Cross-Exchange Arbitrage and Market Efficiency in Cryptocurrency Markets

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I & II. Introduction/Executive Summary

Since the launch of Bitcoin in 2009, cryptocurrencies have evolved from a fringe technological experiment into a sizable, but still relatively immature, asset class. By the mid-2020s, the aggregate market capitalization of crypto assets was in the multitrillion dollar range, with tens of thousands of tokens traded across hundreds of spots and derivatives venues worldwide. Rather than treating "crypto" as a curiosity, an emerging academic literature now analyses it as a distinct segment of global financial markets, with its own market microstructure, liquidity dynamics and price discovery mechanisms (Almeida & Gonçalves, 2024; Makarov & Schoar, 2020).

A key insight from this literature is that cryptocurrency markets blend features of foreign exchange trading and modern electronic equity markets. On the one hand, trading is global, largely borderless and continuous, resembling Foreign Exchange (FX) more than traditional equities. On the other hand, most economic activity occurs on centralized exchanges (CEXs) using central limit order books and continuous double auctions, very similar to equity and futures markets (Almeida & Gonçalves, 2024). Three structural characteristics are particularly important for this thesis.

First, crypto trades on a 24/7 basis, without opening and closing auctions. Second, price discovery is dominated by a handful of large CEXs, even though the underlying assets are settled on decentralized blockchains. Third, trading is heavily fragmented and regionally segmented, with no consolidated tape or binding best execution rule, which creates persistent pockets of illiquidity and cross-exchange price discrepancies (Makarov & Schoar, 2020).

The 24/7 trading environment fundamentally changes the temporal structure of liquidity and volatility. High frequency studies show that crypto markets exhibit clear intraday patterns, but without the sharp open–close effects seen in equities. Instead, activity and volatility “follow the sun,” peaking around the Asian, European and U.S. trading sessions and in response to major macroeconomic releases such as U.S. CPI or FOMC announcements (Wątorek et al., 2023). At the same time, the investor base has shifted from retail dominated trading towards increasing institutional participation, visible in the growth of CME Bitcoin and Ether futures, crypto linked ETFs and the adoption of systematic and high frequency strategies in digital assets. This suggests that cryptocurrency markets are progressively integrating with the broader financial system, both in terms of participants and in their reaction to macro information.

However, while the existence of large, liquid venues might suggest that the law of one price should be held tightly, the evidence points in the opposite direction. Prices for the same crypto asset can differ by economically meaningful amounts across exchanges, sometimes for extended periods. Fragmentation and regional segmentation are central here. Exchanges operate under different regulatory and banking regimes: some are tightly regulated and closely connected to local fiat payment systems, whereas others are offshore platforms with looser oversight. Makarov and Schoar (2020) document that cross-border price deviations in Bitcoin are significantly larger than within country differences and comove with capital controls and banking frictions. The well known “Kimchi premium” on Korean exchanges, where Bitcoin has at times traded at a persistent premium to U.S. venues, is one example of how local demand and capital controls can produce structural price wedges.

Liquidity is also highly uneven. On major BTC/USD or BTC/USDT pairs at top exchanges, quoted spreads can be extremely tight and depth at the best quotes very high, sometimes comparable to or better than small cap equity indices. At the same time, smaller venues and many altcoins exhibit thin order books, wider spreads and poor resiliency, particularly outside peak trading hours. Liquidity is state dependent: during stress episodes or large volume shocks, market makers tend to widen spreads and reduce depth, and these adjustments do not occur uniformly across venues. As a result, cross-exchange price gaps often widen precisely when volatility is high, and arbitrage is most valuable, but also most difficult to execute.

Against this backdrop, cross-exchange arbitrage plays a central role. In theory, arbitrage is a zero investment, riskless profit opportunity, and in a frictionless world its existence would be incompatible with competitive equilibrium (Dybvig & Ross, 1987, 2003). In practice, most “arbitrage” strategies are better described as near arbitrage: they aim to exploit mispricing, but face transaction costs, funding constraints and execution risk (Pontiff, 2006). Cross-exchange arbitrage in crypto is the attempt to buy a coin where it is cheap and sell it where it is expensive, across CEXs or between CEXs and decentralized exchanges (DEXs).

The importance of this activity goes beyond trading profits. The absence (or presence) of effective arbitrage is directly linked to market efficiency and the Law of One Price (Fama, 1970; Cochrane, 2001). In a fragmented environment, cross-exchange arbitrage is the mechanism that aligns prices for the same asset across venues and supports a coherent valuation framework. Empirically, early crypto markets exhibited large and long lived arbitrage opportunities, especially across jurisdictions with capital controls (Makarov & Schoar, 2020). More recent evidence suggests that these opportunities have declined as infrastructure, data quality and professional arbitrage participation have improved, but they have not disappeared completely (Crépellière, Pelster, & Zeisberger, 2023; Hautsch, Scheuch, & Voigt, 2024).

