Perpetual Contracts and Market Quality: Evidence from Cryptocurrencies *

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Abstract

We examine how perpetual futures contracts affect cryptocurrency spot market microstructure from 2017 to 2023. Exploiting the unanticipated termination of perpetual trading at Huobi and 95 contract introductions, we find that perpetual contracts increase spot trading volume but widen bid-ask spreads, suggesting a paradoxical liquidity effect. We reconcile this by showing these phenomena are concentrated during funding hours, driven by arbitrage trading between perpetual and spot markets, and exacerbated by higher funding fees, indicating heightened information risks. Consistent effects around exogenous misinformation shocks further confirm this information channel. Moreover, we find no evidence of perpetual contracts fragmenting spot market liquidity.

Keywords: Perpetual Contracts, Cryptocurrency, Regulation, Market Quality

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1 Introduction

Perpetual futures contracts, introduced by Shiller (1993), are designed to continuously track the price of an underlying asset and can be applied to various assets, such as real estate, human capital, and economic indices like inflation rates. These contracts facilitate price discovery and effective hedging without the need for direct ownership or physical delivery. The advent of cryptocurrencies, underpinned by blockchain technology (Nakamoto, 2008), has brought these previously theoretical contracts to life, with the continuous trading feature of cryptocurrencies providing an ideal environment for their implementation. In the cryptocurrency market, these contracts are commonly referred to as "perpetual contracts."

Continuous trading, while not strictly necessary for perpetual contracts, offers several advantages that enhance their effectiveness and attractiveness. Frequent price updates enable the contract price to closely track the underlying asset's price, reducing basis risk. Continuous trading also improves liquidity by allowing market participants to enter or exit positions at any time, reducing slippage and transaction costs. Furthermore, it helps to mitigate counterparty risk by enabling more frequent margin updates and liquidations, preventing the accumulation of large, unsustainable positions. The 24/7 trading feature of cryptocurrencies aligns well with the global and decentralized nature of the market, making it an ideal environment for the application of perpetual contracts. Moreover, the transparent and immutable nature of blockchain technology provides a reliable foundation for the continuous price feeds necessary for the effective functioning of these contracts.

Compared to direct trading in the cryptocurrency spot markets, perpetual contracts have demonstrated several advantages, including lower transaction fees, faster execution without the need for on-chain verification, the ability to leverage positions, and the facilitation of short-selling. A key feature that distinguishes perpetual contracts from traditional futures is the absence of an expiration date, enabling investors to maintain positions indefinitely without the need to roll over contracts. To keep perpetual prices in line with the underlying cryptocurrency prices, exchanges employ a funding fee mechanism involving periodic payments between long and short position holders based on the price difference between the perpetual and spot markets. If the perpetual price is higher than the spot price, long position holders pay a funding fee to short position holders, and vice versa. By incentivizing traders to take positions that drive the perpetual price closer to the spot price, the funding fee mechanism effectively maintains price consistency. As a result, perpetual contracts typically exhibit smaller basis risk, the potential price discrepancy between the derivative and the underlying asset, compared to traditional futures, further enhancing their attractiveness as a trading and hedging instrument.

Since their introduction by BitMEX in 2016, perpetual contracts have rapidly gained traction in the cryptocurrency space, with trading volumes growing substantially over time. According to Coinglass,[1] perpetual contracts have seen over $90 trillion in trading volume since 2020, surpassing the trading volumes of the underlying cryptocurrencies and accounting for 93% of the cryptocurrency futures market. This volume is twice the total trading volume of the U.S. stock market, which reached $44 trillion in 2022.[2] At the individual contract level, the trading volume of Bitcoin's perpetual contract on February 28th, 2024, reached an impressive $180 billion, six times the daily trading volume of NVIDIA, the most traded U.S. stock, which stood at $30 billion on the same day. The trading volume observed in the Bitcoin perpetual futures market is comparable to the aggregate trading volume of the gold market or the United States Treasury bills market.[3]

As perpetual contracts are novel financial instruments with wide-ranging application potential, as evidenced by their phenomenal trading volume, understanding their specific effects on underlying spot markets is a timely and crucial topic for navigating policies in financial markets. However, identifying the causal effects of perpetual contracts on the spot market is challenging due to endogeneity issues, primarily driven by the potential correlation between the introduction of perpetual contracts and the market quality of underlying cryptocurrencies. Factors such as the popularity or demand for certain cryptocurrencies may influence both the decision to introduce perpetual contracts and the overall market quality, making it difficult to isolate the true impact of perpetual contracts on the spot market. To surmount these challenges and establish a causal relationship, we design several robust identification strategies to examine the effects of perpetual contracts on spot markets.

First, we exploit a unique regulatory event in China that led to the uniform termination of perpetual contracts at Huobi Exchange in October 2021. This exogenous shock provides a natural experiment setting, allowing us to employ a differences-in-differences (DiD) framework with a synthetic control. By comparing the market quality of affected cryptocurrencies before and after the termination, relative to a carefully constructed control group, we can isolate the causal impact of removing perpetual contracts on the spot market.

To further validate our findings and ensure the robustness of our results, we implement a second identification strategy using a staggered DiD framework. This approach leverages the variation in the timing of perpetual futures contract introductions across 95 different

[1] Perpetual Futures trading volume data at Coinglass. https://www.coinglass.com/pro/futures/ExVolume.

[2] Total value of U.S. stocks traded, measured in current US dollars, is available at the World Bank. https://data.worldbank.org/indicator/CM.MKT.TRAD.CD?end=2022&locations=US&start=1975&view=chart.

[3] Gold and U.S. Treasury Bills average daily trading volumes are available from the World Gold Council. https://www.gold.org/goldhub/data/gold-trading-volumes.

cryptocurrencies in three major exchanges: Binance, OKEx, and Huobi, spanning from December 2019 to September 2022. By comparing the market quality of cryptocurrencies before and after the introduction of perpetual contracts, while controlling for potential confounding factors, we provide additional evidence on the causal effects of perpetual contracts on the spot market.

Our results reveal two primary effects of introducing perpetual contracts: an increase in trading volume and a widening of the bid-ask spread. Perpetual contracts trading termination leads to opposite effects that mirror those of their introduction. At first glance, these findings may appear surprising, as a greater trading volume typically implies improved spot market liquidity, while wider bid-ask spreads suggest higher transaction costs. To resolve this apparent paradox, we delve into the mechanisms behind these effects by investigating the unique 8-hour funding time cycle of perpetual contracts and the corresponding dynamics of market quality in the spot market. We find that the effects of increasing volume and widening spread are concentrated during the funding hours when there is more arbitrage activity between perpetual and spot markets, and information contained in the funding fee is being incorporated into the market prices. This suggests that perpetual contracts affect the spot market quality by increasing informed trading and adverse selection risks in the underlying spot markets, which we refer to as the information channel. The effects are stronger when the magnitude of funding fees is larger and thus the fees contain more information. It is worth emphasizing that we are the first to document this 8-hour funding-time effect of perpetual contracts on spot market quality.

We further examine this information channel by investigating pump-and-dump activities in the cryptocurrency space, which generally involve spreading fake positive news about a cryptocurrency to inflate its prices only to sell it at a high price for profit. Pump-and-dump activities are prevalent in the cryptocurrency space due to its weak regulatory environment. These events are exogenous misinformation shocks to cryptocurrency markets which are consequently corrected as verified information is impounded into the prices. We find that pump-and-dump events increase trading volumes and widen the spreads in the spot market. This result matches the pattern of the effects of introducing perpetual contracts to the cyrptocurrency spot market. This alignment provides robust evidence that perpetual contracts affect the spot market via the information channel. Overall, our results are in line with the information-based microstructure theory, which posits that an increase in "toxic" trading volume can lead to wider spreads.

An intriguing hypothesis is whether perpetual futures contracts may lead to market fragmentation of cryptocurrency markets, given that perpetual contracts can replicate the return distribution of underlying cryptocurrencies and offer advantages such as leveraged positions and trading convenience. We examine this hypothesis by analyzing the slippage and market depth of the order book in the spot market. Our findings do not provide consistent evidence that the adoption of perpetual futures contracts reduces liquidity in the spot market's order book. Furthermore, we compute a wash trading measure, that proxies for artificial trading volume inflation, and find that it is significantly higher in the perpetual futures market than in the spot market. Interestingly, we observe that this measure increases in the spot market following the introduction of perpetual contracts, indicating that trades move from perpetual futures market to the spot market instead of the opposite direction. These results do not support the notion that perpetual contracts lead to market fragmentation of the cryptocurrency spot market.

Our study uncovers the nuanced effects of perpetual markets on cryptocurrency market dynamics, highlighting that while they enhance trading volume and informational efficiency, these benefits are accompanied by higher transaction costs and an increased risk of adverse selection. Our findings substantially enrich the understanding of the sophisticated impact of novel perpetual contracts on financial market microstructure. They lay the groundwork for future regulatory and governance considerations in cryptocurrency markets and pave the way for the broader application of perpetual contracts within the financial industry.

1.1 Related Literature

The genesis of perpetual contracts traces back to Robert Shiller in as early as 1993 (Shiller, 1993), but perpetual contracts started to take the center stage only recently with the rapid growth of cryptocurrency trading. Despite the rising interest, the body of literature on perpetual contracts remains relatively sparse. Christin, Routledge, Soska, and Zetlin-Jones (2022) highlight the potential of a carry-trade strategy whereby one simultaneously takes a short perpetual contract position and acquires underlying cryptocurrency, illustrating the financial strategies enabled by these instruments. De Blasis and Webb (2022) investigate the behavior of Bitcoin quarterly and perpetual futures prices at Binance. Ackerer, Hugonnier, and Jermann (2023) and He, Manela, Ross, and von Wachter (2022) delve into the pricing of perpetual contracts, establishing no-arbitrage pricing models in various market scenarios. Our research identifies the causal effects of perpetual contracts on the spot market, which are assumed away in the existing literature. Our findings can inform future theoretical studies about perpetual contracts by shedding light on how perpetual contracts affect the cryptocurrency market microstructure.

Our study enhances the understanding of the impact of futures on the cryptocurrency spot market, building upon valuable insights from previous research on traditional futures from platforms like BitMEX, CME, and CBOE (Alexander, Choi, Park, and Sohn, 2020; Baur and Dimpfl, 2019; Baur and Smales, 2022; Shynkevich, 2021; Aleti and Mizrach, 2021; Hung, Liu, and Yang, 2021; Augustin, Rubtsov, and Shin, 2023). While Augustin et al. (2023) focus on a single BTC-USD futures pair of CME and CBOE, our research aims to provide a more comprehensive perspective by leveraging a granular dataset from Kaiko, examining a wide spectrum of one hundred cryptocurrencies across various exchanges. By delving into both transaction and order book data, we assess the multifaceted impacts of perpetual contracts on spot market microstructure. To establish clean identification and causal effects, we exploit the unanticipated termination of perpetual trading at Huobi and 95 contract introductions, employing robust econometric methodologies such as staggered Differences-in-Differences and synthetic control. Our analysis uncovers nuanced effects on market liquidity, revealing that perpetual contracts increase trading volume but also widen bid-ask spreads, suggesting heightened information risks. This finding differs from the results reported by Augustin et al. (2023), using an average of four liquidity indicators that may not capture such nuanced effects (see their Table 7, Columns 5 and 6). Furthermore, we identify the perpetual funding mechanism as a compelling channel driving these effects, with impacts concentrated during funding windows and exacerbated by higher funding fees. Our research also sheds light on the intriguing hypothesis of whether perpetual contracts lead to liquidity fragmentation of spot markets, finding no consistent evidence to support this notion.

