Pricing and Arbitrage Across 80 Cryptocurrency Exchanges

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Abstract

In this paper, we explore variations in cryptocurrency pricing across 80 cryptocurrency exchanges worldwide. Our analysis demonstrates that the arbitrage spread for Bitcoin, the most widely recognized cryptocurrency, ranges from 8.67% to 15.69% across various exchanges from 2019 to 2023. Arbitrage spreads are higher in non-US domiciled exchanges, decentralized exchanges, and non-trustworthy exchanges. Stablecoins and high liquidity cryptocurrencies exhibit smaller arbitrage. Our analysis, controlling for cryptocurrency volatility, capital controls, restrictions on short selling, and other variables, highlight the impact of exchange characteristics and regulatory environments on arbitrage possibilities, shedding light on the complexities of the cryptocurrency market's global dynamics.

Keywords: Cryptocurrency, Exchanges, Pricing, Arbitrage, Liquidity.

JEL Classification: G12, G15

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1 Introduction

The financial world witnessed a paradigm shift with the launch of Bitcoin in 2009, an innovative concept first outlined by Nakamoto (2008) that introduced the notion of a decentralized digital currency operating beyond the confines of central banking systems. This groundbreaking development not only posed a formidable challenge to established banking and monetary frameworks but also marked the beginning of a new era in financial transactions. With Bitcoin leading the charge as the inaugural and most renowned cryptocurrency, the market has since been flooded with a plethora of alternative digital currencies. Each of these cryptocurrencies brings to the table distinct features, underlying technologies, and specific applications, enriching the diversity and complexity of the digital currency ecosystem. As of 2024, the cryptocurrency space has expanded to encompass over 20,000 distinct cryptocurrencies[1], signaling a vast and rapidly evolving field that continues to redefine the boundaries of financial interaction and exchange.

Cryptocurrency exchanges serve as the backbone of the digital currency ecosystem, providing essential platforms for the buying, selling, or swapping of digital currencies with other digital or traditional fiat currencies. These exchanges are the pillars of the cryptocurrency market, facilitating liquidity and playing a pivotal role in the price discovery of digital assets. The features and services offered by these platforms vary considerably, encompassing their operational model (whether centralized or decentralized), the diversity of supported currencies, the provision of derivatives trading, user accessibility, regulatory adherence, and the efficiency of transactions, among others.

Research in this domain, such as the study by Makarov and Schoar (2020), has revealed significant disparities in cryptocurrency pricing, highlighting the impact of the geographic locations of exchanges on these variations. Crépellière, Pelster, and Zeisberger (2023) suggest that geographic restrictions may partly explain price differences for BTC. Auer and Claessens (2018) note that market participants not being allowed to trade on all markets

[1] https://www.statista.com/statistics/863917/number-crypto-coins-tokens/

leads to market segmentation and fragmentation. Furthermore, the findings of Augustin, Rubtsov, and Shin (2023) indicate a significant increase in the synchrony of prices across cryptocurrency exchanges following the initiation of Bitcoin futures trading in 2017, suggesting a notable change in market dynamics. Additionally, the study by Li, Luo, Wang, and Wei (2022) shows that regulatory oversight significantly affects the performance of cryptocurrencies when listed on exchanges. Cong, Li, Tang, and Yang (2023) find that exchanges with a longer operating history tend to experience fewer wash trades, which leads to reduced price deviations. Arbitrage opportunities in stock markets have been extensively studied in the literature. Chordia, Roll, and Subrahmanyam (2008) find that liquidity stimulates arbitrage activity, thereby enhancing market efficiency. Rösch (2021) finds that arbitrage increases stock market liquidity. Gagnon and Karolyi (2010) find that price parity deviations are positively related to market volatility.

In this paper, we explore the pricing variations and arbitrage spreads in cryptocurrency pricing across 80 cryptocurrency exchanges in various geographical locations around the globe. Our investigation specifically targets the underlying factors that contribute to discrepancies in cryptocurrency pricing, leveraging a comprehensive dataset from a broad spectrum of exchanges that span various global geographical regions. This analysis is not only pivotal for understanding the dynamics of cryptocurrency markets but also for identifying the potential for arbitrage that these pricing disparities may offer to investors and traders alike. By dissecting the mechanisms behind these variations, we aim to shed light on the complexities of the global cryptocurrency ecosystem, offering insights into the interplay between market forces and regulatory environments that shape the landscape of digital currency trading.

We further investigate how these pricing discrepancies are influenced by a variety of determinants, including market liquidity, exchange reputation, regulatory constraints, and geographical locations. This exploration enables us to identify patterns and trends that are characteristic of the global cryptocurrency trading environment, providing valuable insights into how different factors contribute to the observed pricing variations. Moreover, our analysis extends to the comparison of arbitrage spreads among various types of cryptocurrencies, including Bitcoin, stablecoins, and other altcoins. We highlight the distinct behaviors of these categories in terms of arbitrage opportunities, revealing how market maturity, liquidity, and investor perception affect the arbitrage potential of each type. Additionally, we consider the role of technological and operational aspects of cryptocurrency exchanges, such as transaction speed and the number of confirmation blocks required, in influencing arbitrage spreads. This aspect of our study underscores the importance of understanding the technical underpinnings of digital currency exchanges as a factor in the arbitrage equation. This paper makes contribution in several important ways. First, it employs an extensive dataset that encompasses daily pricing data from 80 cryptocurrency exchanges, covering the period from 2019 to 2023. Although our dataset includes pricing data for over 1500 cryptocurrencies, our main regression analysis focuses on the top 30 cryptocurrencies by liquidity. To the best of our knowledge, this is the first study to examine cross-exchange cryptocurrency pricing using such an extensive dataset. Furthermore, our study not only builds upon the foundational insights of Makarov and Schoar (2020) but also expands them by exploring price formation dynamics across a wider array of cryptocurrency exchanges globally and pinpointing potential arbitrage opportunities in the rapidly evolving digital currency market.

Secondly, our analysis reveals significant arbitrage spreads across cryptocurrency exchanges. Notably, even for Bitcoin, the most heavily traded cryptocurrency, we observe arbitrage spreads ranging from 8.67% to 15.69% across different platforms. Furthermore, we demonstrate that stablecoins exhibit smaller arbitrage spreads compared to other cryptocurrencies. This indicates a unique pricing behavior of stablecoins in the cryptocurrency market, highlighting their role in hedge and potentially reducing price discrepancies across exchanges.

Lastly, our findings persist after adjusting for several established control variables, such as Capital Controls (Makarov and Schoar, 2020), Futures Trading (Augustin, Rubtsov, and Shin, 2023), Number of Confirmation Blocks (Augustin, Rubtsov, and Shin, 2023), and the market volatility of the cryptocurrency (Gagnon, and Karolyi, 2010), among others. We discover that arbitrage spreads tend to be wider in decentralized exchanges and those days with relatively lower trading volume. Additionally, cryptocurrencies traded on exchanges domiciled outside the United States or on platforms deemed less trustworthy exhibit higher arbitrage spreads. This underscores the significant impact of exchange characteristics and regulatory environments on the efficiency and opportunity for arbitrage in the cryptocurrency market.

The structure of this paper is organized as follows: Section 2 introduces the Kaiko cryptocurrency data, offering a thorough overview of cryptocurrency pricing across a range of exchanges. In Section 3, we explore the pricing discrepancies and arbitrage profit opportunities, taking into account various factors such as geographical location, liquidity, trading volume, and the types of exchanges, among others. Section 4 details our regression analysis, aimed at identifying the determinants of cryptocurrency arbitrage profits across 80 exchanges. Section 5 presents robustness tests. Finally, Section 6 concludes the paper by summarizing our principal findings and insights, providing a comprehensive synthesis of the research conducted.

2 Kaiko Cryptocurrency Data

2.1 Overview

Our research utilizes data sourced from Kaiko, a premier provider of cryptocurrency market data known for its extensive, real-time, and historical datasets that cover a wide range of cryptocurrencies. Kaiko's comprehensive data offerings include detailed market data, trading volumes, price information, and numerous other metrics essential for analyzing the cryptocurrency markets. We obtain our study's data through the Kaiko API, specifically focusing on the daily OHLCV (Open, High, Low, Close, Volume) data for instruments listed across 80 exchanges.

In our analysis, we focus on pairs quoted as "Crypto-USD stablecoin," which are primarily traded and reported on cryptocurrency exchanges. We prefer USD stablecoins over traditional fiat currencies because stablecoins can be traded across exchanges without facing the same regulatory restrictions. Our dataset shows that more than 97% of transactions involving stablecoins fall within five primary categories: USDT, USDC, BUSD, DAI, and fiat currency USD. These stablecoins are either directly pegged to the U.S. Dollar or algorithmically stabilized, earning widespread trust within the cryptocurrency market. The dominance of these select stablecoins highlights a concentration of trust and liquidity in a narrow segment of the market, enabling us to conduct a focused analysis of stablecoin behavior compared to other cryptocurrencies.

2.2 Data Description

We gathered data spanning from January 2019 to March 2023, comprising daily OHLCV data reported by 80 distinct exchanges. While certain exchanges provide complete data coverage from 2019 to 2023, others offer only partial coverage during this period.

[Insert Figure 1 Here]

Figure 1 illustrates a time series depicting the number of actively operating exchanges. An exchange is considered operational on a given date if it provided data coverage for that date. During the cryptocurrency market's surge in popularity from 2019 to 2021, the daily count of actively operating exchanges rose from 30 in 2019 to 62 in 2021. However, following the market's cooldown in 2022, the daily count experienced a slight decline to 50.

[Insert Table 1 Here]

Makarov and Schoar (2020) take into account the geographical regions of exchanges in their analysis of Bitcoin arbitrage opportunities. In Table 1 of our paper, we detail the geographical information of the 80 exchanges included in our dataset. Centralized exchanges are categorized based on their operational region or the location of their headquarters. Exchanges that function on the blockchain through smart contracts are identified as decentralized exchanges. Of the 80 exchanges, 18 are based in North America, 28 in the Asia-Pacific region, and 19 in Europe. The remaining 15 exchanges either operate in other regions or are based on blockchain platforms.

Figure 2 displays the daily count of unique cryptocurrencies traded against the "Crypto-USD Stablecoin" pair from January 2019 to March 2023. Over this period, the number of distinct cryptocurrencies expanded from 304 in 2019 to 1556 in 2022. This trend closely aligns with the trajectory of the number of active exchanges depicted in Figure 1.

3 Kaiko Cryptocurrency Data

In this section, we outline our primary methodology and findings related to the pricing discrepancies across 80 cryptocurrency exchanges worldwide. Our initial analysis focuses on the daily maximum arbitrage profits for Bitcoin, the most heavily traded cryptocurrency. We calculate the percentage value of the maximum arbitrage profit by assuming a cryptocurrency arbitrageur buys Bitcoin at the lowest price on one exchange and sells it at the highest price on another exchange within the same day. These findings are presented in Table 2 below.