Several frictions explain why cross-exchange price discrepancies persist. First, there is latency in both information transmission and settlement. Moving assets between exchanges often requires chain transfers with stochastic confirmation times (Hautsch et al. 2024). Model this as an arbitrage bound that depends on settlement delay, volatility and default risk, and shows that observed price differences are largely consistent with these bounds. Second, heterogeneous and time varying liquidity means that effective execution prices differ across venues even when quoted mid prices are similar. Third, regional demand, capital controls and regulatory risk can generate structural premia, such as the Kimchi premium, that cannot be arbitraged without taking on legal or operational risk. Finally, fee structures (maker–taker fees, withdrawal costs, funding rates and blockchain transaction fees) and exchange level incentives alter the economics of arbitrage and can turn apparent mispricing's into marginal or unprofitable opportunities once costs are considered.

This thesis takes these observations as its starting point. The overarching aim is to analyze cryptocurrency market microstructure through the lens of cross-exchange pricing and arbitrage. Conceptually, it links classical arbitrage theory and the limits to arbitrage literature (e.g., Shleifer & Vishny, 1997; Gromb & Vayanos, 2010) to the specific frictions of blockchain based markets. Empirically, it views the size, frequency, and persistence of cross-exchange price differences as a quantitative proxy for market maturity and integration. By relating observed pricing patterns to measures of latency, liquidity, regional segmentation and fee structures, the study seeks to contribute to a better understanding of where crypto markets currently sit on the spectrum from "immature and segmented" to "integrated and almost arbitrage free," and what this implies for their future role in global finance.

III. Prior Research and Literature Gap

Although cryptocurrency has existed for over a decade, formal academic research on crypto market efficiency is still relatively young and overwhelmingly short-term in scope. Most published work examines only a few years of data from a period when exchanges, liquidity, and blockchain infrastructure were still developing. As a result, the existing literature provides only a partial view of how cross-exchange pricing actually functions in today's far more mature crypto environment. This makes the topic of cross-exchange arbitrage particularly important, because real-time price differences across exchanges reveal not only potential trading opportunities but also the underlying efficiency—or inefficiency—of a rapidly evolving market.

One of the earliest and most cited studies is Makarov and Schoar (2020), a research paper published through the London School of Economics, which analyzes global Bitcoin markets and documents persistent price gaps across international exchanges. Their analysis highlights how fragmentation, regulatory frictions, and liquidity differences made it possible for prices to diverge for extended periods of time. Importantly, their findings reflect a market that is still in its adolescence. During the sample window examined in that study, many exchanges operated with thin order books, inconsistent liquidity, and slower internal matching engines. As a result, the observed price discrepancies cannot be cleanly compared to those that might occur today in a far more mature trading ecosystem. While the study provides convincing evidence that early crypto markets were inefficient, its conclusions are necessarily tied to the market conditions of that era.

A second major contribution comes from Crépellière, Pelster, and Zeisberger (2022), who extend the literature by incorporating transaction costs and transfer delays into their arbitrage analysis. They find that while price gaps across exchanges do exist, nearly all potential arbitrage profits disappear once realistic frictions—such as withdrawal fees, deposit delays, and volatile network congestion—are accounted for. Their work importantly reframes the question from “Do price gaps exist?” to “Can these gaps actually be captured?” However, this study is also constrained by the state of crypto markets at the time. Their data reflects fee structures that have since changed, blockchain settlement that was slower and less predictable than it is today, and a trading landscape dominated by Bitcoin with relatively little attention paid to multi-asset behavior.

Across these and other related studies, several limitations are apparent. First, most papers rely on data from early-stage or pre-institutional markets (roughly 2015–2020), a period when both technological infrastructure and investor participation were meaningfully different from today. Second, prior research overwhelmingly focuses on Bitcoin alone, even though exchanges now handle high-volume blue-chip assets such as Ethereum and Solana, each with different liquidity profiles and settlement mechanisms. Third, older studies were conducted during a time when blockchain settlement times were slower and significantly more variable, which inflated transfer delays and made cross-exchange trading more difficult. Fourth, the fee structures in earlier research do not reflect the current landscape; major exchanges today offer lower maker–taker rates, VIP tiers, reduced withdrawal fees, and near-instant internal transfers.