Our findings provide empirical evidence supporting information-based market microstructure models, such as those presented in O'Hara (1995) and Easley, Kiefer, O'Hara, and Paperman (1996). These models posit that an increase in informed trading can lead to wider bid-ask spreads and increased price impact, as market makers seek to protect themselves from adverse selection. Glosten and Milgrom (1985) develop a model of a specialist market with heterogeneously informed traders, showing that the bid-ask spread is a function of the degree of information asymmetry. Easley and O'Hara (1992) propose a model of the process of security price adjustment, demonstrating how informed trading affects the speed of price discovery. Our study contributes to this literature by examining the impact of perpetual contracts and information shocks on various aspects of spot market microstructure. We find that the introduction of perpetual contracts leads to increased trading volume, a higher probability of informed trading (VPIN, Easley, L'opez de Prado, and O'Hara (2012)), and wider bid-ask spreads in the spot market. These effects are particularly pronounced during the perpetual contract funding times, when information about market conditions is disseminated through the funding rate. By examining the impact of perpetual contracts and pump-and-dump events on cryptocurrency spot markets, our work extends the application of information-based microstructure models to a new and rapidly evolving asset class, providing novel empirical insights into the relationship between information, derivatives, and market quality.

Our research adds to the literature concerning market quality. O'Hara and Ye (2011) investigates market fragmentation's impact on market quality and efficiency. Holden and Jacobsen (2014) address liquidity measurement in fast markets. Foley and Putniņš (2016) examine dark trading's effects on market quality. Clark-Joseph, Ye, and Zi (2017) highlights the role of Designated Market Makers in liquidity. Comerton-Forde, Grégoire, and Zhong (2019) shows inverted exchange fee models, compensating liquidity demanders, counteract tick size limits, boosting liquidity and pricing accuracy by fostering competition and better information flow. We extend this literature by identifying the causal impacts of perpetual contracts on cryptocurrency market microstructure. Our findings on liquidity, volume, and transaction costs during perpetual contracts' funding hours contributes to the understanding of how a novel financial instrument like a perpetual contract affects spot market quality.

Our study makes significant contributions to the behavioral finance literature by providing a comprehensive analysis of investor reactions to exogenous misinformation shocks, such as pump-and-dump schemes (Li, Shin, and Wang, 2021). We document substantial changes in price, volume, and market quality following these events, as exemplified by the Litecoin pump-and-dump case involving a fake press release about Walmart's adoption of Litecoin. During pump-and-dump episodes, we observe increased volatility, higher trading volume, and wider bid-ask spreads in the spot market, aligning with the predictions of information-based microstructure models. These findings are consistent with the work of Fleming and Remolona (1999), who investigate price formation and liquidity in the U.S. Treasury market in response to public information releases, and provide empirical support for the unified theory of under-reaction, momentum trading, and overreaction in asset markets proposed by Hong and Stein (1999). Moreover, the significant increase in transaction volume during these events is in line with the literature on investor behavior and heterogeneous beliefs, as discussed in the works of Odean (1999), Statman, Thorley, and Vorkink (2006), and Campbell, Grossman, and Wang (1993). By examining the impact of pump-and-dump schemes on cryptocurrency markets, our study sheds light on the immediate effects of misinformation on market dynamics and contributes to the broader understanding of investor behavior under varying informational conditions.

2 Funding Fee Mechanism

To understand the impact of perpetual contracts on the spot market, it is crucial to examine the funding fee mechanism, which plays a vital role in maintaining price alignment between perpetual contracts and the underlying cryptocurrencies.

Perpetual futures contracts, unlike traditional futures, do not have an expiration date, allowing traders to maintain positions indefinitely. To ensure alignment between the prices of perpetual contracts and the underlying cryptocurrency, exchanges employ a critical mechanism in the form of funding fees, which are designed to incentivize traders to keep the perpetual contract price in line with the spot price.

Funding fees are adjusted every eight hours, a period during which perpetual contracts effectively "settle" by evaluating the price differences between the perpetual and spot markets. If the perpetual price is higher than the spot price, traders holding long positions pay a funding fee to those holding short positions; conversely, if the perpetual price is lower than the spot price, long position traders receive a funding fee from short traders. The magnitude of the funding fee is proportional to the deviation between the perpetual and spot prices, creating a financial incentive for traders to actively monitor and adjust their positions to minimize funding costs and maximize potential returns.

Interestingly, funding rates, as the "price" of holding long or short positions determined by the market, serve as a powerful aggregator of various types of information. Informed traders in cryptocurrency markets possess a wide range of information that influences their decision-making process. This includes insights into market sentiment derived from social media, news outlets, and online forums; a deep understanding of the technological aspects of cryptocurrencies, such as their underlying blockchain architecture, consensus mechanisms, and potential vulnerabilities; knowledge of regulatory developments and their potential impact on the adoption and legitimacy of cryptocurrencies; and an awareness of macroeconomic factors, such as global economic conditions and geopolitical events, that can influence cryptocurrency prices. The aggregation of these diverse information sources in the funding rates makes them a valuable indicator of market expectations and sentiment.

Typically, funding fees are positive, indicating the long side's leverage advantage in cryptocurrencies with partial funds. However, in extreme market episodes, funding fees can turn negative, signaling that long traders require compensation for taking leveraged positions. This usually occurs during periods of negative market sentiment and expectations, as observed during the Terra/Luna meltdown, Three Arrows Capital (3AC) bankruptcy, and the FTX collapse.

While perpetual contracts generally track the underlying cryptocurrency prices effectively, there have been instances of significant decoupling. For example, during the COVID-19-induced market crash on March 12, 2020, the BitMEX perpetual contract price for Bitcoin traded at a discount of up to 15% compared to the spot price on Coinbase, while discounts reached 12% on Binance and 10% on Huobi, indicating strong bearish sentiment and selling pressure in the derivatives market. Conversely, during the height of the Bitcoin bull run on January 4, 2021, perpetual contracts traded at a premium of 5.4% on Binance and 4.8% on Huobi relative to spot prices, reflecting bullish sentiment and high demand for leveraged exposure to the cryptocurrency. These episodes of decoupling are typically short-lived, and perpetual contract prices tend to quickly realign with spot prices as market conditions stabilize.

According to data from Binance, the largest cryptocurrency exchange, funding rates across major exchanges average around 0.015%, which translates to an annualized rate of approximately 16%. These funding fees are economically significant for traders to consider, as they can substantially impact the profitability of their positions over time. The effectiveness of the funding fee mechanism in aligning perpetual contract prices with spot prices, coupled with the insights provided by funding rates, highlight the importance of understanding and monitoring this crucial aspect of the perpetual futures market in the cryptocurrency space.

3 Data

Our study leverages an extensive dataset provided by Kaiko, encompassing high-frequency trading data and order book snapshots from a broad spectrum of cryptocurrency exchanges. This dataset features a variety of cryptocurrency pairs denominated in USDT (Tether) across multiple platforms, including more than 100 token pairs in both spot and perpetual markets on 10 exchanges including Coinbase, Binance, Huobi, OKX, ByBit, KuCoin, Bibox, BitFinex, BitMex, and HitBTC. The period covered by this dataset spans from July 2017 to July 2023.

With access to transaction data at millisecond frequency, we compute several established metrics for market liquidity and quality, including dollar volume, the Roll measure (Roll, 1984), Amihud's illiquidity measure (Amihud, 2002), and the Volume-synchronized probability of informed trading (VPIN) (Easley et al., 2012). Dollar volume acts as a fundamental liquidity metric. The Roll measure, which analyzes trade sequences, serves as a proxy for the effective bid-ask spread through price autocovariance. Amihud's measure quantifies market illiquidity, whereas VPIN assesses order flow toxicity, indicating adverse selection risk in high-frequency trading scenarios. The dataset identifies the initiator of each trade (via the 'direction' attribute), enabling the derivation of signed volume estimates, V_t^S and V_t^B, to calculate order imbalance.

Our methodology for analyzing transaction-based measures closely follows the guidelines established by Easley, López de Prado, O'Hara, and Zhang (2021). We partition our dataset into 5-minute intervals and apply a variety of window sizes for calculating moving averages in measures such as VPIN, with window sizes W set to $\{5, 12, 24\}$, equivalent to 25 minutes, 1 hour, and 2 hours, respectively. This approach allows for the examination of the temporal dynamics of market liquidity and trading activity with precision.

Building on transaction-based analysis, we integrate order book data to derive a comprehensive set of microstructure metrics. These include buyer and seller slippage, the bid-ask spread, percentage quoted spread, and estimates of permanent, temporary, and total price impact. Our methodology encompasses both time-weighted and conventional averaging methods within each 5-minute interval, facilitating a detailed assessment of the costs associated with trading, the efficiency of price discovery processes, and the extent of adverse selection in the market. The equations for all the above measures are detailed in the Appendix A.1, ensuring transparency and reproducibility of our methodology.

To assess the impact of trade size on market conditions, we analyze slippage for buyers and sellers across three distinct transaction sizes: \$10,000, \$100,000, and \$1,000,000. Slippage, quantified as the percentage deviation between the volume-weighted execution price and the prevailing top-of-book price, offers insights into liquidity conditions and execution costs associated with varying trade sizes. This measure highlights the market's ability to accommodate significant transactions with minimal price disruption and is inversely related to market quoted depth, which represents the current amount of limit orders in the order book.

Our comparison of spot and perpetual markets, focusing on periods and exchange-token pairs where a perpetual contract is available, reveals statistically significant differences across all examined measures (Table 1). Notably, perpetual markets exhibit considerably higher trading volumes, \$8.8 mln on average across each exchange-token per hour, which is 69 times the average volume of spot markets, \$128,000. However, despite this substantial volume difference, the percentage quoted spread, a measure of direct transaction costs, is 14% higher in perpetual markets. Furthermore, buyer and seller slippage for \$10,000 and \$100,000 transaction sizes are higher in perpetual markets, indicating smaller market quoted depth compared to spot markets.

We attribute this intriguing finding to perpetual traders' awareness of adverse selection risks, leading them to refrain from leaving limit orders in the order book, resulting in reduced depth. Conversely, spot market traders may adopt a different mindset, willingly leaving limit orders to increase the likelihood of order execution at a better price than the current market price. Supporting this claim, we observe that the probability of informed trading in perpetual markets exceeds that in spot markets by 31%, indicating a higher prevalence of informed trading activities within perpetual markets.

Despite the smaller quoted depth and larger percentage quoted spread in perpetual markets, the bid-ask spread is found to be, on average, 11% narrower than in spot markets. The Roll measure, a proxy for the bid-ask spread, is 18% lower in the perpetual market as well. The Amihud measure, an illiquidity indicator, is 101% higher in the perpetual market, while order imbalance is 16% smaller which is potentially related to the availability of short-selling in perpetual markets.