[Insert Table 2 Here]

Table 2 reveals that the average daily arbitrage profit for a Bitcoin arbitrageur ranged from 8.67% to 15.69% during our study period from 2019 to 2023. The minimum and maximum cross-exchange arbitrage profits observed are 0.83% and 69.97%, respectively. These arbitrage profit margins are remarkably high. However, given that an average arbitrageur may not always accurately predict the exchange with the lowest priced Bitcoin, we propose and calculate a more practical metric, the "Daily Arbitrage Spread" in the following section.

3.1 Daily Arbitrage Spread

In this section, we define the notation and methodology employed in calculating of arbitrage spread. For a given cryptocurrency i traded on exchange j at date t, its price $P_{i,j,t}$ is defined as the average of closing price on exchange j at date t across pairs such as "Crypto(i)-USDT", "Crypto(i)-USDC, "Crypto(i)-USD", "Crypto(i)-BUSDT" and "Crypto(i)-DAI". We further define the benchmark price of cryptocurrency i at date t as the median of prices across exchanges, denoted as $M_{i,t}$. Then the dollar value of arbitrage spread $S_{i,j,t,[\$]}$ and percentage value of arbitrage spread $S_{i,j,t,[\%]}$ for cryptocurrency i on exchange j at date t are calculated as follows,

$$S_{i,j,t,[\$]} = P_{i,j,t} - M_{i,t}, \tag{1}$$

$$S_{i,j,t,[\%]} = S_{i,j,t,[\$]}/M_{i,t}. \tag{2}$$

In the equations (1) and (2) above, absolute dollar value $|S_{i,j,t,[\$]}|$ and absolute percentage value $|S_{i,j,t,[\%]}|$ are their unsigned values.

We next report the statistics of arbitrage spreads for Bitcoin (BTC) and Ethereum (ETH), the two cryptocurrencies with the highest market capitalization. Panel A and Panel B present the daily BTC dollar value arbitrage spread $S_{BTC,j,t,[\$]}$ and percentage value $S_{BTC,j,t,[\%]}$ respectively, for each year. Panel C and Panel D present the daily ETH dollar value arbitrage spread $S_{ETH,j,t,[\$]}$ and percentage value $S_{ETH,j,t,[\%]}$ respectively, for each year. Due to the inherent price volatility of cryptocurrencies, we emphasize the percentage values to facilitate more meaningful comparisons across different periods.

[Insert Table 3 Here]

The average and median percentage values of arbitrage spreads are close to zero, indicating that, on average, the cryptocurrency market and exchanges operates efficiently. However, the distribution's tails reveal significant deviations. Specifically, in 2019, 5% of Bitcoin (BTC) prices fell more than 1.31% below their benchmark prices, while another 5%

surpassed their benchmark prices by more than 1.61%. Ethereum (ETH) showed even more significant disparities within the same period: 5% of ETH prices were over 1.19% below the benchmark price, and 5% exceeded the benchmark price by more than 2.51%. Despite the market's maturity, notable price discrepancies for ETH continued into 2023, with exceptional price differences exceeding 1.03% of the benchmark prices.

3.2 Arbitrage Spreads by Geographical Locations of Exchanges

Building on the research by Makarov and Schoar (2019), Auer and Claessens (2018), and Crépellière, Pelster, and Zeisberger (2023), which indicates that geographic restrictions lead to Bitcoin pricing discrepancies and significant barriers to arbitrage between countries compared to within them, we further investigate the percentage value of BTC arbitrage spreads across exchanges located in different regions. The findings are summarized in Table 4.

[Insert Table 4 Here]

Examining the 5th and 95th percentiles of the arbitrage spreads reveals that BTC prices on North American exchanges deviate significantly less from the benchmark compared to those in other regions. This observation aligns with Makarov and Schoar's (2019) finding, which underscores the importance of U.S. exchanges in price discovery. Moreover, exchanges in the Asia-Pacific area have shown increasing efficiency from 2019 to 2023, with the 95th percentile of arbitrage spread narrowing from 1.51% to 0.29% during this period. In contrast, the arbitrage spreads on European exchanges remain notably high, suggesting more pronounced market segmentation in this region. This could be attributed to the presence of 19 exchanges spread across 12 European countries, leading to market participants favoring exchanges within their own countries.

3.3 Arbitrage Profit by Cryptocurrency Trading Volume

Understanding the dynamics between liquidity and arbitrage activity is crucial for comprehending market efficiency mechanisms. Chordia, Roll, and Subrahmanyam (2008) highlight that liquidity not only facilitates arbitrage but also plays a pivotal role in enhancing market efficiency, indicating a foundational element of stable financial markets. Similarly, Rösch (2021) underscores the relationship between arbitrage activity and stock market liquidity, suggesting that liquidity is a key driver of arbitrage opportunities. This relationship is particularly salient in the volatile and rapidly evolving cryptocurrency market, where liquidity can vary significantly across different tokens. Higher liquidity levels are hypothesized to reduce barriers to arbitrage, leading to narrower arbitrage spreads and potentially more efficient markets.

Given the critical role of liquidity in shaping market dynamics and the unique challenges presented by the cryptocurrency market, this section delves into the investigation of how liquidity, as approximated by trading volume, affects arbitrage opportunities in the cryptocurrency market. By categorizing samples for each cryptocurrency based on trading volume—dividing them into "Small Volume" and "Big Volume" groups—we seek to understand the nuanced impact of liquidity on arbitrage spreads. We present our analysis in the following Table 5.

[Insert Table 5 Here]

In Table 5, we present statistical data for three of the most traded cryptocurrencies, segmented by liquidity into "Small Volume" and "Big Volume" groups. Our analysis highlights significant differences in arbitrage spreads between these groups. Specifically, we observe that for the cryptocurrencies analyzed, the 5th percentile arbitrage spreads are consistently lower, and the 95th percentile spreads are higher in samples characterized by lower liquidity. Taking Ethereum (ETH) as an illustrative example, within the Small Volume group, the top 5% of arbitrage spreads exceed 1.53%. In contrast, for the Large Volume group, the 95th percentile of arbitrage spreads is capped at 0.89%, marking a notable reduction of 0.64% in comparison to the Small Volume group.

Furthermore, our analysis extends to the comparative differences across all cryptocurrencies examined. We find that the disparity in the 5th percentile between the Small and Large Volume groups is -0.07%, whereas the difference in the 95th percentile is 0.25%. These findings underscore the crucial role of liquidity in diminishing barriers to arbitrage, thereby facilitating greater price alignment across different trading volumes. This pattern suggests that enhanced liquidity contributes to narrowing arbitrage spreads, aligning with the hypothesis that liquidity decreases impediments to arbitrage, consequently synchronizing prices.

3.4 Arbitrage Profit by Exchange Types (CEX vs DEX)

One of the key contributions of our paper is the examination of price differences across both decentralized exchanges (DEXs) and centralized exchanges (CEXs). CEXs, operated by centralized entities, facilitate trading between buyers and sellers through an order book system, with examples including Coinbase and Binance. In contrast, DEXs function on decentralized blockchain networks, allowing for direct peer-to-peer trading between users' wallets without intermediaries, utilizing automated market maker smart contracts, as seen in platforms like Uniswap and Curve.

While Capponi, Jia, and Yu (2023) have explored price discovery on DEXs for ETH and BTC, the discussion on the arbitrage spreads between cryptocurrencies on DEXs and CEXs remains sparse in the literature. To bridge this gap, we selected 11 cryptocurrencies that are listed on both types of exchanges, using data sourced from Kaiko. Our analysis focuses on their arbitrage spreads on DEXs and CEXs, aiming to shed light on the price deviations from benchmark prices across these exchange platforms.

[Insert Table 6 Here]

Table 6 describes the arbitrage spreads of 11 cryptocurrencies traded both on DEXs and

CEXs. For each cryptocurrency, the first row details the arbitrage spread statistics $S_{i,j,t,[\%]}$ on CEXs, while the second row provides the corresponding statistics on DEXs. Additionally, we analyze the differences between these statistics for DEXs and CEXs. The data from CEXs starts in January 2019, whereas DEX data begins in March 2020. Taking Bitcoin (BTC) as an example, it's observed that the majority of BTC pairs on CEXs closely align with the market price, showing deviations ranging between -0.67% and 0.82%. Conversely, BTC pairs on DEXs exhibit wider spreads, with the 5th and 95th percentiles varying from -2.93% to 2.92%.

Significant differences in the 5th and 95th percentiles of arbitrage spreads between DEXs and CEXs are noted, except for USDT and ETH. The narrow spreads for USDT might be attributed to the nature of stablecoins, while the narrower spreads for ETH could be explained by the preponderance of DEXs on the Ethereum blockchain, which facilitates easier ETH transfers[2]. This dynamic further exacerbates the market segmentation between CEXs, DEXs, and cryptocurrencies on other blockchains. Other potential contributing factors include the complexities of the automated market maker model and the risk of front-running attacks on public blockchains, as discussed by Eskandari, Moosavi, and Clark (2020).

[Insert Figure 3 Here]

In Figure 3, we present the time series of arbitrage spreads differentiated by exchange type. Panel A illustrates the daily average arbitrage spreads $S_{i,j,t,[\%]}$ for all cryptocurrencies i traded on exchange j which are CEXs or DEXs. Panels B and C illustrate the daily average arbitrage spreads specifically for BTC and ETH, respectively, on both types of exchanges. The dataset for CEXs begins in January 2019, whereas for DEXs, it starts from March 2020. Overall, the findings show that the average arbitrage spreads on CEXs are significantly lower than those on DEXs. We attribute this disparity primarily to the effects of blockchain segmentation.

[2] For instance, an arbitrageur can buy ETH in DEX and transfer to CEX directly without interacting with other blockchains.

3.5 Arbitrage Profit by Cryptocurrency Types

As indicated by Table 6, the stablecoin USDT shows remarkably small arbitrage spreads within both DEXs and CEXs, exhibiting less variability compared to other cryptocurrencies listed in the table. Extending this observation, we delve into the behavior of all stablecoins and fiat currencies in this section.

USDT and USDC are stablecoins collateralized by U.S. dollar reserves, designed to maintain a fixed exchange rate with the U.S. dollar. On the other hand, DAI operates as an algorithmic stablecoin on the Ethereum blockchain, achieving stability through ETH collateralization. This setup not only stabilizes DAI's value relative to the U.S. dollar but also enhances decentralization and transparency. Additionally, some exchanges facilitate transactions directly with fiat currency, such as the USD.