Because of these constraints, academic literature does not fully capture the structural changes that have occurred in the crypto ecosystem over the last several years. What is missing is a modern, multi-dimensional assessment that reflects the crypto market as it actually operates today. Specifically, there is no recent study that simultaneously evaluates multiple assets, multiple major exchanges, post-2024 fee structures, and a market environment characterized by dramatically higher liquidity and faster blockchain settlement times. As a result, the existing literature may no longer accurately describe whether arbitrage opportunities meaningfully persist in the present-day market.

This study aims to fill the gap in the existing literature by providing a modern, multi-asset, multi-exchange assessment of cryptocurrency arbitrage during the 2024–2025 period. Unlike earlier research, which relied on data from less developed markets, our analysis evaluates a trading environment marked by far higher liquidity, more reliable exchange infrastructure, and clearer fee structures. We examine three major cryptocurrencies—BTC, ETH, and SOL—across some of the largest centralized exchanges to capture a more accurate picture of how prices behave in today's market. By using updated trading fees, current exchange policies, and a broader asset set, our approach reflects the environment that contemporary traders operate in.

By incorporating these elements, our research provides a clearer understanding of whether meaningful arbitrage opportunities still exist once realistic frictions are considered. The study contributes academically by offering updated evidence from a much more mature market than those examined in previous papers. It also contributes practically by helping traders, institutions, and regulators better understand how exchange design, liquidity, and fees influence real-world market efficiency. Essentially, this project brings the conversation into the present, re-evaluating crypto arbitrage with data and conditions that reflect the modern landscape rather than the early, transitional years of industry.

IV. Qualitative Analysis

Even in highly liquid financial markets, it is common for the same asset to trade at slightly different prices across different venues. Cryptocurrency markets are no exception. Although Bitcoin, Ethereum, and Solana all trade globally and continuously, identical pricing across exchanges is not guaranteed. Instead, small but meaningful discrepancies naturally arise due to structural differences between platforms, geographic trading patterns, and the mechanics of order-book markets. Understanding these drivers is essential for analyzing the presence—or absence—of viable arbitrage opportunities.

One of the primary reasons price differences emerge is latency, or the time it takes for information to travel between exchanges. Each platform processes market data, updates its order book, and adjusts to new trades at slightly different speeds. News, large trades, or sudden market movements are first reflected on the exchange where they occur, and only afterward propagate to others. Even delays measured in milliseconds can produce short-lived but visible price gaps, especially during periods of heightened volatility. In traditional finance, high-frequency firms spend millions to reduce latency; in crypto, the fragmentation of exchanges and global infrastructure makes these small timing gaps almost unavoidable.

A second source of discrepancies is order-book imbalance. Every exchange has its own unique mix of buyers, sellers, and liquidity providers, which means that supply and demand do not perfectly align across platforms. When a large market buy order hits one exchange, it consumes the available sell orders on that platform and pushes the price upward. Until additional sellers arrive or arbitrage traders step in, that exchange will temporarily show a higher price than others. The same dynamic occurs on the downside when a large sell order wipes out local buy liquidity. These imbalances can persist for seconds, minutes, or longer depending on the depth of the order book and the responsiveness of market participants.

Regional demand differences also play a meaningful role. Cryptocurrency trading is a global activity, and different regions operate on distinct time zones and respond to news at different times of the day. For example, Asian markets may react strongly to an overnight regulatory announcement before U.S. traders are awake, leading to temporarily higher or lower prices on exchanges with more Asian user flow. Likewise, U.S.-based platforms may experience unique patterns during major economic releases or market events. This geographic segmentation creates pockets of localized demand that influence price independently on each exchange.

Another contributor to cross-exchange spreads is stablecoin liquidity, particularly for assets priced in USDT or USDC rather than in actual U.S. dollars. Although stablecoins are designed to remain pegged at $1.00, their effective value can drift slightly depending on issuance, redemption flows, and liquidity conditions. When USDT or USDC trades at $1.01 on one exchange and $0.99 on another, the resulting prices of BTC/USDT, ETH/USDC, and similar pairs will naturally differ even if the true underlying value of the asset is the same. These deviations are typically small, but during periods of heavy demand or stress, stablecoin-specific liquidity conditions can create noticeable short-term price differences between exchanges that rely on different quote assets.

Taken together, these factors—latency, order-book dynamics, regional trading behavior, and stablecoin liquidity—create a market environment in which identical prices across exchanges cannot always be expected. Most of these discrepancies are small and resolve quickly as traders respond and liquidity flows in, but they are the foundation of cross-exchange arbitrage. The existence, size, and duration of these gaps ultimately determine whether arbitrage is possible in practice. By understanding the structural forces that generate these differences, our study can more effectively evaluate whether the modern crypto market still allows for meaningful price-based arbitrage opportunities or whether increased maturity has largely eliminated them.