For $1 million slippage, spot and perpetual markets are close to each other, with buyer slippage being 2% lower and seller slippage 3% higher in the perpetual market. Comparing price impact measures, we find that the permanent price impact, reflecting the long-term effect of trades on prices, is 5% lower in perpetual markets. The temporary price impact, capturing the short-term price effect, is 564% higher in perpetual markets, while the total price impact, the sum of permanent and temporary impacts, is 29% lower in perpetual markets compared to spot markets.

This analysis highlights the distinct liquidity and market quality dynamics between spot and perpetual markets, underscoring the nuanced interplay of market structure, investor behavior, and information asymmetry in shaping these environments. The findings suggest that perpetual markets, despite their higher trading volumes, face challenges in terms of quoted depth and adverse selection risks, leading to higher transaction costs for smaller trade sizes. The lower permanent price impact and higher temporary price impact in perpetual markets indicate a more efficient price discovery process, with prices quickly reverting to their fundamental values after temporary deviations caused by trading activity.

[Table 1 about here.]

4 The Effects of Huobi's Perpetual Contract Trading Termination

Identifying the causal effects of perpetual contracts on the cryptocurrency market microstructure is challenging due to the endogenous nature of exchanges' decisions to introduce or terminate these contracts, which are closely correlated with the market quality of the underlying cryptocurrencies. To navigate this complexity, we leverage the unique and exogenous circumstance of Huobi's abrupt cessation of perpetual trading in October 2021, prompted by an unexpected regulatory directive from China, as a natural experiment for examining the causal impact of perpetual contracts on market dynamics.

On September 24, 2021, the People's Bank of China, in conjunction with nine other government agencies, issued a notice declaring all virtual currency-related business activities as illegal financial activities and outlining measures to prevent and dispose of the risks associated with virtual currency trading and speculation within the country.[4] Huobi, a prominent cryptocurrency exchange based in China, promptly responded to these new regulations. On October 1, 2021, Huobi disclosed a detailed plan to comply with the regulatory requirements. The exchange announced that it would unwind and settle all derivative contracts by October 28, 2021, and completely discontinue all derivative trading.[5] Meanwhile, spot market trading on Huobi continued to operate until 3:00 UTC of December 15, 2021, when spot trading for Mainland China users was disabled.[6]

Prior to this regulatory action, Huobi had experienced significant trading volumes in perpetual contracts, driven by the bullish sentiment in the cryptocurrency market. The sudden regulatory change mandated a uniform cessation of all perpetual contract trading on Huobi. In contrast, other major exchanges, such as Binance, chose to continue their perpetual trading operations despite also being subject to the regulatory shock. The divergent responses of these exchanges provide a unique opportunity to isolate and study the specific impacts of perpetual contracts on the spot cryptocurrency market.

Constructing the synthetic control group for Huobi is pivotal for ensuring the presence of parallel trends between Huobi and the control group, which is a crucial identifying assumption for causality in a Difference-in-Differences (DiD) setting. By utilizing exchanges such as OKEX, Binance, Bibox, and KuCoin, which did not cease their perpetual contract operations in response to the regulatory shock, we are able to create a synthetic Huobi that mirrors its pre-termination market conditions without relying on any one specific exchange as control for identification. This methodology ensures that any deviations observed post-termination can be attributed to the absence of perpetual contracts, thus satisfying the parallel trends assumption necessary for causal inference.

[4] People's Bank of China. (2021, September 24). Notice on Further Preventing and Disposing of the Risks of Virtual Currency Trading and Speculation. The notice was jointly issued by the People's Bank of China and nine other government departments. http://www.pbc.gov.cn/goutongjiaoliu/113456/113469/4348521/index.html.

[5] HTX. (2021, October 1). HTX Futures will deliver and settle all users' derivatives contract positions and retire Mainland China user accounts. https://www.htx.com/support/44887379528332.

[6] HTX. (2021, October 1). Retirement Schedule of Existing Mainland China User Accounts for Spot Trading and Fiat Trading. https://www.htx.com/support/64887380267993.

Upon establishing the synthetic control group, we proceed with a DiD analysis to evaluate the effects of perpetual contract termination on market quality. This approach offers several benefits: it controls for unobserved, invariant differences between the treatment and control groups, addresses the influence of concurrent trends that may affect market liquidity and efficiency, and establishes a more definitive causal link between the termination of perpetual contracts and observed market outcomes.

We follow well-established literature (Abadie, Diamond, and Hainmueller, 2010, 2015; Abadie and L'Hour, 2021) and take the classical approach in constructing the synthetic control. We further pair this synthetic control with factual Huobi observations, the treated exchange, to study the effect of perpetual trading termination on spot market microstructure in a Differences-in-Differences framework.

More specifically, for each (treated) token pair on Huobi i we find a vector of weights $\mathbf{W_i^*}$ that combines outcomes $\mathbf{Y^c}$ of n untreated token pairs on other exchanges at all time points and minimizes:

$$\min_{\mathbf{W_i} \in \mathbb{R}^n} \left\| Y_i - \sum_{j=1}^{n} W_{i,j} Y_j^c \right\|_2 \text{ subject to } \mathbf{W_i} \geq 0 \text{ and } \sum_{j=1}^{n} W_{i,j} = 1$$

The synthetic control for token pair i is then estimated as $\hat{Y}_i^c = \sum_{j=1}^{n} W_{i,j}^* Y_j^c$ using outcome data prior to Huobi perpetual trading termination announcement. Constructed this way $(Y_i, \hat{Y}_i^c)$ constitute a valid treatment and control Differences-in-Differences pair. Parallel trends prior to announcement generally hold as can be seen from Figures A1-A5 in the Appendix. After collecting the treatment-control pairs and reshaping the data into a long form we run the following regressions:

$$Market\_Quality_{e,i,t} = \beta D_{e,i,t} + \gamma_{e,i} + \eta_t + \epsilon_{e,i,t}, \tag{1}$$

where $Market\_Quality_{e,i,t}$ denotes the spot market outcome on date t for token i on exchange e (synthetic control exchange or Huobi), $\gamma_{e,i}$ is the exchange-token fixed effect, η_t is a time (date) fixed effect. The coefficient of interest is that corresponding to $D_{e,i,t}$, a dummy variable equal to 1 if the observation is simultaneously from Huobi and after perpetual contract trading termination for token i. The standard errors are clustered at the exchange-token level.

To enhance the robustness of our findings, we examine the consequences of Huobi's perpetual contract termination across various time frames—3, 7, 14, and 30 days—thereby providing a thorough understanding of both the immediate and prolonged effects on market quality. This comprehensive analysis enables a deeper exploration into the intricate effects of perpetual contract dynamics on the cryptocurrency market, illuminating the complex relationship between market structure and regulatory interventions.

We report our estimates of the effects following the termination of perpetual contracts at Huobi, utilizing a synthetic control technique as detailed in Table 2. Initially, a significant decline in cryptocurrency trading volume relative to a synthetic control group was observed. This decline is coupled with a decrease in transaction costs, evidenced by the reduction in the percent quoted and bid-ask spreads. These findings initially appear paradoxical: traditionally, lower trading volumes are associated with reduced liquidity, while a tighter percentage quoted spread, a recognized liquidity metric (Holden and Jacobsen, 2014), suggests improved liquidity. To dissect this paradox, we delve into the mechanisms underpinning these observations, guided by information-based microstructure theory, which posits that an increase in "toxic" trading volume can lead to wider spreads.

The termination of perpetual contracts could diminish the appeal of the spot market for informed traders, who had previously been attracted by the higher leverage, lower trading costs, and the straightforwardness of short-selling in the perpetual contract market. This shift may lead to a decrease in adverse selection within the spot market. Market makers, such as DWF Lab,[7] might then narrow their bid-ask spreads to reflect the reduced risk of trading against informed traders. Thus, the narrowing of bid-ask spreads in the spot market can be seen as a response to the decreased presence of informed trading following the termination of perpetual contracts.

Furthermore, the termination likely reduces spillover effects and cross-market arbitrage opportunities between the spot and perpetual contract markets. The decrease in these activities could lead to a reduction in trading volumes across both markets. As arbitrageurs withdraw, the demand for liquidity to execute trades diminishes, which may also contribute to the reduction of bid-ask spreads in the spot market. This decrease in trading activity and spreads could thus be explained by the diminished cross-market arbitrage following the termination.

Moreover, the end of perpetual contracts may lead to a decline in speculative trading and related market volatility. Speculative traders, drawn by access to leverage and opportunities in the perpetual market, may decrease their activity, leading to less volatility. Market makers in the spot market might then reduce their bid-ask spreads to accommodate the lower volatility and speculative trading, further contributing to the observed reduction in

[7] See discussions about market making business in the cryptocurrency space here: https://www.theblock.co/post/267354/how-dwf-labs-makes-deals-and-its-tendency-to-talk-about-price.

the percentage quoted spread.

5 The Effects of Introducing Perpetual Contracts

To enhance the robustness of our findings, we extend our analysis to assess the impact of perpetual contract introduction on corresponding spot markets. We draw on 95 introduction events for 75 token pairs across three major exchanges: Binance, Huobi, and OKEx, spanning from December 2019 to September 2022. These 95 introductions constitute the complete set of events in our research sample with available order book data. Table A1 provides a comprehensive list of all 95 perpetual contract introduction events, including the exchange, introduction date, and trading pair. Unlike the simultaneous termination of all perpetual contracts at Huobi, these introductions occurred at different times and varied across tokens and exchanges, placing our study within a staggered Differences-in-Differences (DiD) framework. This staggered approach enables us to leverage the introduction of perpetual contracts at varying intervals, offering a richer analysis. By exploiting the variation in the timing of perpetual contract introductions, we can better isolate the causal effect of these contracts on the underlying spot markets, controlling for potential confounding factors and time-varying trends.

Given the potential endogeneity concerns as the introduction of perpetual contracts might be influenced by the market quality of the associated cryptocurrency, we carefully select control groups in the staggered DiD framework to mitigate selection biases. For each introduction, control tokens include those with future introductions and those never treated. Exchanges like Coinbase, for instance, which lacked perpetual contract trading during the study period, serve as a "never treated" control. Additionally, the same tokens on different exchanges with varying statuses regarding perpetual contract trading provide an effective comparison group. We incorporate daily averages in our outcomes and include time and exchange-token fixed effects in all regressions.

Methodologically, Baker, Larcker, and Wang (2022) emphasize that non-staggered difference-in-differences (DiD) is applicable for analyzing both homogeneous and heterogeneous treatment effects, which applies to our analyses of Huobi's uniform termination of all perpetual contracts at the same time. In contrast, staggered DiD is particularly suited for cases with homogeneous treatment effects, which applies to our study of 95 introductions of perpetual contracts at staggered timings across various exchanges. Baker et al. (2022) argue that consistent results across diverse empirical settings enhance the credibility of the methodology. Aligning with this perspective, our findings demonstrate consistency across different research samples and settings, including perpetual contract introduction, termination, and the funding time experiment. These experiments investigate the causal effect of perpetual contract trading on spot market microstructure from multiple angles using various tools, yet they all arrive at the same conclusions, underscoring the robustness of our results.