[Insert Table 7 Here]

Table 7 showcases the arbitrage spreads, expressed as percentage values $S_{i,j,t,[\%]}$, for the 30 most traded cryptocurrencies in our dataset. Panel A details the arbitrage spreads for stablecoins USDC, USDT, USD, and DAI, while Panel B focuses on other traditional cryptocurrencies. The data spans from January 2019 to March 2020. Notably, Ethereum Classic (ETC), which originated from a hard fork of Ethereum (ETH), displays the lowest 5th percentile of arbitrage spread at -2.08%. Conversely, Dogecoin (DOGE), a well-known "meme" cryptocurrency, exhibits a significant 95th percentile of arbitrage spread at 2.77%. In comparison, 90% of stablecoin transactions have an absolute arbitrage spread value of less than 0.61%, except for USD, which has a 5th percentile at -1.18%. This suggests that stablecoins, due to their design and underlying mechanisms, facilitate easier cross-exchange trading free from regulatory constraints, compared to fiat currencies. This observation is consistent with the findings of Makarov and Schoar (2019), who posited that capital controls significantly impact fiat currency pairs.

The comparative analysis between stablecoins and regular cryptocurrencies reveals a consistent pattern: the 5th and 95th percentiles of arbitrage spreads for regular cryptocurrencies are double those of stablecoins. Furthermore, the kurtosis for stablecoins is three times higher than that for regular cryptocurrencies, indicating that stablecoins' arbitrage spreads are more consistently centered around zero.

[Insert Figure 4 Here]

In Figure 4, we depict the time series of average arbitrage spreads for different types of cryptocurrencies from January 2019 to March 2023. Throughout this period, the average arbitrage spreads remain generally small and stable, with a notable exception in the early months of 2019. This initial volatility can largely be attributed to capital regulations impacting fiat currency transactions. In essence, the intrinsic value of stablecoins, which is anchored to U.S. dollar assets, leads to their arbitrage spreads being less significant and volatile in comparison to those of other cryptocurrencies.

3.6 Arbitrage Profit by Trustworthiness of Cryptocurrency Exchanges

Beyond geographical segmentation, when exchanges operate within the same region or country, investors often show a preference for platforms with a superior reputation or higher levels of trust. This trend is particularly pronounced in the cryptocurrency market, where regulation is sparse, and the risks of fraud, wash trades and security breaches are concerns. Investors gravitate towards reputable exchanges as they are perceived to offer better protection against these risks, underlining the importance of an exchange's credibility in attracting investor engagement. Cong, Li, Tang, and Yang (2023) study that exchanges with a longer operating history tend to experience fewer wash trades, thereby leading to reduced price deviations.

To quantify the trustworthiness of cryptocurrency exchanges in our study, we first calculate the median operational period of the exchanges in our dataset, which stands at 1,102 days. Based on this benchmark, exchanges operational for more than 1,102 days from January 2019 to March 2023 are considered trustworthy. In contrast, those with shorter operational periods are classified as non-trustworthy. This criterion serves as a proxy for gauging an exchange's reliability and its perceived security in the eyes of investors.

[Insert Table 8 Here]

Table 8 outlines the statistical data for three of the most traded cryptocurrencies, segmented into two distinct periods: from January 2019 to June 2021, and from June 2021 to March 2023. During the initial period, significant differences are observed in the arbitrage spreads of these cryptocurrencies between trustworthy and non-trustworthy exchanges. For instance, the average arbitrage spread for BTC on trustworthy exchanges was 0.11%, compared to -0.65% on non-trustworthy exchanges. Moreover, the 5th percentile of BTC arbitrage spreads on trustworthy exchanges was -0.73%, in stark contrast to -3.75% on non-trustworthy exchanges. However, these disparities have notably diminished in the subsequent period. The difference in the 5th percentile of BTC arbitrage spreads between the two types of exchanges has narrowed significantly, from -3.02% to just 0.82%.

A compelling rationale for the observed reduction in arbitrage spread disparities can be attributed to the tightening of regulations around cryptocurrency exchanges. Notably, in 2021, the U.S. government enacted legislation mandating digital asset exchanges to report to the IRS, marking a significant step towards greater regulatory oversight. In the same year, Coinbase distinguished itself as the first major cryptocurrency exchange to be listed on the Nasdaq, setting a precedent for transparency and regulatory compliance within the industry. These developments, alongside the introduction of stricter regulations, have played a pivotal role in alleviating investor concerns regarding the trustworthiness of cryptocurrency exchanges.

The cumulative effect of these regulatory and market milestones has been a marked increase in investor confidence in cryptocurrency investing. This heightened confidence has contributed to diminishing the perceived risk differential between more and less trustworthy exchanges. As a result, the landscape of cryptocurrency investing has evolved, with a decreased impact of trustworthiness on investor decision-making and market dynamics.

[Insert Figure 5 Here]

Figure 5 offers a time series summary for all 30 cryptocurrencies studied. It features the daily average arbitrage spreads $S_{i,j,t,[\%]}$ for each cryptocurrency i traded on exchange j, categorized by their trustworthiness. Notably, prior to June 2021, arbitrage spreads on non-trustworthy exchanges exhibited greater magnitude and volatility compared to their trustworthy counterparts. However, these disparities significantly diminished after June 2021. Additionally, the non-trustworthy exchanges experienced volatile arbitrage spreads in end of 2022, prompted by re-emerging concerns about trustworthiness following the collapse of FTX, the third-largest cryptocurrency exchange by volume.

4 Cross-Exchange Arbitrage Spread Regression Analysis

In the preceding sections, we explored a range of factors affecting arbitrage spreads, encompassing the characteristics of cryptocurrencies (such as type, volatility, and trading volume) and the attributes of exchanges (including their type, geographic location, and level of trustworthiness). Building on this foundation, Makarov and Schoar (2020) uncovered that arbitrage spreads tend to widen outside the U.S. in response to increased buying pressure within the U.S. To investigate this phenomenon, they applied the Hodrick-Prescott filter to derive a smoothed log of Bitcoin prices on a weekly basis in the U.S. market. They then measured Bitcoin's buying pressure as the deviations from the actual log price to this smoothed log price.

4.1 Summary Statistics of Regression Variables

Adopting a similar methodology, we calculate the buying pressures for the 30 primary cryptocurrencies in our dataset. This approach enables us to examine the influence of U.S. market dynamics on arbitrage opportunities and spreads across different cryptocurrencies and exchanges.

In our analysis, we incorporate control variables consistent with those identified in existing literature, such as Capital Controls (Makarov and Schoar, 2020), Futures Trading (Augustin, Rubtsov, and Shin, 2023), Number of Confirmation Blocks (also Augustin, Rubtsov, and Shin, 2023), and the past 30-day volatility of the cryptocurrency (Gagnon and Karolyi, 2010), among others. Here's a brief rationale for each:

• Capital Controls: In countries with stringent capital controls, investors may pay a premium for cryptocurrencies as a hedge against local financial restrictions. This dynamic can influence arbitrage spreads, as cryptocurrencies become a tool for circumventing financial constraints, thereby increasing demand in these regions. Capital control measures are constructed by the exchange location's capital control index as in Fernández et al (2016).

• Futures Trading: Exchanges that offer perpetual futures trading enable investors to short overpriced cryptocurrencies or hedge the risk associated with arbitrage trades (leg risk). We hypothesize that the availability of futures trading promotes price efficiency on these exchanges and, consequently, narrows arbitrage spreads. The Futures indicator is 1 if the exchange supports trading futures.

• Number of Confirmation Blocks: This metric gauge the number of blockchain confirmations required by an exchange to recognize a deposit or withdrawal. It's a proxy for the 'leg risk' in arbitrage trading, with fewer confirmation blocks potentially reducing this risk and, thus, arbitrage spreads.

• Past 30-day Volatility: The market volatility[3] of a cryptocurrency Past Volatility$_{i,j,t}$ is

[3] Past Volatility$_{i,j,t}$ is is the logarithmic value of past 30-day rolling price volatility, calculated as log(price volatility)) for cryptocurrency i on exchange j at date t.

a critical measure of market conditions. High volatility periods often see more significant price discrepancies across exchanges, increasing the holding risk and complicating arbitrage opportunities.

Other variables we used in this section include volume represents the log trading volume of cryptocurrency. Buying pressure denotes the deviation from the actual log price to this smoothed log price. The Stablecoin indicator is 1 if it's pegged to the dollar. The DEX indicator is 1 if the exchange runs on the blockchain. The U.S. indicator is 1 if the exchange is in the U.S. The Trustworthiness indicator is 1 if the exchange's operational days exceed the median of operational days. We provide a summary statistics and correlation matrix of all variables used in the following Table 9.

[Insert Table 9 Here]

Table 9, Panel A, describes the correlation matrix of regression variables. The control variable "Past Volatility" exhibits a robust correlation of 76.19% with the "Volume" variable. This is consistent with the findings in Chordia, Sarkar, and Subrahmanyam (2005), which confirm that common factors drive liquidity and volatility in the stock and bond markets. Additionally, "Past Volatility" demonstrates a notably negative relationship of -27.40% with stablecoins, aligning with the stability inherent to their nature. It is also noted that derivative trading is restricted on most U.S. cryptocurrency exchanges, resulting in a significant negative correlation of -22.80% between the "U.S. Indicator" and the "Futures Indicator". Panel B reports the statistics of the regression variables. The skewness of "Volume" and "Buying Pressure" is less than 0.64, indicating they are close to a symmetric distribution. "Past Volatility" exhibits positive skewness, indicating a long right tail in the distribution.

4.2 Regression Results

To precisely identify the factors influencing arbitrage opportunities among cryptocurrency exchanges, our analysis incorporates panel regression techniques, controlling for the aforementioned variables. This methodological approach allows us to isolate the effects of individual factors on arbitrage spreads while accounting for the dynamic and multifaceted nature of the cryptocurrency market.

We begin our empirical investigation by clearly defining "arbitrage spread" as the absolute percentage value of the arbitrage spread $|S_{i,j,t,[\%]}|$ as the dependent variable. The unsigned value of buying pressure for cryptocurrency i at date t ($|\text{Crypto Buying Pressure}|_{i,t}$ serves as a principal independent variable. This approach ensures a consistent and focused analysis, aligning with the methodologies and variables discussed in previous sections.

In Table 10, we report the panel regression result with following form:

$$\begin{aligned}
|S_{i,j,t,[\%]}| = &\beta_1 \text{Volume}_{i,t} + \beta_2 |\text{Crypto Buying Pressure}|_{i,t} \times \mathbb{I}(1 \text{ if not in U.S})_j \\
&+ \beta_3 \mathbb{I}(1 \text{ if stable})_i + \beta_4 \mathbb{I}(1 \text{ if DEX})_j + \beta_5 \mathbb{I}(1 \text{ if in U.S})_j \\
&+ \beta_6 \mathbb{I}(1 \text{ if trustworthy})_j \times \mathbb{I}(\text{Before June 2021})_t + \beta_7 \text{Past Volatility}_{i,j,t} \\
&+ \beta_8 \text{Capital Control}_{j,t} + \beta_9 \mathbb{I}(1 \text{ if has futures})_j \\
&+ \beta_{10} \# \text{ of Confirmation Blocks}_j + \text{Fixed Effect} + \epsilon_{i,j,t}.
\end{aligned} \tag{3}$$

[Insert Table 10 Here]

Incorporating all four control variables into our model reveals that all 10 coefficients are statistically significant at the 1% level, standard errors are clustered by time[4], affirming the robustness of our findings. These results align with our hypotheses, indicating that liquidity, the presence of stablecoins, and exchange trustworthiness inversely relate to arbitrage spreads. This suggests they play a pivotal role in reducing price discrepancies across exchanges. In contrast, other examined factors contribute to widening these spreads.