V. Barriers to Arbitrage

Even when price discrepancies appear across cryptocurrency exchanges, exploiting them in practice is far more difficult than simple theory suggests. A number of structural frictions reduce or eliminate the profitability of cross-exchange arbitrage, especially in real-world market conditions.

First, trading fees represent an immediate drag on potential returns. Major centralized exchanges use maker–taker fee structures, and the rate a trader pays varies based on volume tiers, liquidity provided, and specific platform rules. These fees accumulate quickly, meaning a price gap must be large enough to overcome both the entry and exit fees for the trade to be profitable. Spreads that appear attractive on paper often shrink significantly once realistic fee schedules are considered.

Second, withdrawal fees and blockchain network fees introduce another layer of friction. Even if the trader captures a price gap on the initial purchase, transferring the asset to a second exchange to complete the arbitrage requires paying the network's transaction cost. These fees fluctuate based on network congestion and differ by blockchain, sometimes rising sharply at peak activity times. As a result, the actual cost to move funds between venues can materially reduce or even eliminate an otherwise profitable opportunity.

Third, transfer times vary substantially across blockchains, creating significant execution risk. Bitcoin transactions can take 10–60 minutes depending on network conditions, while Ethereum and Solana finalize much more quickly. During these transfer windows, market prices on the target exchange can change, causing the spread to disappear before the arbitrage leg is completed. This delay is one of the primary reasons many arbitrage strategies fail in live markets: even small price movements during the transfer window can erase the entire opportunity.

Finally, price volatility during the transfer period magnifies the difficulty. Crypto markets operate 24/7 and react rapidly to order-flow changes, sentiment shifts, and liquidations. Because a trader is effectively exposed to the market while waiting for the transferred asset to settle, even minor fluctuations can convert a profitable spread into a loss. This execution risk is one of the most important qualitative frictions limiting real-time arbitrage across exchanges.

VI. VIX Spikes and Macro Conditions

To better understand how broader financial conditions might influence crypto market behavior, we examined days when the CBOE Volatility Index (VIX) moved by at least ±10% and documented the major macro events occurring on those dates. This qualitative review allowed us to identify whether large volatility shocks in traditional markets tend to coincide with structural changes in crypto liquidity, order-book depth, or price synchronicity across exchanges. A detailed list of these events and corresponding VIX movements is provided in Appendix A.

Although the cryptocurrency market operates independently of equities, large VIX spikes often reflect periods of heightened global uncertainty—economic data releases, geopolitical headlines, policy announcements, or abrupt shifts in investor sentiment. During these high-stress environments, crypto order books may temporarily thin out, traders reduce risk exposure, and exchanges update prices at different speeds. These conditions create brief windows where cross-exchange spreads can widen or appear more frequently, even without any asset-specific news.

By qualitatively reviewing the real-world catalysts behind major VIX movements, we establish a contextual framework for understanding why macro volatility might matter for crypto microstructure. This approach does not assume a direct relationship between the VIX and crypto prices. Instead, it offers a conceptual rationale for testing whether broader financial stress aligns with the cross-exchange pricing behavior observed in our later quantitative analysis. The appendix evidence supports the intuition that extreme macro days can affect liquidity conditions across markets, making VIX a reasonable factor to include in the study's broader framework.

VI. Methods

When it came time to search for arbitrage opportunities in crypto, the first real step was finding a dataset that actually made sense for what we were trying to measure. We needed clean, consistent price data for Bitcoin, Ethereum, and Solana across several of the major centralized exchanges. To do this, we pulled daily historical prices from Coinbase, Binance, Kraken, Bitfinex, HTX, and Bitget, all taken directly from "Investing.com's" time series database (*Investing.com - Stock Market Quotes & Financial News*, n.d.). Our time window ran from November 1st, 2024, through November 1st, 2025, which gave us a full year of matched observations to work with.

Each exchange reports prices based on its own order book, which means that quotes do not always align perfectly in real-time. To fix this, we aligned everything to UTC-0, ensuring the comparisons were actually valid. After cleaning it all up, we ended up with a dataset that matched prices across all exchanges every single day, letting us pinpoint exactly when and where prices diverged. Since these exchanges make up most of the liquidity in the entire crypto market, this dataset reflects how the modern market really behaves.