Mathematically speaking, the classical staggered DiD setup takes the form a two-way fixed effect regression (TWFE):

$$Market\_Quality_{e,i,t} = \beta D_{e,i,t} + \gamma_{e,i} + \eta_t + \epsilon_{e,i,t}, \tag{2}$$

where $Market\_Quality_{e,i,t}$ denotes the spot market outcome on date t for token i on exchange e, $\gamma_{e,i}$ is the exchange-token fixed effect, η_t is a time (date) fixed effect. The coefficient of interest is that corresponding to $D_{e,i,t}$, a dummy variable equal to 1 if the observation is simultaneously from a treated token exchange with a perpetual introduction event and after such introduction took place. The standard errors are clustered at the exchange-token level.

Our staggered DiD analyses reveal significant findings: the introduction of perpetual contracts leads to an increase in spot market daily dollar volume by \$70,486 or 160% on average relative to the pre-treatment average of treated exchange-tokens. It also raises the probability of informed trading by 1.3 percentage points (or 16%) and the percentage quoted spread by 0.007 (or 112%). The liquidity added to the spot market from perpetual contract introductions also deepens order books, reducing slippage for larger positions (\$100,000) by an average of 0.004 (or 20%).

These findings underscore a recurrent theme in our data—the "largest common divisor" being the increase in trading volume and bid-ask spreads with the introduction of perpetual contracts, and their decrease upon termination. To disentangle these effects, we draw upon the framework of information-based microstructure theory, which suggests that a rise in "toxic," or informed, trading volume can lead to an expansion of bid-ask spreads (Easley et al., 1996; O'Hara, 1995). We argue that the introduction of perpetual contracts increases the proportion of informed trading in the spot market, rendering the increased volume more "toxic." Consequently, market makers in the spot market optimally widen the bid-ask spreads to protect themselves from adverse selection. We refer to this mechanism as the information channel, which provides a coherent explanation for the simultaneous increase in spot trading volume and bid-ask spreads following the introduction of perpetual contracts.

[Table 2 about here.]

[Table 3 about here.]

6 Examining the Information Channel

To further investigate the impact of perpetual contracts on the spot market, we examine the information channel through three distinct and complementary avenues: the effects of perpetual funding times on spot market microstructure, the association between perpetual funding rates and their magnitude with funding time effects, and the effects of exogenous information shocks in the form of pump-and-dump events. These analyses provide valuable insights from different aspects into the information channel through which perpetual contracts influence the spot market.

6.1 Perpetual Funding Times and Spot Market Microstructure

Building upon our exploration of the overall effects of perpetual futures contracts on cryptocurrency spot market quality, we now delve deeper into the impacts of these contracts within the context of the unique and predetermined eight-hour funding time cycle. This detailed examination enhances our insights in several significant ways. First, it enables us to confirm the causal effects by utilizing the exogenous nature of the perpetual contracts' funding time cycle. Secondly, it provides an opportunity to observe the high-resolution dynamics of the effects of perpetual contracts throughout the entire eight-hour funding cycle. Finally, it offers evidence to examine the underlying mechanisms that drive the impacts of perpetual contracts on the cryptocurrency spot market.

Perpetual contracts "settle" every 8 hours—at the designated funding times—through a funding mechanism: when the price of a perpetual contract is higher than that of the underlying asset, traders on the long side of the perpetual market pay a funding fee to those on the short side. Conversely, if the perpetual price is lower than the cryptocurrency price, the roles are reversed, with the long side receiving funding payments from short traders. These funding fees are designed to motivate traders to maintain close alignment between the prices in the perpetual and spot markets. This simple funding fee mechanism has proven effective in synchronizing the prices of perpetual contracts with cryptocurrency prices in our sample.

Given the predetermined, intrinsic, and unique nature of the 8-hour funding time windows to perpetual markets, it is unlikely that other factors could systematically skew our estimates, given the sample size at hand. Consequently, we are able to ascertain the causal effects of the perpetual market's funding mechanism on the spot market microstructure and delineate the dynamic impacts of perpetual contracts throughout the funding time cycle.

This contractually enforced exchange of funds every 8 hours in the perpetual market disturbs the system in several ways. First, around the funding time window (every 8 hours) perpetual market traders and arbitrageurs are more likely to trade strategically in anticipation of the funding payments. Secondly, the existence of funding fees implies that every 8 hours a certain number of tokens automatically change hands to keep the perpetual and spot market prices close. This exchange likely affects the strategies of the traders not only on the perpetual, but also on the spot market. Together, our prediction is that these two factors increase trading volume and information efficiency of the spot market around funding times.

Our first step is to confirm bunching of trading volume in the perpetual markets around funding times (i.e. every 8 hours). If there is no bunching, one should expect trading volume to be roughly uniformly distributed within each 8-hour period. Figure 1 plots the cross sectional (across exchange-tokens) distribution of dollar volume ratios by hour to their respective 8-hour average with a 99% confidence interval. We can clearly see that the distribution is W-shaped and is far from the Uniform baseline of equal share. Observe also that the volume spikes 1 hour before and after the funding time and is considerably smaller in-between. We scale the volume by the average dollar volume in each 8-hour window so that different time windows, tokens and exchanges are comparable.

We further statistically confirm that the distribution of trading volume within each 8-hour window is different from uniform. We compute the Cressie-Read power divergence test (Cressie and Read, 1984) and reject at the 1% significance level the null hypothesis that the samples come from a uniform distribution.

[Figure 1 about here.]

Having confirmed bunching in the perpetual market around funding times, we can now study whether market liquidity and quality measures improve in the spot market around the perpetual market funding times. More specifically, we use 5-minute bins and compute the microstructure liquidity measures discussed in Section 3. To verify robustness of our results in computing these measures we consider several window sizes (W) in constructing transactions-based measures: 5 (25-minute window), 12 (1-hour window), 24 (2-hour window).

From Figures 2-6 we can see that around the perpetual market funding time the following phenomena tend to be observed: market illiquidity (Amihud measure) drops (Figure 2), dollar volume spikes (Figure 3), bid-ask spread goes up (Figure 4), probability of informed trading ($VPIN$) increases (Figure 5), order imbalance is relieved (Figure 6).

[Figure 2 about here.]

[Figure 3 about here.]

[Figure 4 about here.]

[Figure 5 about here.]

[Figure 6 about here.]

We further confirm these observations in a regression setting, but we construct the outcomes somewhat differently. More specifically, for each exchange-token pair we first take averages of the 5-minute frequency outcomes within each hour, we further divide the now hourly outcome observations within each treatment window (2 hours before and after each funding time) by the average outcome in the respective 4 hours prior, i.e., those outcomes corresponding to untreated times in prior funding window. This approach is traceable to Foley and Putniņš (2016), adding an hourly average of dependent variable as an explanatory variable in the equation. In essence, in this way we estimate the percentage change during treatment windows relative to control immediately before treatment and use these estimates as outcomes in the following regressions:

$$Market\_Quality_{e,i,t} = \beta D_t + \gamma_{e,i} + \eta_t + \epsilon_{e,i,t}, \tag{3}$$

where $Market\_Quality_{e,i,t}$ denotes the outcome at time t at an hourly frequency for token i on the spot market of exchange e computed as a ratio relatively to the non-funding time average immediately before, $\gamma_{e,i}$ is the exchange-token fixed effect, η_t is an 8-hour window time fixed effect (different each 8 hours), and D_t is 1 if the observation is within the treatment window around the funding time. The standard errors are clustered at the exchange-token level. We consider the following windows around funding times to determine the treatment effect: 1 hour after a funding time; 1 hour before and after a funding time, $[-1, 1]$; 2 hours before and after a funding time, $[-2, 2]$.

Notice that the exchanges in our sample have a global presence and have primary business activity in different regions and therefore different time zones. Primary investors of each exchange then operate at a different time of day relative to Coordinated Universal Time (UTC). This indicates that our results are not driven by time-of-day effects.

[Table 4 about here.]

Given the vastness of our dataset and the high-frequency nature of the regressions, we are able to include a large number of observations in our regressions - up to 104 million observations. We present the findings from our baseline funding time experiment in Table 4, analyzing different treatment windows: 1 hour post-funding, 1 hour before and after funding, and 2 hours before and after funding. This study employs time-weighted averaging of order book measures and utilizes window sizes of 5 and 12 for transaction-based methods (corresponding to 25 and 60 minutes respectively; a window size of 24, or 2 hours, is deemed less relevant in this context given the 8-hour frequency of funding events).

The data reveal that the impact of perpetual contracts on increasing trading volume and bid-ask spread is consistent with observations from sections discussing the termination or introduction of perpetual contracts, with effects predominantly observed around funding times. This suggests that perpetual contracts facilitate arbitrage activities, elevating trading volume (by 50% around funding times on average), while increased bid-ask spreads (by 3.2%) may be attributed to market makers facing enhanced information risks, as supported by the spike in the VPIN measure (by 17.4%), a proxy for the probability of informed trading. These findings indicate that perpetual markets contribute to the enhancement of spot market trading volume and informational efficiency, with trading activity around funding times appearing more informed and correlating with larger effective bid-ask spreads, aligning with predictions from information-based market microstructure theories (Easley et al., 1996). The robustness of these findings across chosen hyperparameters is confirmed (Internet Appendix A).

6.2 Perpetual Funding Rates and Spot Market Microstructure

Building upon the results of funding time effects, we explore the relationship between funding fees, their magnitudes, and the effect of perpetual markets' funding times on spot market microstructure. These distinct tests utilize the information content of funding fees, providing a unique and complementary avenue to examine the information channel through which perpetual contracts affect the spot market.

Given the role of funding rates as the price of holding cryptocurrencies and a powerful aggregator of market supply and demand information, as we have emphasized in Section 2 and throughout the paper, we anticipate that the impact of perpetual contracts on the spot market intensifies with the increase in the magnitude of funding fees. Larger magnitudes of funding fees lead to more arbitrage activities and are associated with more market information and informed trading, as there is plausibly some information behind every unit of willingness to pay funding fees. Consequently, market makers face higher information risks and widen bid-ask spreads and percentage quoted spreads.

A common measure of funding fees in the cryptocurrency space is the funding rate, which is the funding amount divided by the nominal value of positions. For lack of an actual funding rate dataset at a large scale, we construct a funding rate proxy for each exchange-token as follows:

$$FRate_{e,i,t} = \frac{P^{\text{perp}}_{e,i,t} - P^{\text{spot}}_{e,i,t}}{P^{\text{spot}}_{e,i,t}} \tag{4}$$

where $P^{\text{perp}}_{e,i,t}$ denotes the price of the perpetual futures contract for token i on exchange e at hour t, $P^{\text{spot}}_{e,i,t}$ refers to the spot price of the underlying cryptocurrency for token i on exchange e at hour t, e indicates the exchange, i represents the token, and t corresponds to the hour. This proxy essentially measures the price deviation of the perpetual contract price from its corresponding spot price, which, albeit in a more intricate manner, lies at the heart of the true funding fee mechanism. When the funding rate is positive, long perpetual position holders pay a funding fee to short position holders. Conversely, when the funding rate is negative, long perpetual position holders receive a funding payment from short position holders.