Specifically, a one standard deviation increase in trading volume—a proxy for liquidity—results in a 0.21%[5] decrease in the arbitrage spread $|S_{i,j,t,[\%]}|$. Similarly, a one standard deviation increase in buying pressure within the U.S. market correlates with a 0.07% increase

[4]We follow the methodology from Petersen (2008), and the test suggests clustered by time is appropriate.
[5]0.21% is obtained by 0.0488 × 4.23.

in the arbitrage spread $|S_{i,j,t,[\%]}|$ for exchanges located outside the US.

Our analysis further delineates the impact of cryptocurrency types on arbitrage opportunities, with stablecoins associated with 0.48% lower arbitrage spreads than traditional cryptocurrencies. Moreover, decentralized exchanges display arbitrage spreads that are 1.43% higher compared to their centralized counterparts for the same cryptocurrency. Notably, before June 2021, exchanges considered trustworthy—those whose operational days exceed the median—witnessed an average reduction of 0.29% in arbitrage spreads. Additionally, exchanges located in the U.S. experienced a 0.10% reduction in these spreads.

The examination extends to the nuanced effects of stricter capital controls, futures trading, and confirmation times. Exchanges in jurisdictions with more stringent capital controls face higher arbitrage spreads, highlighting the influence of regulatory constraints on arbitrage strategies' execution. Conversely, the presence of futures trading on an exchange is linked with smaller price deviations, suggesting these instruments help harmonize prices across markets. Lastly, longer blockchain confirmation times are tied to decreased price efficiency, underscoring the critical nature of transaction speed in exploiting arbitrage opportunities.

We next study the impact of liquidity (proxied by trading volume) on aribrage spreads. We run panel regression analysis of the following form:

$$
\begin{aligned}
|S_{i,j,t,[\%]}| = &\beta_1 |\text{Crypto Buying Pressure}|_{i,t} \times \mathbb{I}(1 \text{ if not in U.S})_j \\
&+ \beta_2 \mathbb{I}(1 \text{ if stable})_i \times \text{Volume}_{i,t} + \beta_3 \mathbb{I}(1 \text{ if DEX})_j \\
&+ \beta_4 \mathbb{I}(1 \text{ if DEX})_j \times \text{Volume}_{i,t} + \beta_5 \mathbb{I}(1 \text{ if in U.S})_j \times \text{Volume}_{i,t} \\
&+ \beta_6 \mathbb{I}(1 \text{ if trustworthy})_j \times \mathbb{I}(\text{Before June 2021})_t \times \text{Volume}_{i,t} \\
&+ \beta_7 \text{Past Volatility}_{i,j,t} + \beta_8 \text{Capital Control}_{j,t} + \beta_9 \mathbb{I}(1 \text{ if has futures})_j \\
&+ \beta_{10} \# \text{ of Confirmation Blocks}_j + \text{Fixed Effects} + \epsilon_{i,j,t}.
\end{aligned}
\tag{4}
$$

We report our analysis results in the following Table 11.

[Insert Table 11 Here]

In model (1), the majority of the coefficients are statistically significant, and their signs align with our hypotheses, demonstrating the robustness of our initial assumptions about the market dynamics. However, an exception arises with β_1, which does not reach significance at the 10% level, indicating that its influence might be more nuanced than initially anticipated. Additionally, there is a particular concern regarding the sign of β_5, which unexpectedly contradicts our assumption; it was hypothesized to be negative, reflecting a belief that higher volume liquidity should reduce arbitrage spreads. This anomaly suggests that while increased liquidity indeed narrows arbitrage spreads, its effect is overshadowed by the significant influence of decentralized exchanges (DEX) on widening these spreads.

To clarify this complex interplay between liquidity and the type of exchange, model (2) incorporates an additional variable, $\mathbb{I}(1 \text{ if DEX})_j$, to distinguish between trades occurring in decentralized versus centralized exchanges. The adjusted analysis reveals that cryptocurrencies traded on decentralized exchanges experience a significant 2.66% increase in arbitrage spreads. Conversely, a one standard deviation increase in liquidity is associated with only a 0.27% decrease in arbitrage spreads (calculated as 0.0656 multiplied by the standard deviation of 4.23), underscoring the limited impact of liquidity in the face of the pronounced effect of DEX exchanges.

The results from model (2) further solidify this interpretation, with all coefficients being statistically significant and their signs consistently aligning with our assumptions. This nuanced understanding helps reconcile the observed discrepancies and confirms the overarching narrative that while liquidity influences arbitrage spreads, the type of exchange—particularly the presence of decentralized exchanges—plays a crucial role in determining the magnitude of these spreads.

5 Robustness Test

Previous Section 4 details the model outcomes for the 30 primary cryptocurrencies featured in our dataset. To test the robustness of our findings, we significantly expand our sample size to include 240 cryptocurrencies, encompassing 3,131,135 observations. This broader dataset introduces a challenge, as some cryptocurrencies in our expanded sample do not have available data on buying pressure due to their absence from U.S. exchanges. To circumvent this data limitation, we innovate by utilizing the short-term change in trading volume as a surrogate for unsigned buying pressure. Specifically, we define $|\text{Crypto Buying Pressure}|_{i,t}$ as the difference in volume liquidity between two consecutive time periods: $\text{Volume}_{i,t} - \text{Volume}_{i,t-1}$. This methodological adjustment allows us to maintain the integrity and comprehensiveness of our analysis across a wider array of cryptocurrencies.

[Insert Table 12 Here]

Despite this exception, the consistency of other coefficient results with our initial assumptions underscores the robustness of our model. These findings validate our analytical approach and confirm the validity of our conclusions across a more extensive sample of the cryptocurrency market. The adaptation of volume liquidity changes as a proxy for buying pressure, and the substantial expansion of our dataset, not only strengthen the foundation of our analysis but also enhance the generalizability of our results to a wider array of cryptocurrencies and market conditions.

This comprehensive examination of the robustness tests ensures our model's applicability and reliability in capturing the nuances of arbitrage opportunities and market dynamics across the diverse landscape of the cryptocurrency market.

6 Conclusion

In conclusion, our comprehensive analysis of cryptocurrency pricing across 80 exchanges worldwide reveals significant insights into the dynamics of the digital currency market. We have meticulously explored the factors contributing to pricing discrepancies and arbitrage opportunities, employing an extensive dataset that encompasses daily pricing data from a wide array of exchanges. Our findings underscore the diversity and complexity of the global cryptocurrency ecosystem, highlighting the impact of market liquidity, exchange reputation, regulatory constraints, and geographical locations on pricing variations.

Our research reveals substantial arbitrage spreads across cryptocurrency exchanges, with notable disparities even among the most heavily traded cryptocurrencies such as Bitcoin. Interestingly, we observe that stablecoins exhibit a distinct pricing behavior, often demonstrating smaller or negative arbitrage spreads compared to other digital currencies. This suggests that stablecoins play a unique role in the cryptocurrency market, potentially facilitating more consistent pricing across different platforms.

Furthermore, our analysis indicates that decentralized exchanges tend to exhibit wider arbitrage spreads. Cryptocurrencies traded on platforms outside the United States or on less reputable exchanges also show higher arbitrage spreads, pointing to the influence of exchange characteristics and regulatory environments on market efficiency and arbitrage opportunities.

By leveraging a dataset unparalleled in its breadth and depth, our study not only builds upon existing research but also contributes new insights into the price formation dynamics of cryptocurrencies across global exchanges. We pinpoint potential arbitrage opportunities that persist despite the evolving market, highlighting the need for investors and traders to consider a range of factors, including technological and operational aspects of exchanges, when evaluating these opportunities.

This paper enriches our understanding of the cryptocurrency market, offering valuable insights into the interplay between various factors that influence pricing variations and arbitrage potential. As the digital currency ecosystem continues to evolve, our findings provide a foundation for future research and practical applications, emphasizing the importance of a nuanced approach to understanding and navigating the complex landscape of cryptocurrency trading.

Table 1: Cryptocurrency Exchanges by Geographical Regions.
Table 1 describes the geographical regions of exchanges describes the geographical information of 80 exchanges appearing in our dataset. For centralized exchanges, they are categorized by operational region or headquarters location. Exchanges operating on blockchain with smart contracts are classified as decentralized exchanges.

Geographical Regions of Exchanges							
North America (Canada, Mexico, United States)							
Allcoin,	Binance,	Binance Futures,	Binance V2,	BinanceUS,	Bitso,	Coinbase,	Currency.com,
ErisX,	FTX,	FTX US,	Gemini,	Itbit,	Kraken,	LGOMarkets,	OkCoin,
Poloniex,	Yobit.						
Asia-Pacific (Australia, Hongkong, Japan, New Zealand, Singapore, South Korea)							
ACX,	BCEX,	Bibox,	BinanceJEX,	Bit-Z,	Bitfinex,	bitFlyer,	BitForex,
Bithumb,	BitMEX,	Bitpanda,	Bittrex,	C-CEX,	CoinEx,	Coinflex,	CRCO,
EXX,	Gatecoin,	Huobi,	Huobi Derivative Market,	KuCoin,	OkEX,	OSL,	Quoine,
TideBit,	UEX,	UPbit,	Cobinhood.				
Europe (Austria, Finland, France, Ireland, Italy, Lithuania, Luxembourg, Netherland, Poland, Sweden, Switzerland, United Kingdom)							
BeQuant,	BigONE,	BitBay,	Bitlish,	Bitstamp,	BTC-Alpha,	CEX.IO,	CoinEgg,
Coinfloor,	CoinMate,	Deribit,	Ethfinex,	HitBTC,	LMAX,	LocalBitcoins,	Stronghold,
The Rock Trading,	Tidex,	ZB.					
Others (Argentina, Brazil, Israel, Turkey, United Arab Emirates)							
Bitibu,	BtcTurk,	Bybit,	Bybit Spot,	Bybit V2,	SouthXchange.		
Decentralized Exchanges							
Balancer,	Balancer V2,	BinanceDEX,	Curve,	Curve V2,	OneInch,	Sushiswap,	Uniswap V2,
Uniswap V3.							

Table 2: Daily Maximum Arbitrage Profit Across Exchanges.
Table 2 describes the statistics of percentage value of daily maximum arbitrage profits for Bitcoin. The daily maximum arbitrage profit is the percentage value of the percentage value of the highest BTC price among exchanges minus lowest BTC price among exchanges. And its percentage value is the maximum arbitrage profit divided by the median price among exchanges.