In total, we worked with 1,460 matched observations per asset. Each exchange had 365 separate observations, which is well over the credible amount to observe a level of significance. That amount of data gave us enough of a window to see both the normal price differences and the more unusual gaps that only show up during heavier market activity. Ultimately, this dataset gave us the foundation we needed to figure out whether cross-exchange pricing inefficiencies still happen in a market that is supposedly more efficient than ever.

After building the dataset, the next thing we needed to figure out was how big the price differences actually were. To measure this, we calculated the percentage spread between the highest price and the lowest price across the exchanges for each asset. The formula is simple, but it gives a direct look at the theoretical profit someone could make before factoring in any real-world limitations.

When we looked at these raw spreads, it became obvious that all three cryptocurrencies had mispricing almost every single day. This makes sense. Each exchange processes orders at different speeds, and liquidity can shift around at any moment. Even in a market that is supposed to be very efficient, small discrepancies will naturally pop up.

Ethereum stood out the most here. Not only did it have pricing spreads every day like the others, but the size of its spread was significantly larger during the time frame of November 2024 to January 2025. After this, the price spread seemed to decrease significantly and settle at a much lower level. That clearly shows periods where the market was not aligning across exchanges as fast as usual. If someone only looked at the raw spreads, Ethereum would absolutely look like the best arbitrage candidate. At this stage, remember, we were not applying any fees at all. This meant Ethereum had the strongest theoretical arbitrage potential in the dataset. Bitcoin and Solana both had spreads, too, but they were usually tight and much more controlled.

Bitcoin showed exactly the type of spread behavior you would expect from the largest and most liquid cryptocurrency. There were small differences across exchanges almost every day, but nothing extreme. The spreads were tight and did not last long. This suggests that automated trading activity, especially from market makers, quickly closes gaps as they appear.

Solana was essentially a non-factor in our analysis. It had daily pricing like the other two, but the gaps were usually 1 to 10 cents maximum. Solana's network structure and ultra-fast block times probably help keep its prices more stable across exchanges, even before adding fees into the equation.

These points are in a pretty clear direction. Mispricing's exist everywhere in crypto, but the size and consistency of these gaps vary a lot between assets. This sets up the real question our project needs to answer, which is whether any of these spreads still matter after factoring in the reality of cryptocurrency trading costs.

The purpose of this stage was not to decide whether someone could actually execute these trades. It was simply about mapping out what the market looks like before costs get involved. That next step comes later in our analysis. What we show here is that price fragmentation absolutely exists and appears consistently throughout the entire sample period.

We also looked at whether bigger economic or geopolitical events influenced the size of these spreads. To test this, we compared the spreads to movements in the VIX index and tracked twenty-eight major market events defined by moves of plus or minus ten percent (*Investing.com - Stock Market Quotes & Financial News*, n.d.). If crypto spreads widened during volatile periods, that could suggest a link between broader market risk and exchange-level inefficiencies.

What we found instead was basically no connection at all. Only four of the twenty-eight large events had any arbitrage activity, and the correlation between daily spreads and the VIX was extremely low for all three assets. This supports the idea that these inefficiencies are not coming from macroeconomic events. They are coming from the structure of the crypto market itself, especially the fact that each exchange operates as its own liquidity pool. This is important because it shows that spreads emerge from internal market mechanics rather than outside market shocks. Crypto still behaves like its own ecosystem, even with growing institutional involvement.

Everything in this section lays out the landscape of cross-exchange mispricing before introducing real-world constraints. The next step is to figure out how many of these theoretical opportunities survive after including trading fees, withdrawal costs, and especially transfer times.

The act of buying, selling, and transferring cryptocurrencies to and from centralized exchanges incur different fees. Each exchange has its own preset base rate that is charged per transaction. There are three different fees that are encountered when performing the trading strategy.

The first fee is caused by buying the cryptocurrency from the target exchange. This is expressed as a percentage of the total transaction value. The second fee is generated from transferring the cryptocurrency to an external wallet on a different exchange. This transaction interacts directly with the blockchain, causing the miners to charge a miner fee if using Bitcoin or a gas fee charged by Ethereum stakes. Solana has a fixed rate fee of 0.000005 SOL (*Understanding Solana Transaction Fees | Solana*, n.d.). The third fee is caused by selling the cryptocurrency on secondary exchange, also expressed as a percentage of the total transaction value. Each of these fees are considered to measure if any arbitrage opportunities can exist.