To investigate how the funding time cycle of spot market depends on the funding rate or its magnitude, we perform the following experiments. First, we analyze the funding time effects by contemporaneous funding rate proxy quintile. This approach allows us to discover the nonlinear patterns between funding rates and the funding time effects on the spot market, providing an intuitive and accessible introduction to the relationship between these variables. Secondly, we complement the quintile analysis with a treatment effect regression, using the funding rate proxy (or its absolute value) in the period leading up to the funding time as the treatment dosage. This regression analysis helps us determine, with statistical rigor, whether the magnitude of the funding rate significantly affects the spot market during the funding cycle, thereby verifying and extending the insights gained from the quintile results.

To begin with, we sort the eight-hour funding time windows based on their associated funding rate proxy, from low to high, into five quintiles (Q1 to Q5). We then juxtapose funding time effects in the spot market by funding rate proxy quintile in Table 5. The first and last quintiles (Q1 and Q5) indicate a relatively large deviation, where the perpetual price is smaller (Q1) or larger (Q5) than the spot price, respectively. In contrast, observations in Q3 are during times when the price discrepancy between the perpetual and spot market is small and close to 0. Within each quintile group of the funding rate proxy, we perform the following regression:

$$Market\_Quality_{e,i,t} = \beta D_t + \gamma_{e,i} + \eta_t + \epsilon_{e,i,t}, \tag{5}$$

where $Market\_Quality_{e,i,t}$ denotes the outcome at time t at an hourly frequency for token i on the spot market of exchange e computed as a ratio relatively to the non-funding time average immediately before, $\gamma_{e,i}$ is the exchange-token fixed effect, η_t is an 8-hour window time fixed effect (different each 8 hours), and D_t is 1 if the observation is within the treatment window around the funding time. Here, we focus on the result of hour 1, the one hour right after the funding time. The standard errors are clustered at the exchange-token level.

We find a non-linear relation between the funding rate and the funding time effects on spot trading volume and percentage quoted spread, with Q1 (lowest funding rate) and Q5 (highest funding rate) presenting stronger effects than Q3 (median level). This demonstrates that when the magnitude of the funding rate is larger, the U-shaped pattern of spot market trading volumes and percentage quoted spread over the funding cycle is steeper and more pronounced, supporting our information channel.

[Table 5 about here.]

Further, we complement the quintile analysis with a treatment effect regression, using the funding fee (or its absolute value) in the period leading up to the funding time as the treatment dosage. We compute the average funding rate proxy for each exchange-token 8-hour period and use it to estimate the treatment dosage for the following funding time. The choice of lagged funding rate proxy may help alleviate the concern that market quality measures may reversely affect the funding rate in the same period. The regression is:

$$Market\_Quality_{e,i,t} = \beta FRate_{e,i,t} + \gamma_{e,i} + \eta_t + \epsilon_{e,i,t}, \tag{6}$$

where $Market\_Quality_{e,i,t}$ denotes the outcome at time t at an hourly frequency for token i on the spot market of exchange e, $\gamma_{e,i}$ is the exchange-token fixed effect, η_t is an 8-hour window time fixed effect (different each 8 hours), and $FRate_{e,i,t}$ is either the 8-hour average funding rate proxy or its absolute value prior to the funding time. This variable is set to 0 during non-funding time hours, and the average funding rate proxy for the 8-hour window before each funding time (or its absolute value) is assigned as the respective treatment dosage of each funding event. The standard errors are clustered at the exchange-token level.

Table 6 presents the results of funding time regressions with average funding rate proxy before funding time (or its absolute value) as treatment dosage. We find that both the funding rate and the magnitude of the funding rate are associated with a more positive funding time effect on spot trading volume, percentage quoted spread, and VPIN. More specifically, the coefficients of magnitude of the funding rate for percentage quoted spread and VPIN are significant at the 1% level and a 1% increase in funding rate magnitude is on average associated with a 3.9 and 12.2 percentage point greater probability of informed trading and wider spread respectively. The magnitude of the funding rate (its absolute value) is associated with larger effects than the funding rate itself. This is consistent with the non-linear pattern in Table 5, where Q1 and Q5, the groups with the lowest or highest funding rate, present the most prominent funding time effects. This result, complementing the funding rate quintile analysis, further corroborates our information channel through which perpetual futures affect the spot market.

Overall, we find that perpetual contracts exert a significant influence on spot market microstructure through their structured 8-hour funding fee cycle, enhancing trading volume but also leading to higher transaction costs. This effect is particularly pronounced during periods of elevated funding fees, which are associated with arbitrage trading volume and informed trading from sophisticated traders, necessitating wider bid-ask spreads by market makers to mitigate risks associated with elevated information asymmetry. The exogenous nature of the funding mechanism enables a clear identification of the causal impact of perpetual funding times on spot market microstructure.

[Table 6 about here.]

6.3 Pump-and-Dump Events as Exogenous Information Shocks

To complement the analysis of funding rates, which provide indirect information, we examine pump-and-dump (P&D) events in the cryptocurrency space as specific, direct, and exogenous information shocks. These events serve as an independent source of information shocks to evaluate the information channel, lending credibility to our findings on the effects of perpetual contracts on the spot market. Together with funding times and rates, P&D events provide a cohesive picture for understanding and examining the information channel through which perpetual contracts affect the spot market.

P&D schemes involve the dissemination of fake news about cryptocurrencies, allowing perpetrators to sell the targeted assets at artificially inflated prices. The prevalence of P&D events in the cryptocurrency market can be attributed to its relatively weak regulatory framework, creating an ideal environment for a natural experiment to isolate the effects of information shocks generated by these schemes. If perpetual contracts indeed affect the spot market through an information channel, as we hypothesize, then we should expect to observe similar effects during P&D events, such as increased trading volumes, wider bid-ask spreads, and higher Volume-Synchronized Probability of Informed Trading (VPIN) values.

To test this hypothesis, we examine a significant case of a P&D event: the Litecoin-Walmart incident in September 2021. On September 13, 2021, a fake press release was published, claiming that Walmart had entered into a partnership with Litecoin, a prominent cryptocurrency. The news quickly spread through various media outlets and social media platforms, causing a sharp increase in Litecoin's price. However, the news was soon revealed to be false, and Litecoin's price rapidly declined to its pre-announcement levels. This event provides a clear example of a significant and unanticipated (mis)information shock, allowing us to study the causal effects of such shocks on the spot market.

Figure 7 presents the dynamics of key market quality measures around the Litecoin-Walmart P&D event. Panel (a) depicts the volume-weighted average price of Litecoin, revealing a sharp increase followed by a rapid decline as the fake news is disseminated and subsequently debunked. The trading volume in Panel (b) exhibits a significant spike during the event window, indicating heightened market activity. Panel (c) shows a notable increase in percentage quoted spreads, suggesting a deterioration in market liquidity and an increase in transaction costs. Finally, the Volume-Synchronized Probability of Informed Trading (VPIN) metric in Panel (d), calculated using a 5-bucket approach (25-minute rolling averages), shows a marked increase, implying the presence of informed trading during the event.

These findings demonstrate that volatility, trading volumes, bid-ask spreads, and VPIN all increase during the P&D window, closely resembling the effects of perpetual contracts on spot markets identified in our research. The similarity in market behavior during P&D events and in the presence of perpetual contracts supports our hypothesis that perpetual contracts affect spot markets through an information channel.

In summary, our examination of the information channel through three distinct and complementary avenues—funding times, funding rates, and pump-and-dump events—provides a comprehensive understanding of how perpetual contracts influence spot market dynamics. The exogenous nature of funding times allows us to establish causal effects, while the analysis of funding rates and their magnitudes reveals the nuanced relationship between information content and market microstructure. Furthermore, the study of pump-and-dump events as exogenous information shocks reinforces our findings, demonstrating that the effects of perpetual contracts on the spot market are consistent with the predictions of information-based market microstructure theories. By employing a multi-faceted approach to investigating the information channel, our research offers robust evidence of the mechanisms through which perpetual contracts shape spot market microstructure.

[Figure 7 about here.]

7 Examining the Market Fragmentation Hypothesis

The impact of perpetual contracts on the spot market through the information channel, as demonstrated in the previous section, highlights the complex interactions between these two markets. While our findings suggest that perpetual contracts complement cryptocurrency trading by increasing spot market trading volumes and informational efficiency, a natural question arises: do perpetual contracts also have the potential to substitute spot market activity, leading to market fragmentation? This concern is particularly relevant given the attractive features of perpetual contracts, such as their ease of use, return distributions that closely mimic those of the underlying cryptocurrencies, and the ability to employ leverage. These advantages may incentivize traders to shift their activities from spot markets to perpetual contract markets, potentially dividing liquidity and trading activity between the two markets. To address this question and investigate the potential fragmentation effect, we employ two complementary approaches.

First, we examine the effects of perpetual contract introductions on spot market liquidity using the data presented in Table 3. Our analysis reveals no consistent increase in buyer or seller slippage for orders of \$10,000, \$100,000, and \$1,000,000 following the introduction of perpetual contracts. This finding suggests that limit orders in the spot market do not significantly migrate to the perpetual contract market. Although we observe a widening of the percentage quoted spread, this may be attributed to heightened risks of adverse selection, as evidenced by the increase in VPIN (Volume-Synchronized Probability of Informed Trading), rather than market fragmentation.

Secondly, following the methodology of Cong, Li, Tang, and Yang (2023) on crypto wash trading, a practice of artificial trading volume inflation, we extract information based on trade flows to determine the direction of trade migration between spot and perpetual markets. Our analysis reveals that wash trading in perpetual markets is generally greater than in spot markets, indicating differences in trade characteristics between perpetual and cryptocurrency spot markets. Further, we find that the introduction of perpetual contracts leads to a significant increase in the wash trading measure in the spot market (by 47%). This finding implies that trades migrate from perpetual contracts to the spot market, rather than the reverse, further corroborating the absence of market fragmentation caused by perpetual markets. Internet Appendix B presents a comprehensive examination of our wash trading findings.

The evidence we present does not support the hypothesis that perpetual markets divide liquidity or trades from the cryptocurrency spot market. This lack of fragmentation may be attributed to differences in investor composition between spot and perpetual markets. Spot traders transact in crypto tokens, while perpetual traders hold USDT (Tether), a stablecoin pegged to the U.S. dollar. These distinct asset preferences may prevent market fragmentation caused by the introduction of perpetual contracts in the cryptocurrency spot market.

Furthermore, the absence of market fragmentation may be explained by the complementary nature of spot and perpetual markets. Perpetual contracts, being derivative instruments, rely on the underlying spot market for price discovery and settlement. Arbitrageurs, who play a crucial role in maintaining price efficiency across markets, actively engage in both spot and perpetual markets to capitalize on any price discrepancies. This interconnectedness between the two markets may counteract the potential fragmentation effects of perpetual contract introduction.

Additionally, the unique characteristics of the cryptocurrency market, such as its 24/7 trading availability and the presence of a diverse range of market participants, including retail and institutional investors, may contribute to the resilience of spot market liquidity in the face of perpetual contract introduction. The high volatility and speculative nature of cryptocurrencies may attract traders who seek exposure to both spot and derivative markets, thereby maintaining liquidity across both markets.