BTC Percentage Value of Maximum Arbitrage Profit							
Year	**Mean**	**Std**	**Min**	**25%**	**50%**	**75%**	**Max**
2019	14.40%	12.58%	0.83%	4.94%	9.38%	19.84%	59.84%
2020	15.69%	13.02%	1.00%	5.84%	10.64%	22.20%	59.96%
2021	11.29%	9.50%	1.36%	5.54%	8.51%	13.56%	62.85%
2022	11.93%	9.90%	0.97%	5.39%	9.32%	15.00%	69.97%
2023	8.67%	9.09%	0.84%	2.81%	5.27%	11.37%	42.98%

Table 3: Description of BTC and ETH Daily Arbitrage Spread.
Table 3 reports the statistics of arbitrage spreads for Bitcoin (BTC) and Ethereum (ETH), from January 2019 to March 2023. Panel A and Panel B present the daily BTC dollar value arbitrage spread $S_{BTC,j,t,[\$]}$ and percentage value $S_{BTC,j,t,[\%]}$ respectively, for each year. Panel C and Panel D present the daily ETH dollar value arbitrage spread $S_{ETH,j,t,[\$]}$ and percentage value $S_{ETH,j,t,[\%]}$ respectively, for each year. The p95 and p95 represent the 5th and 95th percentiles of the arbitrage spreads, respectively.

Panel A. BTC Daily Dollar Value of Arbitrage Spread

Year	Mean	Std	Median	p5	p95
2019	-8.67	253.48	0.00	-98.15	98.53
2020	-32.63	524.07	0.00	-114.91	60.33
2021	38.26	1070.16	0.25	-354.72	471.3
2022	44.17	586.79	0.00	-109.12	244.96
2023	10.71	367.41	0.00	-115.23	144.61

Panel B. BTC Daily Percentage Value of Arbitrage Spread

Year	Mean	Std	Median	p5	p95
2019	-0.05%	2.90%	0.00%	-1.31%	1.61%
2020	-0.15%	3.11%	0.00%	-0.98%	0.58%
2021	0.08%	2.14%	0.00%	-0.77%	1.04%
2022	0.16%	2.06%	0.00%	-0.41%	0.90%
2023	0.06%	1.71%	0.00%	-0.51%	0.62%

Panel C. ETH Daily Dollar Value of Arbitrage Spread

Year	Mean	Std	Median	p5	p95
2019	0.04	5.77	0.00	-2.31	4.29
2020	-0.25	6.45	0.00	-3.22	2.44
2021	-2.18	65.59	0.00	-25.63	23.95
2022	1.52	27	0.00	-10.4	16.89
2023	1.22	16.38	0.00	-10.05	16.27

Panel D. ETH Daily Percentage Value of Arbitrage Spread

Year	Mean	Std	Median	p5	p95
2019	0.07%	3.08%	0.00%	-1.19%	2.51%
2020	-0.02%	1.99%	0.00%	-1.03%	0.95%
2021	-0.10%	2.43%	0.00%	-0.94%	0.89%
2022	0.08%	1.31%	0.00%	-0.52%	0.82%
2023	0.08%	1.02%	0.00%	-0.64%	1.03%

Table 4: Description of BTC Daily Arbitrage Spread by Regions.

Table 4 reports the statistics of arbitrage spreads for Bitcoin (BTC) across different regions from January 2019 to March 2023. Panel A, Panel B, Panel C, and Panel D present the daily BTC percentage value $S_{BTC,j,t,[\%]}$ respectively, for each year in North America, Europe, Asia-Pacific and Other Areas, respectively. The p95 and p95 represent the 5th and 95th percentiles of the arbitrage spreads, respectively.

Panel A. BTC Daily Percentage Value of Arbitrage Spread (North America)

Year	Mean	Std	Median	p5	p95
2019	-0.42%	3.83%	0.00%	-0.80%	0.41%
2020	-0.39%	3.52%	0.01%	-0.27%	0.22%
2021	0.05%	1.65%	0.01%	-0.14%	0.26%
2022	0.00%	0.21%	0.00%	-0.10%	0.11%
2023	0.00%	0.18%	0.00%	-0.16%	0.15%

Panel B. BTC Daily Percentage Value of Arbitrage Spread (Europe)

Year	Mean	Std	Median	p5	p95
2019	-0.01%	2.23%	0.00%	-1.67%	2.03%
2020	0.26%	2.99%	0.00%	-1.40%	2.00%
2021	0.22%	2.56%	0.00%	-1.66%	2.40%
2022	0.63%	3.26%	0.01%	-0.58%	5.35%
2023	0.49%	2.96%	0.01%	-0.39%	1.78%

Panel C. BTC Daily Percentage Value of Arbitrage Spread (Asia-Pacific)

Year	Mean	Std	Median	p5	p95
2019	0.17%	2.47%	0.00%	-0.93%	1.51%
2020	-0.32%	3.15%	-0.01%	-0.89%	0.45%
2021	-0.13%	2.04%	-0.01%	-0.42%	0.25%
2022	0.00%	1.46%	0.00%	-0.22%	0.25%
2023	-0.04%	1.25%	0.00%	-0.43%	0.29%

Panel D. BTC Daily Percentage Value of Arbitrage Spread (Others)

Year	Mean	Std	Median	p5	p95
2019	0.31%	2.91%	0.05%	-2.66%	3.69%
2020	-0.06%	0.65%	0.00%	-1.09%	0.57%
2021	0.53%	1.93%	0.02%	-1.09%	5.12%
2022	0.01%	1.39%	-0.02%	-0.19%	1.05%
2023	0.05%	0.49%	-0.01%	-0.38%	0.89%

Table 5: Description of Arbitrage Spread by Trading Volume.

Table 5 reports the arbitrage spreads $S_{i,j,t,[\%]}$ of cryptocurrencies segmented into two volume groups. We classify $S_{i,j,t,[\%]}$ into "Small Volume" group if Volume$_{i,t}$ is larger than its median, otherwise grouped in "Large Volume" group. The reported difference indicates the spread disparity between two groups. The summary data covers all 30 cryptocurrencies from January 2019 to March 2020. The p95 and p95 represent the 5th and 95th percentiles of the arbitrage spreads, respectively.

Coin	Group	Start	End	N	Std	Mean	Median	p5	p95
BTC	Small Volume	1/1/19	6/30/21	35965	2.46%	0.02%	0.00%	-0.91%	1.05%
	Big Volume	1/1/19	6/30/21	35965	2.60%	0.01%	0.00%	-0.74%	0.89%
Difference						0.00%	0.00%	-0.17%	0.15%
ETH	Small Volume	7/1/21	3/30/23	35571	2.34%	0.03%	0.00%	-0.96%	1.53%
	Big Volume	7/1/21	3/30/23	35571	1.99%	-0.02%	0.00%	-0.75%	0.89%
Difference						0.05%	0.00%	-0.21%	0.64%
XRP	Small Volume	1/1/19	6/30/21	24181	1.96%	0.04%	0.00%	-0.86%	1.16%
	Big Volume	1/1/19	6/30/21	24181	2.39%	-0.15%	0.00%	-0.73%	0.53%
Difference						0.19%	0.00%	-0.14%	0.63%
Summary	Small Volume	7/1/21	3/30/23	507493	2.51%	0.06%	0.00%	-0.96%	1.14%
	Big Volume	7/1/21	3/30/23	507493	2.54%	-0.06%	0.00%	-0.89%	0.89%
Difference						0.11%	0.00%	-0.07%	0.25%

Table 6: Description of Average Arbitrage Spread on CEX vs DEX.
Table 6 reports the arbitrage spreads of cryptocurrencies traded both on DEXs and CEXs. For each cryptocurrency panel, the first row reports the statistics of the cryptocurrency arbitrage spreads $S_{i,j,t[\%]}$ on CEXs, the second row reports the statistics on DEXs. The difference between the statistics on DEXs and CEXs is also reported. The data from CEXs started from January 2019, and the data from DEXs reported from March 2020. The p95 and p95 represent the 5th and 95th percentiles of the arbitrage spreads, respectively.

Currency	Exchange	Start	End	N	Mean	Median	p5	p95
DAI	CEX	1/1/19	3/30/23	25915	-0.02%	0.00%	-0.52%	0.43%
	DEX	3/22/20	3/30/23	5397	0.02%	0.01%	-0.76%	0.88%
Difference					0.04%	0.01%	-0.24%	0.45%
ZEC	CEX	1/1/19	3/30/23	27715	0.01%	0.00%	-0.65%	0.63%
	DEX	9/29/20	11/3/22	221	1.06%	-1.16%	-29.69%	41.05%
Difference					1.05%	-1.16%	-29.04%	40.41%
BTC	CEX	1/1/19	3/30/23	68139	0.02%	0.00%	-0.67%	0.82%
	DEX	4/28/20	3/30/23	3852	0.02%	-0.02%	-2.93%	2.92%
Difference					0.01%	-0.02%	-2.26%	2.10%
BAT	CEX	1/1/19	3/30/23	31407	0.02%	0.00%	-1.41%	1.39%
	DEX	4/6/20	3/25/23	1124	-0.46%	-0.49%	-11.28%	10.19%
Difference					-0.49%	-0.49%	-9.87%	8.80%
LINK	CEX	1/1/19	3/30/23	35459	-0.01%	0.00%	-0.73%	0.70%
	DEX	4/24/20	3/30/23	3185	-0.05%	-0.13%	-6.45%	6.62%
Difference					-0.05%	-0.13%	-5.72%	5.92%
USDT	CEX	1/1/19	3/30/23	35493	0.09%	0.00%	-0.34%	0.51%
	DEX	5/18/20	3/30/23	4620	-0.08%	-0.01%	-0.55%	0.40%
Difference					-0.16%	-0.01%	-0.20%	-0.12%
BNB	CEX	1/1/19	3/30/23	17697	0.03%	0.00%	-0.45%	0.37%
	DEX	6/23/19	8/28/22	926	-2.31%	-0.15%	-35.91%	23.16%
Difference					-2.34%	-0.15%	-35.46%	22.80%

Currency	Exchange	Start	End	N	Mean	Median	p5	p95
ZRX	CEX	1/1/19	3/30/23	26558	0.00%	0.00%	-1.05%	0.90%
	DEX	4/2/20	3/30/23	794	-0.14%	-0.31%	-12.78%	14.70%
Difference					-0.14%	-0.31%	-11.73%	13.80%
DOGE	CEX	1/1/19	3/30/23	34784	0.15%	0.00%	-1.12%	2.83%
	DEX	4/19/21	3/30/23	708	0.09%	0.02%	-1.19%	1.53%
Difference					-0.06%	0.02%	-0.07%	-1.30%
MKR	CEX	1/1/19	3/30/23	26653	0.00%	0.00%	-1.21%	1.18%
	DEX	3/18/20	3/29/23	2115	0.50%	0.09%	-5.69%	8.38%
Difference					0.49%	0.09%	-4.49%	7.20%
USDC	CEX	1/1/19	3/30/23	27533	-0.06%	0.00%	-0.45%	0.28%
	DEX	3/22/20	3/30/23	5581	-0.03%	0.00%	-1.14%	0.86%
Difference					0.03%	0.00%	-0.69%	0.58%
ETH	CEX	1/1/19	3/30/23	65482	0.01%	0.00%	-0.82%	1.22%
	DEX	3/15/20	3/30/23	5685	0.00%	0.00%	-1.10%	0.97%
Difference					-0.01%	0.00%	-0.28%	-0.24%

Table 7: Description of Arbitrage Spread by Token Types (Stable vs Other Tokens.