After all fees are considered, a net value is determined by the difference between the spreads of the identified central exchanges and the fees incurred. This would be considered the arbitrage profit, if any exists. To truly understand if this trading strategy is risk-free, total variance must be considered. A regression equation is defined as:

$$y = \beta_0 + \beta_1 x + \varepsilon. \text{ (Barnett, 2025)}$$

We can take this regression equation to explain the total variance of the assets.

$$\mathrm{Var}[rbtc] = \beta^2_{btc}\sigma^2_M + \sigma^2_{btc} \text{ (Barnett, 2025, Slide 14)}$$

$\beta^2_{btc}\sigma^2_M$ is defined as Systematic risk

σ^2_{btc} is defined as Idiosyncratic risk

Idiosyncratic risk is the inherent risk that is associated with holding a specific asset. This is typically defined as 0 because this type of risk can be diversified away. Systematic risk is associated with overall fluctuations in the market.

Careful consideration of transfer time must be made to truly assess the risk level of this trading strategy. Transfer time between exchanges creates an inherent market risk. For our model, systematic risk cannot be defined as 0 because there is an inherent risk that the price can change in between each transfer of the asset. Therefore, this trading strategy comes with small and minimal risk.

Each blockchain has different block placement times. This can help measure the level of the Systematic risk assessed when using this model. Based on our analysis of the average confirmation time for Bitcoin over the past year, the average time was determined to be 47.40 minutes (*Blockchain.com | Charts - Average Confirmation Time*, n.d.). The same analysis was conducted for Ethereum, over the same time, and was determined to be 12.06 minutes to confirm (Etherscan.Io, n.d.). Solana has a very stable block confirmation time between 1-2 seconds (*Transaction Confirmation & Expiration*, n.d.). Based on this assessment, Solana is the least risky and Bitcoin being the riskiest.

Geo-political events can also have an impact on the Systematic risk of our model. These are events that occur outside the fundamental analysis of the cryptocurrencies but still have a small effect on the overall price levels.

VII. Results

Cross-exchange spreads result from multiple different exchanges having different order books and liquidity. Across 3 separate exchanges for each coin, Bitcoin experienced the highest spreads with an average of $61.20. Ethereum was in the middle with an average spread of $21.14. Solana had the least with an average spread of $0.13. When adjusting for the price level of each coin, Bitcoin's average spread was 0.06% of the price while Ethereum experienced 0.68% of its respective price level. Even though Bitcoin has a higher average spread, the relative price of Bitcoin decreases the profitability ratio of the coin. Ethereum resulted in having the highest average spread to price ratio between the different coins.

After accounting for all spreads and fees, it was determined that Bitcoin observed 2 arbitrage opportunities, Ethereum observed 67 arbitrage opportunities, and Solana observed 2 arbitrage opportunities. Each of these opportunities varied in total profit. Bitcoin experienced a total of $12.61 in total profit. Ethereum experienced a total of $3,260.94 in total profit. Solana experienced a total of $2.15 in total profit.

Accounting for the fees reduced a significant amount of the total profit that could have been realized. Before fees, Bitcoin experienced a level of $22,398.50 in total profit.

After fees, 99.9437% of the profit was eroded away. This suggests that the amount of fees naturally plays a big role in the success of the model.

The VIX, defined by the Chicago Board of Options and Exchanges, is “a leading measure of market expectations of near-term volatility conveyed by S&P 500 Index®(SPX) option prices” (*VIX Volatility Products | CBOE*, n.d.). This provides a great measure of how broad the United States stock market moves on a day-to-day basis. The CBOE is only open 5 days of the week, as opposed to cryptocurrency markets being open 24/7. Analyzing the daily changes of the VIX index can provide insight into any effects that the index might have on cryptocurrency markets. A regression was run that defined the changes in the VIX index as the independent variable and the changes in the targeted cryptocurrency’s spreads were the dependent variable. The results showed that each respective cryptocurrency had a p-value > 0.05, suggesting that there is no significance between the variables (Appendix b-d).

Correlation was also a significant statistic to measure. Between all the different cryptocurrencies, the level of correlation was minimal but was structured in a ladder fashion. Bitcoin had the highest level of correlation at 0.13 and decreased to 0.03 for Solana (Appendix b and d). This could suggest that Bitcoin has minimal exposure to overall fluctuations in the broad stock market and has a higher level of Systematic risk. This still largely remains uncorrelated and can become a hedge against most Systematic risk but is still prevalent.

VIII. Conclusion

This study analyzed cross-exchange pricing for Bitcoin (BTC), Ethereum (ETH), and Solana (SOL) across major centralized exchanges from November 2024 to November 2025. The primary objective was to evaluate whether arbitrage opportunities persist in the modern cryptocurrency ecosystem once realistic frictions—fees, transfer delays, and settlement costs—are incorporated. The results consistently point toward a market that is highly efficient, with only narrow and fleeting price discrepancies.