8 Conclusion

This study introduces the perpetual contract market within the cryptocurrency domain, providing a comprehensive analysis of its structure and documenting stylized facts and causal effects for the first time. Employing robust identification strategies, we find that the introduction of perpetual contracts leads to increased spot trading volume, accompanied by wider bid-ask spreads. We attribute this effect to the greater prevalence of informed trading in the spot market following the introduction of perpetual contracts, aligning with the predictions of information-based market microstructure theories. We confirm the reverse of these findings using unexpected Huobi perpetual futures trading termination.

Our examination of the funding mechanism reveals that the effects of increased volume and wider spreads are particularly pronounced during funding times that take place every 8 hours, underscoring the role of the funding mechanism in facilitating information transmission between perpetual and spot markets. Furthermore, our analysis does not find consistent evidence of market fragmentation in the spot market following the introduction of perpetual contracts.

Our findings highlight the nuanced benefits and challenges associated with perpetual contracts, emphasizing the need for balanced regulatory oversight in the cryptocurrency market. As the cryptocurrency market evolves, it is essential to foster a deeper understanding of the complex interplay between perpetual contracts and spot markets. This understanding will help develop effective regulatory frameworks and market practices that harness the benefits of perpetual contracts while mitigating potential risks. Our study contributes to this understanding and provides valuable insights for market participants, regulators, and researchers.

Moreover, our study informs the ongoing debate on the role of derivatives in financial markets and has implications for the potential incorporation of perpetual contracts into traditional financial markets. It underscores the importance of assessing the viability and suitability of perpetual contracts for other asset classes, as the lessons learned from the cryptocurrency market may have broader applications.

As financial markets continue to evolve and integrate new instruments, future research could explore the potential extension of perpetual contracts to traditional asset classes and investigate the factors influencing their adoption and impact. The development of regulatory frameworks that balance the benefits of perpetual contracts with the need to maintain market integrity will be crucial in fostering a stable and efficient financial market ecosystem.

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Tables

Table 1: Comparison of Average Outcomes in Perpetual and Spot Markets

Outcome	Perpetual	Spot	Perpetual to Spot (%)
Amihud Measure	0.00	0.00	101***
Bid-Ask Spread	0.27	0.31	-11***
Buyer Slippage ($10K)	0.00	0.00	48***
Buyer Slippage ($100K)	0.01	0.01	2***
Buyer Slippage ($1M)	0.02	0.02	-2***
Dollar Volume	8,807,518	127,597	6,803***
Order Imbalance	0.33	0.39	-16***
Percentage Quoted Spread	0.00	0.00	14***
Permanent Price Impact	0.22	0.23	-5***
Roll Measure	0.09	0.11	-18***
Seller Slippage ($10K)	0.00	0.00	78***
Seller Slippage ($100K)	0.01	0.01	14***
Seller Slippage ($1M)	0.02	0.02	3***
Temporary Price Impact	-0.19	-0.03	564***
Total Price Impact	0.16	0.23	-29***
VPIN	0.13	0.10	31***

Notes: This table compares average hourly market quality and liquidity measures between perpetual and spot markets. Asterisks (***, **, *) denote significance at the 1%, 5%, and 10% levels, respectively testing whether the means are different using heteroskedasticity and autocorrelation consistent standard errors. Definitions include Amihud Measure (market illiquidity based on the last 12 five-minute windows), Bid-Ask Spread (time-weighted difference between lowest ask and highest bid prices), Buyer and Seller Slippage ($10K, $100K, $1M) (price slippage for hypothetical buy or sell orders of $10,000, $100,000, and $1,000,000, respectively), Dollar Volume (total value of transactions within five-minute bins), Order Imbalance (difference in volume between buy and sell orders relative to total volume, averaged over the last 12 five-minute windows), Percentage Quoted Spread (time-weighted bid-ask spread relative to the midpoint price), Permanent and Temporary Price Impacts (long-term and short-term effects of trades on prices), Roll Measure (proxy for the effective bid-ask spread based on price autocovariance), and VPIN (volume-synchronized probability of informed trading, averaged over the last 12 five-minute windows).

Table 2: Effect of Huobi Perpetual Trading Termination on Spot Market Microstructure: DiD with a Synthetic Control

Outcome	[-3,3]	[-7,7]	[-14,14]	[-30,30]
Amihud Measure 5	0.000	0.000***	0.000***	0.000***
Amihud Measure 12	0.000***	0.000***	0.000***	0.000***
Bid-Ask Spread	-0.001	-0.001	-0.000	-0.001
Buyer Slippage ($10K)	0.000	0.000	0.000	0.000
Buyer Slippage ($100K)	0.002	0.002	0.003	0.003
Buyer Slippage ($1M)	0.001	-0.000	0.000	0.001
Dollar Volume	-24,464	-63,029***	-72,530***	-75,091**
Order Imbalance 5	0.052***	0.051***	0.041**	0.030*
Order Imbalance 12	0.053***	0.052***	0.041**	0.031*
Percentage Quoted Spread	-0.000***	-0.000***	-0.000*	-0.000
Permanent Price Impact	0.000	0.000	0.000	0.000
Roll Measure	-0.004	-0.001	0.002	0.004
Seller Slippage ($10K)	-0.000**	0.000	0.000	0.000
Seller Slippage ($100K)	0.001	0.001	0.001*	0.001**
Seller Slippage ($1M)	0.001	-0.002	-0.002*	-0.001
Temporary Price Impact	0.001	0.001	0.001	0.000
Total Price Impact	0.001	0.001*	0.001*	0.001*
VPIN 5	0.006	0.009	0.009	0.014
VPIN 12	0.005	0.009	0.009	0.013

Notes: This table quantifies the impact of Huobi's perpetual trading termination on the spot market's microstructure, utilizing a synthetic control method in a Differences-in-Differences framework across different time windows. Significance levels are denoted by asterisks: *** p<0.01, ** p<0.05, * p<0.1.

Using 1 month before perpetual trading termination announcement for each (treated) token pair on Huobi i we find a vector of weights $\mathbf{W_i^*}$ that combines outcomes $\mathbf{Y^c}$ of n untreated token pairs on other exchanges at all time points and minimizes:

$$\min_{\mathbf{W_i} \in \mathbb{R}^n} \left\| Y_i - \sum_{j=1}^{n} W_{i,j} Y_j^c \right\|_2 \text{ subject to } \mathbf{W_i} \geq 0 \text{ and } \sum_{j=1}^{n} W_{i,j} = 1$$

Synthetic control for token pair i is then $\hat{Y}_i^c = \sum_{j=1}^{n} W_{i,j}^* Y_j^c$ and $(Y_i, \hat{Y}_i^c)$ constitute a treatment and control Differences-in-Differences pair. The regression is:

$$Market\_Quality_{e,i,t} = \beta D_{e,i,t} + \gamma_{e,i} + \eta_t + \epsilon_{e,i,t},$$

where $Market\_Quality_{e,i,t}$ denotes the spot market outcome on date t for token i on exchange e (synthetic control exchange or Huobi), $\gamma_{e,i}$ is the exchange-token fixed effect, η_t is a time (date) fixed effect. The coefficient of interest is that corresponding to $D_{e,i,t}$, a dummy variable equal to 1 if the observation is simultaneously from Huobi and after perpetual contract trading termination for token i. The standard errors are clustered at the exchange-token level.

Table 3: Staggered Differences-in-Differences: Causal Effect of Perpetual Contract Introduction on Spot Market Microstructure

Outcome	Coefficient
Amihud Measure 5	-17,548.8
Amihud Measure 12	-15,892.9
Bid-Ask Spread	1.552
Buyer Slippage ($10K)	0.002
Buyer Slippage ($100K)	-0.004***
Buyer Slippage ($1M)	-0.002
Dollar Volume	70,487**
Order Imbalance 5	-0.0
Order Imbalance 12	-0.01
Percentage Quoted Spread	0.007***
Permanent Price Impact	0.045
Roll Measure	-0.237*
Seller Slippage ($10K)	0.003*
Seller Slippage ($100K)	-0.003***
Seller Slippage ($1M)	-0.001
Temporary Price Impact	0.281
Total Price Impact	0.328
VPIN 5	0.013***
VPIN 12	0.013***

Notes: This table presents the causal effect of perpetual contract introduction on various spot market microstructure outcomes. Variables involving time-weighted averaging that adjusts for the temporal distribution of trading activity include Bid-Ask Spread, Buyer Slippage (for $10,000, $100,000, and $1,000,000), Percentage Quoted Spread, Permanent Price Impact, Seller Slippage (for $10,000, $100,000, and $1,000,000), Temporary Price Impact, and Total Price Impact. Significance levels are denoted by asterisks: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Variable Definitions: Amihud Measure assesses market liquidity and efficiency; Bid-Ask Spread reflects the cost of immediate execution; Buyer and Seller Slippage indicate the cost impact of trade execution at varying sizes; Dollar Volume measures the total trading volume; Order Imbalance captures the absolute value difference in buy and sell volume relative to total volume; Percentage Quoted Spread and Roll Measure evaluate market depth and liquidity; Permanent and Temporary Price Impacts capture the lasting and immediate effects of trades on prices; VPIN quantifies the probability of informed trading.

The regression is:

$$Market\_Quality_{e,i,t} = \beta D_{e,i,t} + \gamma_{e,i} + \eta_t + \epsilon_{e,i,t},$$

where $Market\_Quality_{e,i,t}$ denotes the spot market outcome on date t for token i on exchange e, $\gamma_{e,i}$ is the exchange-token fixed effect, η_t is a time (date) fixed effect. The coefficient of interest is that corresponding to $D_{e,i,t}$, a dummy variable equal to 1 if the observation is simultaneously from a treated token exchange with a perpetual introduction event and after such introduction took place. The standard errors are clustered at the exchange-token level.

Table 4: Funding time outcome percentage change relative to non-funding time period immediately prior

Outcome	Hour 1	[-1, 1]	[-2, 2]
Amihud Measure 5	-3.5***	-0.4	5.6***
Amihud Measure 12	-0.1	4.0***	10.0***
Bid-Ask Spread	3.2***	2.4***	3.1***
Buyer Slippage ($10K)	4.9***	4.0***	4.8***
Buyer Slippage ($100K)	4.0***	2.9***	3.5***
Buyer Slippage ($1M)	2.7***	2.0***	2.5***
Dollar Volume	50.4***	37.3***	37.8***
Order Imbalance 5	-4.5***	-2.7***	-1.2***
Order Imbalance 12	-3.4***	-1.6***	-0.7***
Percentage Quoted Spread	3.1***	2.4***	3.0***
Permanent Price Impact	23.6***	17.1***	19.1***
Realized Volatility	4.4***	3.3***	3.4***
Roll Measure	2.8***	2.5***	3.4***
Seller Slippage ($10K)	4.4***	3.5***	4.1***
Seller Slippage ($100K)	3.3***	2.5***	2.8***
Seller Slippage ($1M)	2.0***	1.6***	1.8***
Temporary Price Impact	-32.9***	-35.2***	-52.6***
Total Price Impact	14.9***	10.4***	10.5***
VPIN 5	17.4***	12.1***	11.4***
VPIN 12	13.6***	10.1***	10.9***

Notes: This table presents percentage changes (in %) in market quality and liquidity measures during funding times compared to non-funding periods immediately before each respective funding time. All regressions include time and exchange-token fixed effects. We consider different treatment windows: 1 hour after funding time, 1 hour before and after, [-1,1], and 2 hours before and after, [-2,2]. Asterisks (***) indicate significance at the 1% level. The "5" or "12" in variable names denote calculations based on the last 5 or 12 five-minute windows, respectively, to provide insights into short-term market dynamics and as a robustness check.
The regression is:

$$Market\_Quality_{e,i,t} = \beta D_t + \gamma_{e,i} + \eta_t + \epsilon_{e,i,t},$$

where $Market\_Quality_{e,i,t}$ denotes the outcome at time t at an hourly frequency for token i on the spot market of exchange e relative to non-funding time average outcome prior to funding time, $\gamma_{e,i}$ is the exchange-token fixed effect, η_t is an 8-hour window time fixed effect (different each 8 hours). Finally, D_t is 1 if the observation is within the treatment window around the funding time. The standard errors are clustered at the exchange-token level.