Table 7 describes the percentage value of arbitrage spreads $S_{i,j,t[\%]}$ for the 30 mostly traded cryptocurrencies in our dataset. Panel A provides the arbitrage spreads for stablecoins and fiat currency USDC, USDT, DAI and USD. Panel B presents the arbitrage spreads for other regular cryptocurrencies. The data covers all 30 cryptocurrencies from January 2019 to March 2023. The p95 and p95 represent the 5th and 95th percentiles of the arbitrage spreads, respectively.

Panel A. USD Stable Cryptocurrencies Arbitrage Spreads Statistics									
Cryptocurrency	**Start**	**End**	**N**	**Mean**	**Std**	**p5**	**p95**	**Skew**	**Kurt**
DAI	1/1/19	3/30/23	31312	-0.01%	1.21%	-0.55%	0.49%	-8.64	630.65
USD	1/1/19	3/30/23	18660	-0.07%	1.37%	-1.18%	0.61%	-3.51	321.81
USDC	1/1/19	3/30/23	33114	-0.05%	1.17%	-0.58%	0.43%	-3.31	390.04
USDT	1/1/19	3/30/23	40113	0.07%	1.44%	-0.39%	0.49%	0.7	389.17
Sum	-	-	123199	-	-	-	-	-	-
Average	-	-	-	0.00%	1.30%	-0.57%	0.49%	-2.67	434.05

Panel B. Regular Cryptocurrencies Arbitrage Spreads Statistics									
Cryptocurrency	**Start**	**End**	**N**	**Mean**	**Std**	**p5**	**p95**	**Skew**	**Kurt**
ADA	1/1/19	3/30/23	30955	-0.02%	1.95%	-0.48%	0.53%	-1.21	175.44
BAT	1/1/19	3/30/23	32531	0.01%	2.70%	-1.79%	1.71%	1.57	99.2
BCH	1/1/19	3/30/23	44040	0.18%	3.03%	-0.82%	0.88%	10.16	159.93
BCHSV	1/1/19	3/30/23	22720	-0.30%	3.52%	-2.06%	1.36%	-6.46	78.5
BNB	1/1/19	3/30/23	18623	-0.09%	3.78%	-0.69%	0.60%	-3.23	77.2
BTC	1/1/19	3/30/23	71991	0.02%	2.53%	-0.82%	0.97%	-4.4	143.75
DASH	1/1/19	3/30/23	34834	0.26%	3.35%	-0.99%	2.71%	2.69	91.19
DOGE	1/1/19	3/30/23	35492	0.15%	3.40%	-1.13%	2.77%	-0.1	73.62
EOS	1/1/19	3/30/23	38939	0.01%	1.87%	-0.58%	0.52%	1.37	173.28
ETC	1/1/19	3/30/23	34559	-0.78%	5.78%	-2.08%	1.11%	-4.97	32.12
ETH	1/1/19	3/30/23	71167	0.01%	2.17%	-0.86%	1.18%	-5.04	190.8
EUR	1/1/19	3/30/23	12594	-0.05%	0.99%	-0.64%	0.35%	-11.53	471.98
LINK	1/1/19	3/30/23	38644	-0.01%	1.93%	-1.28%	1.22%	-1.32	178.92
LTC	1/1/19	3/30/23	54085	0.11%	1.51%	-0.60%	1.24%	1.3	221.5
MKR	1/1/19	3/30/23	28768	0.04%	2.10%	-1.59%	1.71%	0.5	140.82
NEO	1/1/19	3/30/23	31632	-0.01%	1.32%	-0.63%	0.59%	-6.32	398.28
OMG	1/1/19	3/30/23	30300	-0.02%	2.34%	-1.37%	1.26%	1.56	112.6
QTUM	1/1/19	3/30/23	27472	-0.02%	1.13%	-0.62%	0.54%	-2.67	614.92
REP	1/1/19	3/30/23	13738	0.61%	4.07%	-1.76%	5.61%	4.08	38.63
SC	1/1/19	3/30/23	13827	0.03%	2.75%	-1.60%	1.52%	1.4	90.27
TRX	1/1/19	3/30/23	37647	0.14%	2.71%	-0.93%	1.62%	3.16	111.17
XLM	1/1/19	3/30/23	36048	0.00%	1.51%	-0.76%	0.79%	1.87	218.55
XRP	1/1/19	3/30/23	48399	-0.06%	2.18%	-0.79%	0.76%	-8.56	189.01
XTZ	1/1/19	3/30/23	27543	-0.12%	2.41%	-1.06%	0.82%	-6.74	147.11
ZEC	1/1/19	3/30/23	27936	0.01%	2.07%	-0.70%	0.67%	2.67	238.27
ZRX	1/1/19	3/30/23	27352	-0.01%	2.67%	-1.36%	1.13%	1.64	110.14
Sum	-	-	891836	-	-	-	-	-	-
Summary	-	-	-	0.00%	2.66%	-0.97%	1.12%	-2.11	134.56

Table 8: Description of Arbitrage Spread by Exchange Trustworthiness.
Table 8 presents the statistics of percentage value of arbitrage spread $S_{i,j,t,[\%]}$ for BTC, ETH and XRP. The samples are segmented into two periods: the first period spans from January 2019 to June 2021, and the second period covers June 2021 to March 2023. We classify exchanges with an operation time exceeding 1102 days during the period from January 2019 to March 2023 as trustworthy exchanges, while those with a shorter operation time are categorized as non-trustworthy exchanges. The reported difference indicates the spread disparity between non-trustworthy and trustworthy exchanges. The p95 and p95 represent the 5th and 95th percentiles of the arbitrage spreads, respectively.

Currency	**Trustworthiness**	**Start**	**End**	**N**	**Mean**	**p5**	**p95**
BTC	Non-Trustworthy	1/1/19	6/30/21	8901	-0.65%	-3.75%	1.65%
	Trustworthy	1/1/19	6/30/21	32033	0.11%	-0.73%	1.02%
Difference					-0.76%	-3.02%	0.63%
BTC	Non-Trustworthy	7/1/21	3/30/23	8127	0.02%	-1.07%	1.14%
	Trustworthy	7/1/21	3/30/23	22930	0.15%	-0.25%	0.55%
Difference					-0.12%	-0.82%	0.58%
ETH	Non-Trustworthy	1/1/19	6/30/21	8934	-0.60%	-4.42%	1.63%
	Trustworthy	1/1/19	6/30/21	30286	0.12%	-0.75%	1.50%
Difference					-0.72%	-3.68%	0.13%
ETH	Non-Trustworthy	7/1/21	3/30/23	9134	-0.02%	-0.81%	0.74%
	Trustworthy	7/1/21	3/30/23	22813	0.10%	-0.50%	0.93%
Difference					-0.12%	-0.31%	-0.19%
XRP	Non-Trustworthy	1/1/19	6/30/21	4898	-0.82%	-4.90%	2.21%
	Trustworthy	1/1/19	6/30/21	23771	0.06%	-0.80%	1.06%
Difference					-0.87%	-4.10%	1.15%
XRP	Non-Trustworthy	7/1/21	3/30/23	2793	0.00%	-0.12%	0.13%
	Trustworthy	7/1/21	3/30/23	16937	0.00%	-0.55%	0.44%
Difference					0.00%	0.43%	-0.31%

Table 9: Regression Variables Statistics Summary

Table 9 Panel A describes the correlation matrix of regression variables. (1) Volume represents the log trading volume of cryptocurrency. (2) Buying pressure denotes the deviation from the actual log price to this smoothed log price. (3) The stablecoin indicator is 1 if it's pegged to the dollar. (4) The DEX indicator is 1 if the exchange runs on the blockchain. (5) The U.S. indicator is 1 if the exchange is in the U.S. (6) The Trustworthiness indicator is 1 if the exchange's operational days exceed the median of operational days. (7) Past Volatility represents the logarithmic value of past 30-day rolling price volatility. (8) Capital control measures the exchange location's capital control index by Fernández et al (2016). (9) The Futures indicator is 1 if the exchange supports trading futures. (10) The Number of confirmation blocks is the number of blockchain confirmations required by an exchange to recognize a deposit or withdrawal. Table 9 Panel B summarize the statistics for these variables.

Panel A. Correlation Matrix of Regression Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Volume (1)	-									
Buying Pressure (2)	21.98	-								
Stablecoin Indicator (3)	-26.04	-2.35	-							
DEX Indicator (4)	9.26	1.45	19.13	-						
U.S. Indicator (5)	-6.52	-0.64	4.64	-10.78	-					
Trustworthiness Indicator (6)	-10.36	-2.01	-4.32	-34.83	13.50	-				
Past Volatility (7)	76.19	15.52	-27.40	4.93	-1.93	-8.05	-			
Capital Control (8)	5.02	2.44	2.60	3.18	-3.70	5.44	1.98	-		
Futures Indicator (9)	-5.08	-2.49	1.59	13.08	-22.80	12.66	-7.44	-23.89	-	
# of confirmation block (10)	-3.62	0.49	-0.85	-14.29	-4.13	10.28	-2.23	-10.83	-0.97	-

Panel B. Summary Statistics of Regression Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mean	17.39	0.04	0.12	0.03	0.25	0.84	1.63	0.13	0.67	2.88
Median	16.67	0.00	0.00	0.00	0.00	1.00	0.41	0.13	1.00	3.00
Std	4.23	0.60	0.33	0.18	0.43	0.37	2.20	0.12	0.47	2.46
p5	12.44	-0.81	0.00	0.00	0.00	0.00	0.00	0.05	0.00	1.00
p95	26.67	1.09	1.00	0.00	1.00	1.00	6.61	0.33	1.00	6.00
Skew	0.64	0.57	2.32	5.16	1.16	-1.84	1.44	3.50	-0.73	3.45
Kurt	2.23	0.50	3.38	24.65	-0.66	1.40	1.14	13.75	-1.47	13.04

Table 10: Contributing Factors to Arbitrage Spread Among Exchanges (I). Table 10 shows how arbitrage spread $|S_{i,j,t,[\%]}|$ react to the variables: (1) Volume represents the log trading volume of cryptocurrency. (2) Buying pressure denotes the deviation from the actual log price to this smoothed log price. (3) The stablecoin indicator is 1 if it's pegged to the dollar. (4) The DEX indicator is 1 if the exchange runs on the blockchain. (5) The U.S. indicator is 1 if the exchange is in the U.S. (6) The Trustworthiness indicator is 1 if the exchange's operational days exceed the median of operational days. (7) Past Volatility represents the logarithmic value of past 30-day rolling price volatility. (8) Capital control measures the exchange location's capital control index by Fernández et al (2016). (9) The Futures indicator is 1 if the exchange supports trading futures. (10) The Number of confirmation blocks is the number of blockchain confirmations required by an exchange to recognize a deposit or withdrawal. The standard errors in parentheses are clustered by time. *** denotes statistical significance at the 1% level.