The empirical findings reveal that cross-exchange spreads were present almost every day, reaffirming the naturally fragmented structure of cryptocurrency markets. Each exchange maintains its own order book, liquidity pool, and update latency, which causes temporary deviations in quoted prices. As shown in our findings, spreads were present across BTC, ETH, and SOL prices virtually daily, especially during periods of volatile trading conditions.

However, the critical insight from our analysis is that most of these apparent spreads were not economically exploitable. Once we applied realistic frictions—including exchange trading fees (maker/taker), blockchain withdrawal fees, and transfer confirmation delays—the profitable windows narrowed dramatically.

Transfer-time disparities played a particularly influential role. Bitcoin required an average of 47 minutes and 24 seconds for a typical transfer, Ethereum required 12 minutes and 3 seconds, while Solana completed transfers in 1–2 seconds. The slow settlement speed of BTC and ETH means that by the time the transferred asset arrived at the destination exchange, the mispricing had already disappeared. This timing risk is a fundamental barrier preventing arbitrage from being widely profitable.

Fee structures reinforced this limitation. Bitcoin miner fees and Ethereum gas fees played a small but important role in the model, materially reducing potential net profits. Exchange trading fees were charged twice—once when purchasing and once when selling—ranging from 0.1% (Binance) to 1% (Kraken). Applying these fees together, for example, Bitcoin's potential profit eroded 99.9437% away.

Ethereum emerged as the only asset with occasional positive net-profit arbitrage opportunities. Even then, these occurred almost exclusively in a short, isolated cluster in late 2024 and early 2025 and did not reappear later in the year. This pattern suggests a temporary liquidity dislocation rather than an ongoing inefficiency.

Additionally, our examination of the VIX and macro-volatility events showed no measurable correlation between U.S. equity market volatility and cross-exchange arbitrage spreads. Despite 28 significant VIX events—defined as ±10% swings—only four coincided with arbitrage observations, and even those appeared unrelated to broader equity-market stress.

Overall, these findings support the conclusion that modern centralized cryptocurrency exchanges—especially large venues like Binance and Coinbase—operate with a high degree of pricing efficiency, leaving little room for persistent arbitrage. Minor deviations continue to occur due to microstructural fragmentation, but they are quickly neutralized by market forces.

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Appendix

A.