Table 5: Spot Market Funding Time Effect by Contemporary Funding Rate Proxy Quintile

Outcome	Q1	Q2	Q3	Q4	Q5
Amihud Measure 5	-1.9***	-4.3***	-4.3***	-4.0***	-5.2***
Amihud Measure 12	3.8***	-1.6***	-2.3***	-1.6***	-2.7***
Bid-Ask Spread	3.3***	2.2***	2.3***	2.2***	4.2***
Buyer Slippage 10000	6.8***	4.8***	4.4***	4.2***	4.8***
Buyer Slippage 100000	5.6***	3.6***	3.6***	3.4***	3.8***
Buyer Slippage 1000000	3.9***	2.4***	2.3***	2.2***	2.5***
Dollar Volume	60.4***	45.6***	46.2***	48.3***	49.8***
Order Imbalance 5	-4.8***	-5.0***	-4.8***	-4.5***	-4.3***
Order Imbalance 12	-3.6***	-3.7***	-3.6***	-3.3***	-3.1***
Percentage Quoted Spread	3.3***	2.1***	2.2***	2.1***	4.1***
Roll Measure	3.4***	1.0***	1.5***	2.4***	5.0***
Seller Slippage 10000	5.3***	4.5***	3.9***	3.7***	4.9***
Seller Slippage 100000	3.4***	3.1***	3.3***	3.1***	3.5***
Seller Slippage 1000000	2.1***	1.9***	1.9***	1.7***	1.9***
VPIN 5	17.8***	17.0***	18.0***	18.6***	15.4***
VPIN 12	14.0***	13.1***	13.9***	14.5***	12.0***

Notes: This table presents percentage changes (in %) in market quality and liquidity measures by funding rate proxy quintile during funding times compared to non-funding periods immediately before each respective funding time. Each sample is grouped by the contemporaneous funding rate proxy from low to high, segmented into quintiles (Q1 to Q5). All regressions include time and exchange-token fixed effects. Significance levels are denoted by asterisks: *** p<0.01, ** p<0.05, * p<0.1.

Variable Definitions: Amihud Measure is an illiquidity measure based on the price impact of trades. Bid-Ask Spread is the difference between the lowest price a seller is willing to accept and the highest price a buyer is willing to pay. Buyer/Seller Slippage is the cost incurred due to changes in price between the time a trade order is placed and the time it is executed, for orders of various sizes ($10,000, $100,000, and $1,000,000). Dollar Volume is the total value of tokens traded over a specific time period. Order Imbalance is the absolute value difference in volume between buy and sell orders over a specific time period relative to total volume. Percentage Quoted Spread is the bid-ask spread as a percentage of the midpoint price. Permanent Price Impact is the long-term impact of trades on the price of an asset. Roll Measure is a proxy for bid-ask spread based on the covariance of consecutive price changes. Temporary Price Impact is the short-term impact of trades on the price of an asset. VPIN is the Volume-synchronized probability of informed trading, indicating the likelihood of informed trading based on trade volume and order imbalance. Funding rate proxy measures the percentage deviation of the perpetual future price from its underlying spot market price. The regression is:

$$Market\_Quality_{e,i,t} = \beta D_t + \gamma_{e,i} + \eta_t + \epsilon_{e,i,t},$$

where $Market\_Quality_{e,i,t}$ denotes the outcome at time t at an hourly frequency for token i on the spot market of exchange e relative to non-funding period average immediately prior, $\gamma_{e,i}$ is the exchange-token fixed effect, η_t is an 8-hour window time fixed effect (different each 8 hours). Finally, D_t is 1 if the observation is within the treatment window around the funding time. The standard errors are clustered at the exchange-token level.

Table 6: Funding Time Effect with Average Fee Proxy Before Funding Time as Treatment Dosage

Spot Market Quality	$FRate$	$\|FRate\|$
Amihud Measure 5	0	2.241***
Amihud Measure 12	0	4.297***
Bid-Ask Spread	2.276***	12.574***
Buyer Slippage ($10K)	-2.009	21.935***
Buyer Slippage ($100K)	-1.581	15.372***
Buyer Slippage ($1M)	-1.787**	10.614***
Dollar Volume	1,282,670	17,646,834
Order Imbalance 5	-0.07	-5.380***
Order Imbalance 12	-0.364	-4.017***
Percentage Quoted Spread	2.344***	12.172***
Roll Measure	-4.715**	2.243
Seller Slippage ($10K)	-0.602	15.833***
Seller Slippage ($100K)	0.485	10.942***
Seller Slippage ($1M)	-0.437	6.149***
VPIN 5	0.992*	3.904***
VPIN 12	1.032**	3.016***

Notes: This table reports regression coefficients of spot market metrics against the average funding rate proxy before funding time, serving as a treatment dosage. Significance levels are denoted by asterisks: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Variable Definitions: Amihud Measure is an illiquidity measure based on the price impact of trades. Bid-Ask Spread is the difference between the lowest price a seller is willing to accept and the highest price a buyer is willing to pay. Buyer/Seller Slippage is the cost incurred due to changes in price between the time a trade order is placed and the time it is executed, for orders of various sizes ($10,000, $100,000, and $1,000,000). Dollar Volume is the total value of tokens traded over a specific time period. Order Imbalance is the absolute value difference in volume between buy and sell orders over a specific time period relative to total volume. Percentage Quoted Spread is the bid-ask spread as a percentage of the midpoint price. Permanent Price Impact is the long-term impact of trades on the price of an asset. Roll Measure is a proxy for bid-ask spread based on the covariance of consecutive price changes. Temporary Price Impact is the short-term impact of trades on the price of an asset. VPIN is the Volume-synchronized probability of informed trading, indicating the likelihood of informed trading based on trade volume and order imbalance. Funding rate proxy measures the percentage deviation of the perpetual future price from its underlying spot market price. The regression is:

$$Market\_Quality_{e,i,t} = \beta FRate_{e,i,t} + \gamma_{e,i} + \eta_t + \epsilon_{e,i,t},$$

where $Market\_Quality_{e,i,t}$ denotes the outcome at time t at an hourly frequency for token i on the spot market of exchange e, $\gamma_{e,i}$ is the exchange-token fixed effect, η_t is an 8-hour window time fixed effect (different each 8 hours). Finally, $FRate_{e,i,t}$ is either the 8-hour average funding rate proxy or its absolute value prior to funding time. This variable is set to 0 during non-funding time hours and the average funding rate proxy for the 8-hour window before each funding time (or its absolute value) is assigned as the respective treatment dosage of each funding event. The standard errors are clustered at the exchange-token level.

Figures

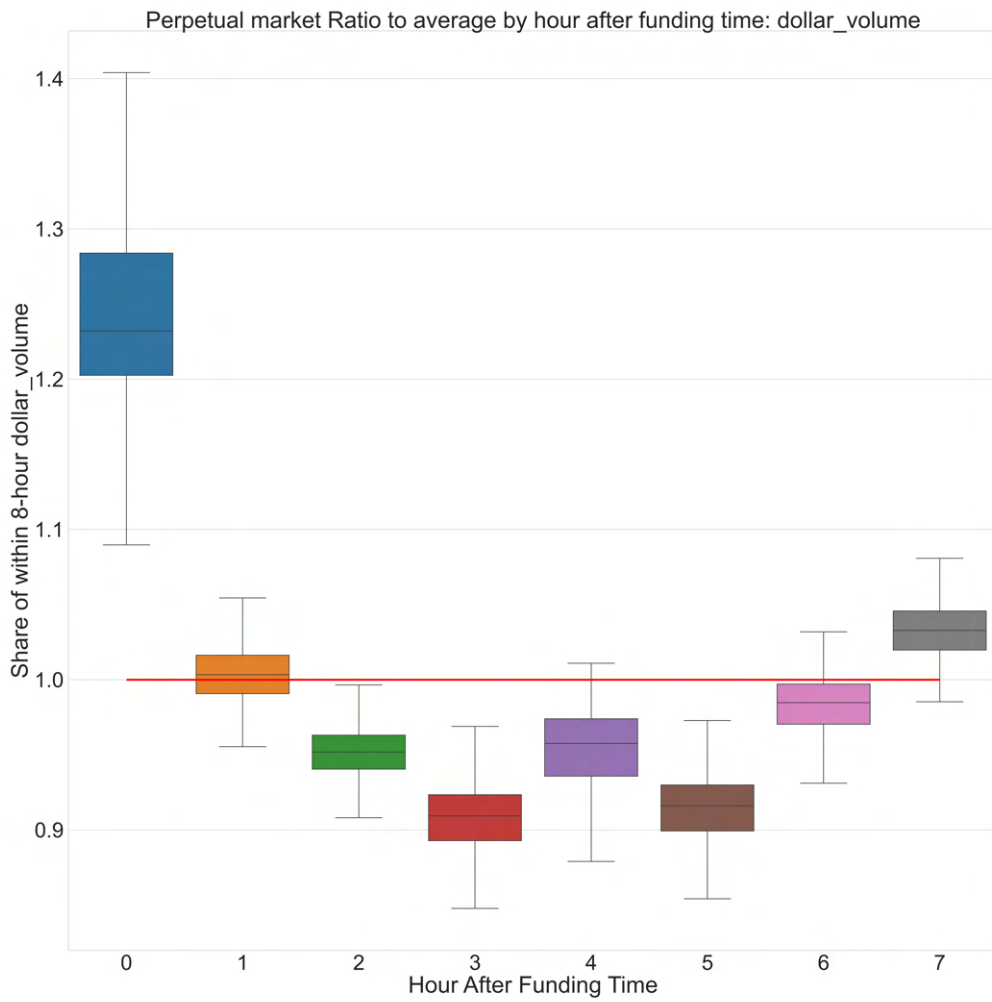


Figure 1: Hourly Trading Volume Ratios to 8-Hour Average in Perpetual Markets

Note: This figure displays the cross-sectional (across exchange-token pairs) distribution of average perpetual market trading volume by hour after funding time relative to their respective 8-hour funding window averages, accompanied by a 99% confidence interval. We compute measures relatively to each 8-hour window for comparability as trading volumes can vary drastically across different tokens, exchanges and times. 0 in the x-axis covers data points up to 1 hour after each funding time, 7 represents the last hour before each funding time. The red horizontal line at the level of 1 represents the uniform distribution whereas trading volume is spread evenly within each 8-hour period. The deviations from this line suggest that trading is not uniform but instead is concentrated around funding events.

