214
	25	39	96	42	29	1	1	96	38	92
kraken_bitso_arbitrage_lag_-60	225	0,205	0,168	0,472	0,223	-	-	-	-	-
	10	21	48	98	71	1,758	0,053	0,168	0,376	2,307
							8	48	41	86
kraken_coinsph_arbitrage_lag_-30	225	0,010	0,013	0,368	0,135	1,781	0,201	0,013	0,238	1,321
	40	55	75	7	94	4	6	75	56	07
kraken_coinsph_arbitrage_lag_-45	225	0,012	0,015	0,398	0,158	-	0,213	0,015	0,266	1,401
	25	8	62	6	88	2,288	1	62	55	55
kraken_coinsph_arbitrage_lag_-60	225	0,015	0,016	0,424	0,180	2,141	0,223	0,016	0,294	1,440
	10	33	7	54	23	2	4	7	27	15

kraken_bithumb_arbitrage_lag_-30	225 40	- 1	- 8	- 36	- 4	- 4	- 5	- 8	- 2	- 26
kraken_bithumb_arbitrage_lag_-45	225 25	- 8	- 7	- 31	- 05	- 6	- 3	- 7	- 7	- 74
kraken_bithumb_arbitrage_lag_-60	225 10	- 2	- 4	- 85	- 14	- 1	- 6	- 4	- 0,716	- 0,739 37
kraken_binanceus_arbitrage_lag_-30	225 40	- 1	- 9	- 04	- 52	- 7	- 1	- 9	- -0,06	- 0,992 95
kraken_binanceus_arbitrage_lag_-45	225 25	- 9	- 6	- 93	- 64	- 2,373	- 9	- 6	- 8	- 1,089 04
kraken_binanceus_arbitrage_lag_-60	225 10	- 6	- 2	- 16	- 73	- 2,373	- 9	- 2	- 1	- 1,047 03