VIX Change %	Date	Date Significance Event	Event Details
-12.27%	10/20/2025	Relief	Markets calmed ahead of earnings season, with no new negative banking headlines and improving risk sentiment after the prior week's selloff.
-17.90%	10/17/2025	Stabilization	After a large volatility spike on 10/16, traders unwound hedges as markets stabilized and no further regional-bank surprises appeared.
22.63%	10/16/2025	Bank Stress	Regional-bank fears surged after Zions revealed unexpected loan-loss issues, sparking broad equity selling.
-12.14%	10/13/2025	Geopolitical	U.S.–China trade tensions eased after softer rhetoric and a pause in tariff escalation, boosting equity markets.
31.83%	10/10/2025	Tarrif Shock	A major selloff followed a new U.S. tariff package on Chinese goods, triggering fears of renewed trade-war escalation.
-14.34%	8/22/2025	NA	NA
-14.03%	8/4/2025	Rate-Cut Optimism	Markets rebounded as rate-cut expectations strengthened following a weak jobs report that reduced Fed uncertainty.
21.89%	8/1/2025	Tarrif Shock	U.S. tariffs on multiple Chinese imports + weak jobs data shocked markets and raised recession concerns.
-11.85%	6/24/2025	Geopolitical	A surprise Israel–Iran ceasefire temporarily relieved geopolitical stress, boosting global risk assets.
10.08%	6/19/2025	NA	NA
13.03%	6/17/2025	Geopolitical	Renewed Middle East conflict concerns + weak consumer-spending data weighed on markets.
15.54%	6/13/2025	Geopolitical	Reports of Israeli military action against Iran drove oil prices sharply higher and triggered global risk-off.
15.37%	5/21/2025	US Debt Concerns	A large tax-and-spending proposal raised deficit concerns, pushing yields higher and stocks lower.
-16.03%	5/12/2025	Trade Relief	U.S. and China agreed to a temporary tariff freeze, easing trade tensions significantly.
-17.76%	4/14/2025	Geopolitical	Markets rallied as Iran–Israel tensions cooled after a tense prior weekend; oil stabilized as risk faded.
21.12%	4/10/2025	Inflation Risk	CPI inflation came in hotter than expected, pushing bond yields higher and delaying expected Fed cuts.
-35.75%	4/9/2025	NA	NA
11.39%	4/8/2025	NA	NA
50.93%	4/4/2025	Tarrif Shock	One of the biggest volatility spikes of the year — driven by Trump's sweeping new tariff announcements and China's immediate retaliation.
39.56%	4/3/2025	Tarrif Shock	Markets plunged after the initial U.S. tariff announcement, pricing in severe trade-war risk.
15.84%	3/28/2025	Tarrif Fears	Stocks fell sharply on rising inflation expectations and concern over new auto-tariff plans.
-11.72%	3/14/2025	NA	NA
19.21%	3/10/2025	NA	NA
13.41%	3/6/2025	NA	NA
16.05%	3/3/2025	Tech Sell Off	The "Magnificent Seven" extended a multi-day decline following weak tech guidance, triggering risk-off sentiment across the market.
10.63%	2/27/2025	Inflation Risk	Bond yields moved higher as inflation expectations firmed, pressuring equities and lifting demand for downside protection.
16.28%	2/21/2025	Fed Uncertainty	Several Fed officials delivered hawkish commentary, signaling hesitation about cutting rates and shaking market confidence.
13.33%	2/3/2025	Earnings Volatility	A week of mixed earnings, including several large-cap disappointments, pushed traders into protective hedging.
20.54%	1/27/2025	Geopolitical	Markets fell as geopolitical tensions briefly re-escalated in the Middle East, driving oil higher and risk assets lower.
-13.84%	1/15/2025	Inflation Relief	Investors reacted positively to softer inflation data and stabilizing yields, reducing the need for hedging.
11.10%	1/7/2025	NA	NA
-10.04%	1/3/2025	NA	NA
-14.96%	12/24/2024	NA	NA
-23.79%	12/20/2024	NA	NA
-12.78%	12/19/2024	NA	NA
74.04%	12/18/2024	Fed Shock	One of the largest volatility spikes of the year — triggered by a sharp market selloff following a surprise inflation uptick and hawkish Fed tone.
11.12%	12/9/2024	Macro Weakness	Markets dipped as renewed concerns about weakening consumer demand and rising oil prices pressured sentiment.
12.79%	11/15/2024	Macro Weakness	Stocks fell after signs of slowing growth overseas and elevated yields continued to weigh on risk assets.
-20.60%	11/6/2024	Political Clarity	Post-election relief rally after a clean, controversy-free U.S. election outcome reduced political uncertainty.

B.

Bitcoin

SUMMARY OUTPUT

	VIX Change %	Bitcoin Spread
VIX Chang	1	
Bitcoin Spr	0.138230498	1

Regression Statistics	
Multiple R	0.000973
R Square	9.48E-07
Adjusted R	-0.00391
Standard E	0.098693
Observatic	258

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regressior	1	2.36E-06	2.36E-06	0.000243	0.987585025
Residual	256	2.493544	0.00974		
Total	257	2.493546			

	Coefficients	*tandard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Date	9.07E-07	5.82E-05	0.015576	0.987585	-0.00011378	0.000115594	-0.00011	0.000116

C.

Ethereum

SUMMARY OUTPUT

	VIX Change %	Ethereum Spread
VIX Chang	1	
Ethereum :	0.06632176	1

Regression Statistics	
Multiple R	0.066322
R Square	0.004399
Adjusted R	0.00051
Standard E	0.098476
Observatic	258

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regressior	1	0.010968	0.010968	1.13101	0.288562077
Residual	256	2.482578	0.009698		
Total	257	2.493546			

	Coefficients	*tandard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	0.000508	0.006657	0.076286	0.939251	-0.012601022	0.013616646	-0.0126	0.013617
Spread	0.000114	0.000107	1.06349	0.288562	-9.68809E-05	0.000324378	-9.7E-05	0.000324

D.

Solana

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.034504
R Square	0.00119
Adjusted R	-0.00271
Standard E	0.098635
Observatic	258

	VIX Change %	Solana Spread
VIX Chang	1	
Solana Spr	0.03450355	1

ANOVA

	df	SS	MS	F	Significance F
Regressior	1	0.002969	0.002969	0.30513	0.581166075
Residual	256	2.490578	0.009729		
Total	257	2.493546			

	Coefficients	tandard Err	t Stat	P-value	Lower 95%	Upper 95%	ower 95.0%	pper 95.0%
Intercept	-0.0005	0.009181	-0.05497	0.956204	-0.018584892	0.017575493	-0.01858	0.017575
Spread	0.029325	0.053088	0.552386	0.581166	-0.075219801	0.133869936	-0.07522	0.13387

E.