	$\lvert S_{i,j,t,[\%]}\rvert$
$\text{Volume}_{i,t}$	-0.0488***
	(0.003)
$\lvert\text{Crypto Buying Pressure}\rvert_{i,t} \times \mathbb{I}(\text{1 if not in U.S})_j$	0.1204***
	(0.032)
$\mathbb{I}(\text{1 if stable})_i$	-0.4842***
	(0.033)
$\mathbb{I}(\text{1 if DEX})_j$	1.4298***
	(0.073)
$\mathbb{I}(\text{1 if in U.S})_j$	-0.0997
	(0.026)
$\mathbb{I}(\text{1 if trustworthy})_j \times \mathbb{I}(\text{Before June 2021})_t$	-0.2911***
	(0.066)
$\text{Past Volatility}_{i,j,t}$	0.0492***
	(0.007)
$\text{Capital Control}_{j,t}$	0.9999***
	(0.138)
$\mathbb{I}(\text{1 if has futures})_j$	-0.5874***
	(0.035)
# of Confirmation Blocks_j	0.0198***
	(0.003)
Year-Month Fixed Effects	Yes
R^2	0.014
# of Observations	1015035

Table 11: Contributing Factors to Arbitrage Spread Among Exchanges.
Table 11 shows how arbitrage spread $|S_{i,j,t,[\%]}|$ react to the variables and their interaction variables: (1) Volume represents the log trading volume of cryptocurrency. (2) Buying pressure denotes the deviation from the actual log price to this smoothed log price. (3) The stablecoin indicator is 1 if it's pegged to the dollar. (4) The DEX indicator is 1 if the exchange runs on the blockchain. (5) The U.S. indicator is 1 if the exchange is in the U.S. (6) The Trustworthiness indicator is 1 if the exchange's operational days exceed the median of operational days. (7) Past Volatility represents the logarithmic value of past 30-day rolling price volatility. (8) Capital control measures the exchange location's capital control index by Fernández et al (2016). (9) The Futures indicator is 1 if the exchange supports trading futures. (10) The Number of confirmation blocks is the number of blockchain confirmations required by an exchange to recognize a deposit or withdrawal. The standard errors in parentheses are clustered by time. **, *** denotes statistical significance at the 5% and 1% level, respectively.

	$\|S_{i,j,t,[\%]}\|$	
	(1)	(2)
$\|\text{Crypto Buying Pressure}\|_{i,t} \times \mathbb{I}(1 \text{ if not in U.S})_j$	0.0466	0.0633**
	(0.040)	(0.039)
$\mathbb{I}(1 \text{ if stable})_i \times \text{Volume}_{i,t}$	-0.0227***	-0.0234***
	(0.007)	(0.008)
$\mathbb{I}(1 \text{ if DEX})_j$		2.6623***
		(0.237)
$\mathbb{I}(1 \text{ if DEX})_j \times \text{Volume}_{i,t}$	0.0623***	-0.0656***
	(0.003)	(0.010)
$\mathbb{I}(1 \text{ if in U.S})_j \times \text{Volume}_{i,t}$	-0.0086***	-0.0080***
	(0.001)	(0.001)
$\mathbb{I}(1 \text{ if trustworthy})_j \times \mathbb{I}(\text{Before June 2021})_t \times \text{Volume}_{i,t}$	-0.0189***	-0.0186***
	(0.003)	(0.003)
$\text{Past Volatility}_{i,j,t}$	0.1557***	0.1697***
	(0.022)	(0.023)
$\text{Capital Control}_{j,t}$	1.0715***	1.0424***
	(0.139)	(0.140)
$\mathbb{I}(1 \text{ if has futures})_j$	-0.6078***	-0.6123***
	0.033	(0.033)
$\# \text{ of Confirmation Blocks}_j$	0.0174***	0.0190***
	(0.003)	(0.002)
Year-Month Fixed Effects	Yes	Yes
Cryptocurrency Fixed Effects	Yes	Yes
R^2	0.029	0.031
# of Observations	1015035	1015035

Table 12: Robustness Test for 240 Cryptocurrencies.

Table 12 shows robustness of 240 cryptocurrencies and their reaction to arbitrage spread $|S_{i,j,t,[\%]}|$ in response to the variables: (1) Volume represents the log trading volume of cryptocurrency. (2) Unsigned buying pressure is proxied by $|\text{Crypto Buying Pressure}|_{i,t} = \text{Volume}_{i,t} - \text{Volume}_{i,t-1}$. (3) The stablecoin indicator is 1 if it's pegged to the dollar. (4) The DEX indicator is 1 if the exchange runs on the blockchain. (5) The U.S. indicator is 1 if the exchange is in the U.S. (6) The Trustworthiness indicator is 1 if the exchange's operational days exceed the median of operational days. (7) Past Volatility represents the logarithmic value of past 30-day rolling price volatility. (8) Capital control measures the exchange location's capital control index by Fernández et al (2016). (9) The Futures indicator is 1 if the exchange supports trading futures. (10) The Number of confirmation blocks is the number of blockchain confirmations required by an exchange to recognize a deposit or withdrawal. The standard errors in parentheses are clustered by time. *** denotes statistical significance at the 1% level.

Panel A	$\lvert S_{i,j,t,[\%]} \rvert$	**Panel B**	$\lvert S_{i,j,t,[\%]} \rvert$
$\text{Volume}_{i,t}$	-0.0799***	$\lvert\text{Crypto Buying Pressure}\rvert_{i,t} \times \mathbb{I}(1 \text{ if not in U.S})_j$	0.0268***
	(0.003)		(0.004)
$\lvert\text{Crypto Buying Pressure}\rvert_{i,t} \times \mathbb{I}(1 \text{ if not in U.S})_j$	0.0490***	$\mathbb{I}(1 \text{ if stable})_i \times \text{Volume}_{i,t}$	-0.0315***
	(0.008)		(0.008)
$\mathbb{I}(1 \text{ if stable})_i$	-0.7288***	$\mathbb{I}(1 \text{ if DEX})_j$	3.0002***
	(0.026)		(0.139)
$\mathbb{I}(1 \text{ if DEX})_j$	2.0688***	$\mathbb{I}(1 \text{ if DEX})_j \times \text{Volume}_{i,t}$	-0.0534***
	(0.078)		(0.005)
$\mathbb{I}(1 \text{ if in U.S})_j$	0.0771	$\mathbb{I}(1 \text{ if in U.S})_j \times \text{Volume}_{i,t}$	0.0033
	(0.042)		(0.002)
$\mathbb{I}(1 \text{ if trustworthy})_j \times \mathbb{I}(\text{Before June 2021})_t$	-0.2546***	$\mathbb{I}(1 \text{ if trustworthy})_j \times \mathbb{I}(\text{Before June 2021})_t \times \text{Volume}_{i,t}$	-0.0184***
	(0.066)		(0.003)
$\text{Past Volatility}_{i,j,t}$	0.0730***	$\text{Past Volatility}_{i,j,t}$	0.2127***
	(0.005)		(0.021)
$\text{Capital Control}_{j,t}$	1.0010***	$\text{Capital Control}_{j,t}$	1.0154***
	(0.167)		(0.170)
$\mathbb{I}(1 \text{ if has futures})_j$	-0.4689***	$\mathbb{I}(1 \text{ if has futures})_j$	-0.5314***
	(0.040)		(0.043)
$\#\text{ of Confirmation Blocks}_j$	0.0146***	$\#\text{ of Confirmation Blocks}_j$	0.0131***
	(0.002)		(0.002)
Year-Month Fixed Effects	Yes		Yes
Cryptocurrency Fixed Effects			Yes
R^2	0.029		0.027
# of Observations	3131135		3131135

Figure 1: Number of Active Cryptocurrency Exchanges.
Figure 1 plots the daily time series for number of active exchanges, from January 2019 to March 2023. Active exchanges refer to those exchanges that were operational on each respective date.

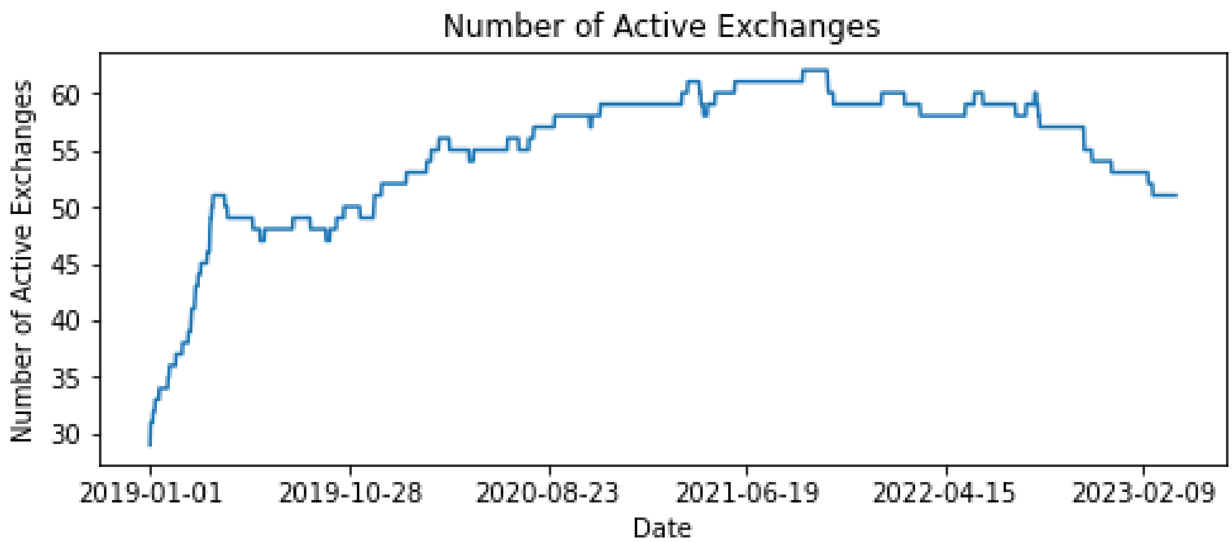


Figure 2: Number of Actively Traded Cryptocurrencies.
Figure 2 plots the daily time series for number of different cryptocurrencies are traded, from January 2019 to March 2023.

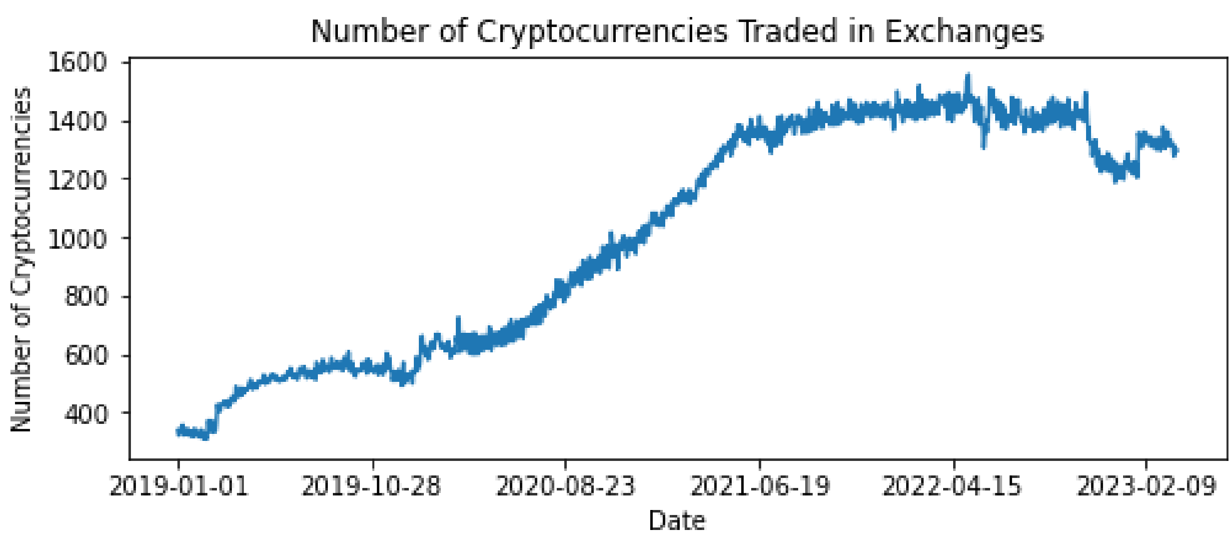
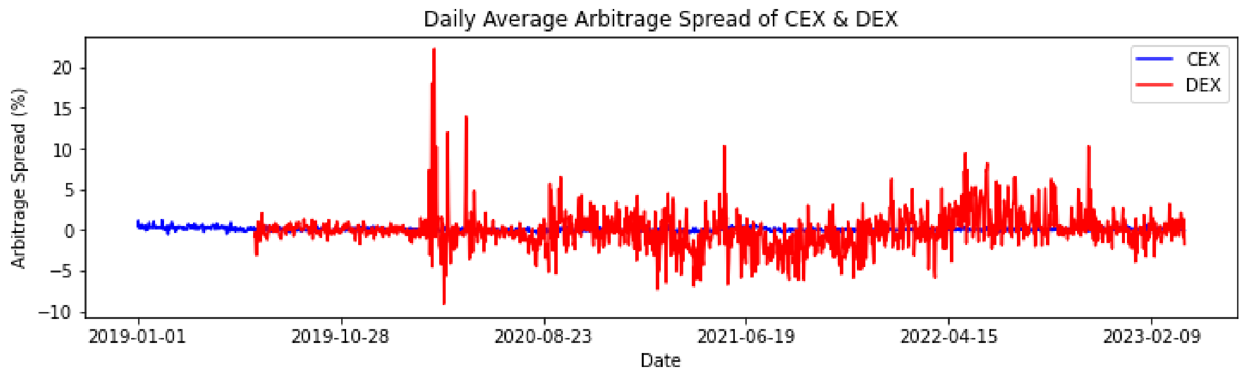
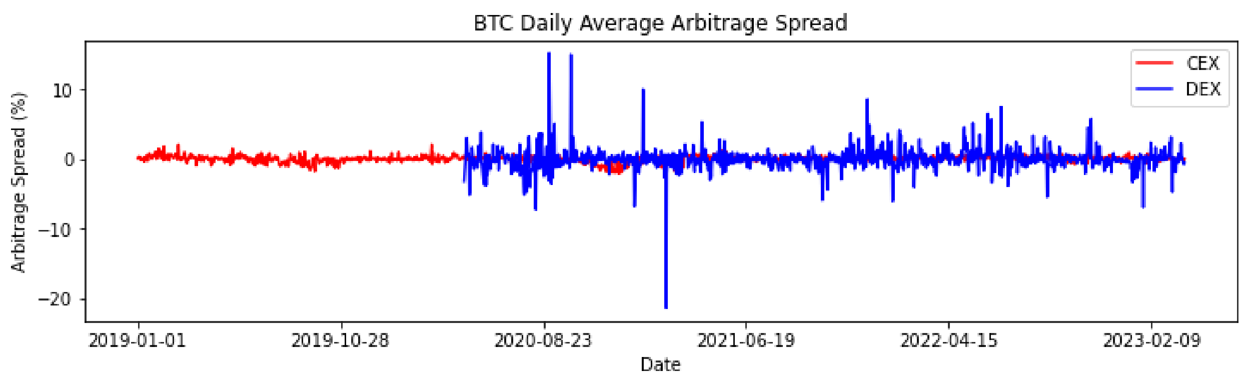


Figure 3: Arbitrage Spread by Exchange Type (CEX vs DEX).
Figure 3 plots the time series of average percentage value of arbitrage spreads $S_{i,j,t,[\%]}$ by exchange type. Panel A plots the daily average arbitrage spreads for all cryptocurrencies i traded on exchange j which are CEXs or DEXs. Panel B plots the daily average arbitrage spreads for BTC on CEXs or DEXs. Panel C plots the daily average arbitrage spreads for ETH on CEXs or DEXs. The data reported from CEXs started from January 2019, and the data from DEXs reported from March 2020.

Panel A. Average Arbitrage Spread on CEX vs DEX.



Panel B. Bitcion Arbitrage Spread on CEX vs DEX.



Panel C. Ethereum Arbitrage Spread on CEX vs DEX.

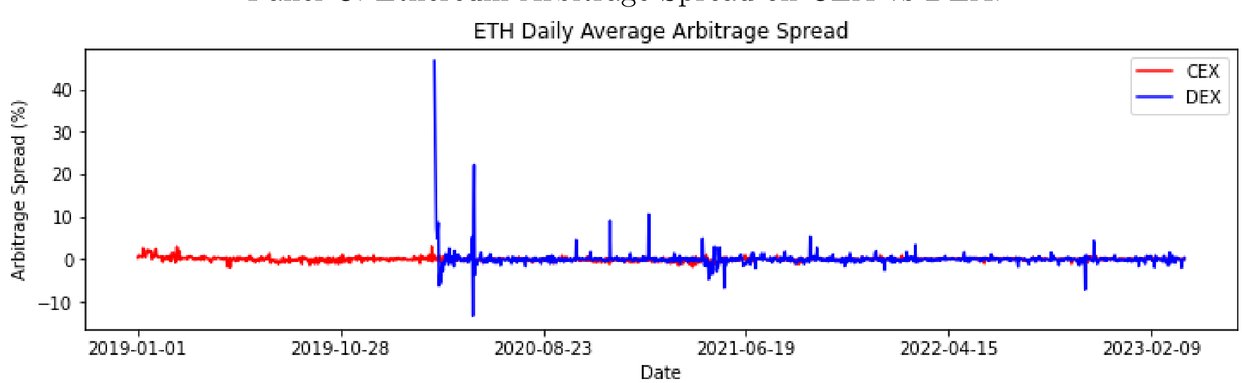


Figure 4: Arbitrage Spread by Token Types (Stable vs Other Tokens).
Figure 4 plots the time series of average arbitrage spreads by cryptocurrency types from January 2019 to March 2023. Cryptocurrencies are categorized as stablecoins if they are pegged to the U.S. dollar; otherwise, they are categorized as regular cryptocurrencies.

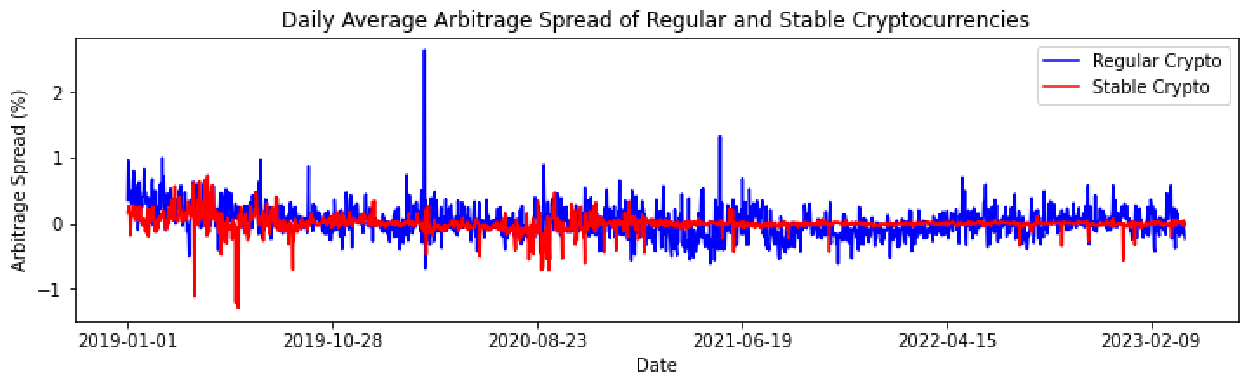
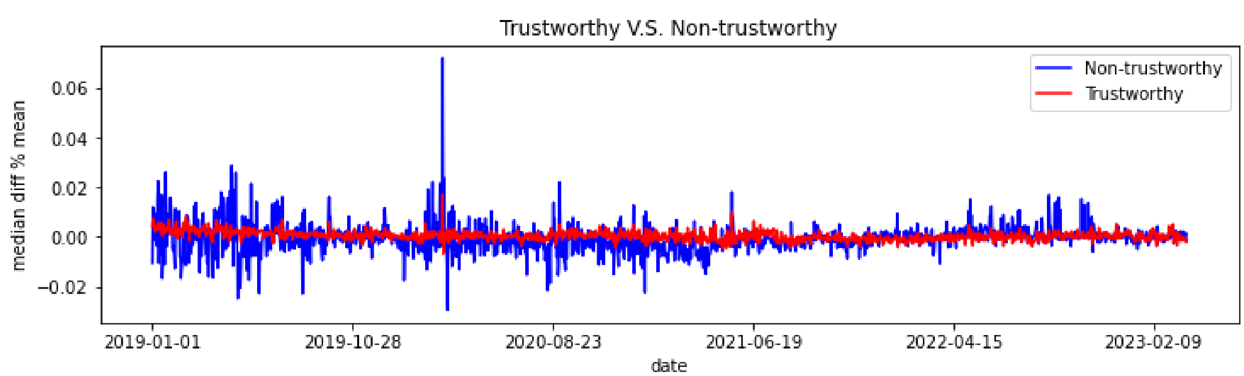


Figure 5: Arbitrage Spread by Exchange Trustworthiness.
Figure 5 illustrates the daily average arbitrage spreads $S_{i,j,t,[\%]}$ for cryptocurrencies i traded on exchange j categorized as trustworthy or non-trustworthy. We classify exchanges with an operation time exceeding 1102 days during the period from January 2019 to March 2023 as trustworthy exchanges, while those with a shorter operation time are categorized as non-trustworthy exchanges.



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