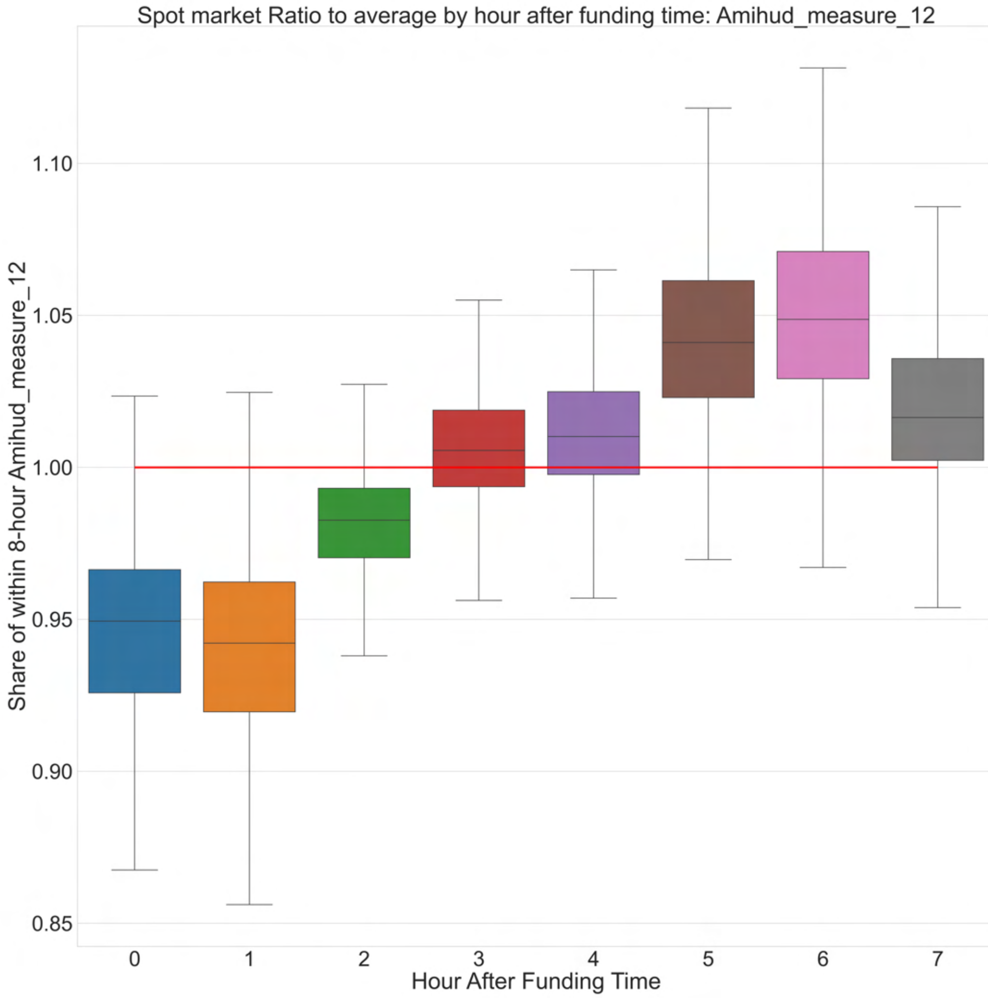


Figure 2: Spot Market Amihud Measure by Hour After Funding Time

Note: This figure illustrates the cross-sectional (across exchange-tokens) distribution of the spot market Amihud illiquidity measure by hour after funding time relative to each respective 8-hour window average, accompanied by a 99% confidence interval. The Amihud measure is calculated for each 5-minute interval using a 1-hour moving average window ($W = 12$), further averaged to an hourly frequency and normalized by the respective 8-hour funding window average. 0 in the x-axis covers data points up to 1 hour after each funding time, 7 represents the last hour before each funding time. Spot market illiquidity seems to increase shortly before each perpetual market funding time only to drop substantially at the funding time.

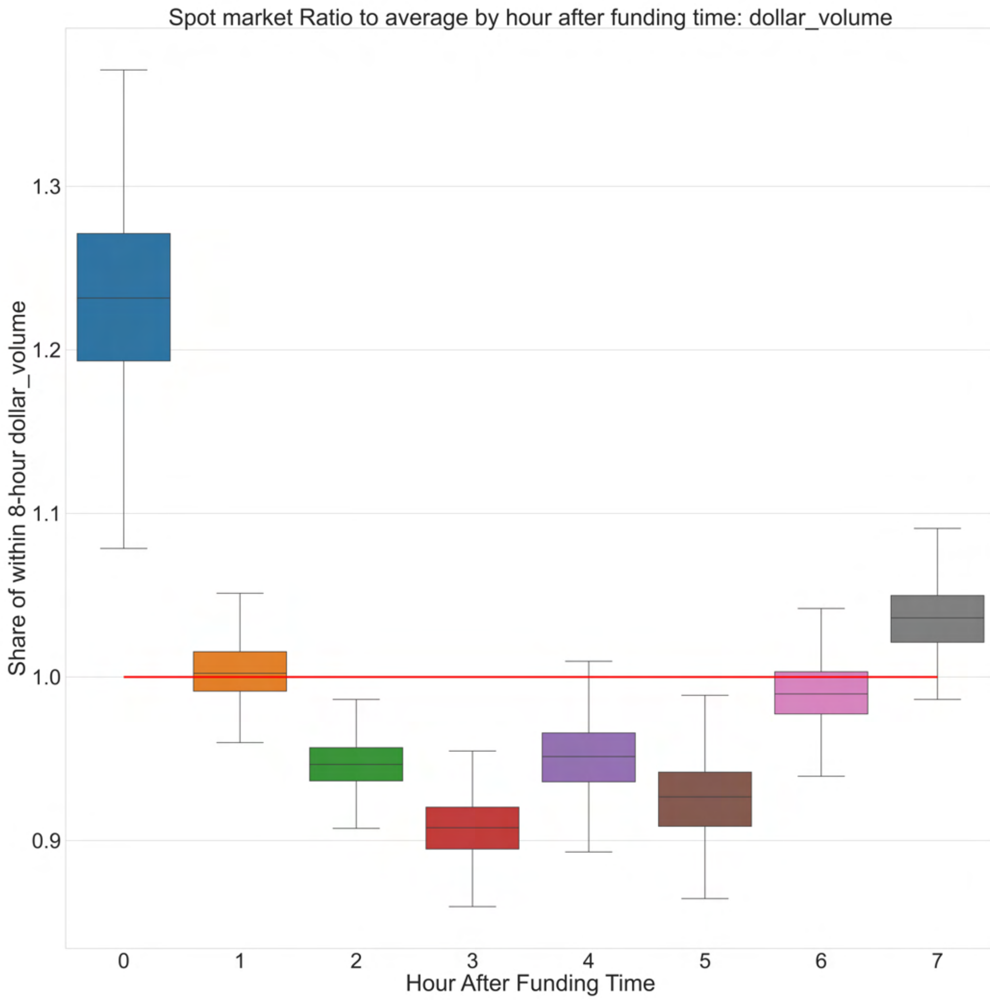


Figure 3: Spot Market Dollar Volume by Hour After Funding Time

Note: This figure presents the cross-sectional (across exchange-tokens) distribution of spot market dollar volume by hour after perpetual market funding time relative to each respective 8-hour average, accompanied by a 99% confidence interval. 0 in the x-axis covers data points up to 1 hour after each funding time, 7 represents the last hour before each funding time. Spot market dollar volume jumps substantially around perpetual market funding times.

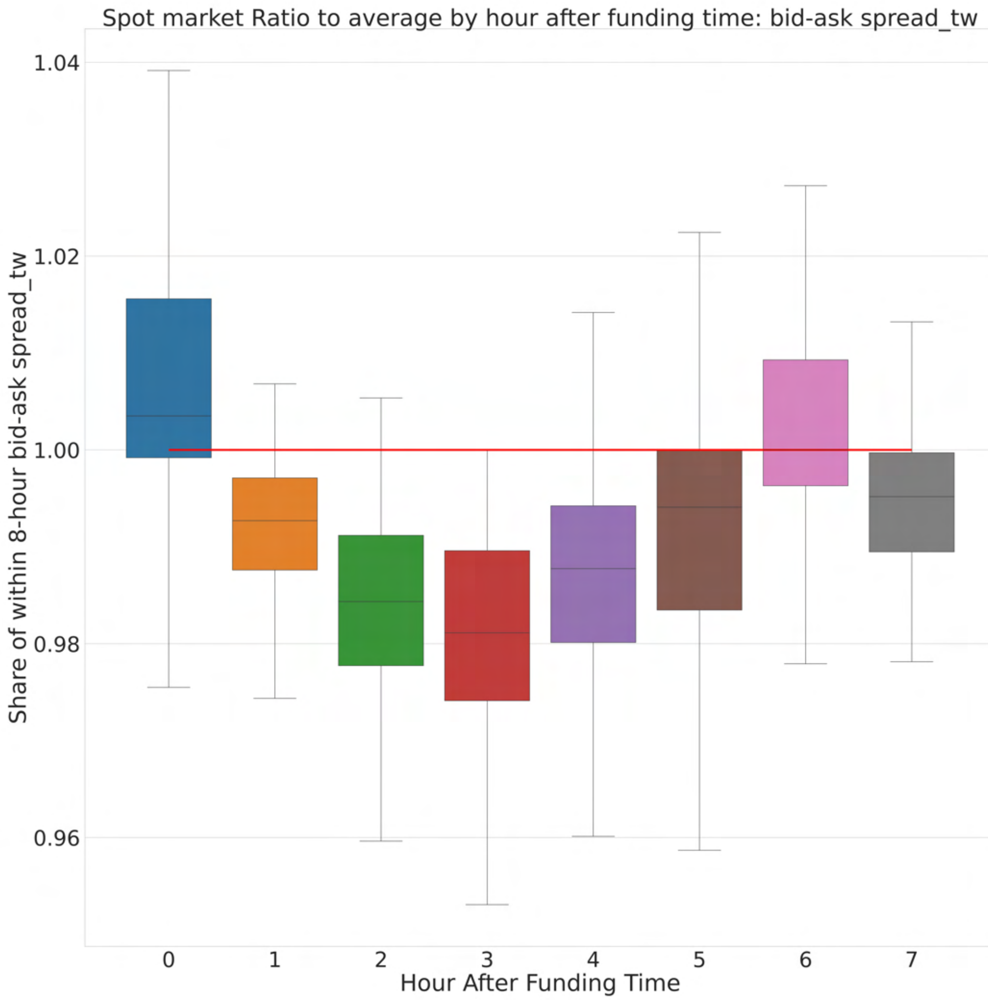


Figure 4: Spot Market Bid-Ask Spread by Hour After Funding Time

Note: This figure depicts the cross-sectional (across exchange-tokens) distribution of spot market bid-ask spread by hour after funding time relative to each respective 8-hour average, accompanied by a 99% confidence interval. 0 in the x-axis covers data points up to 1 hour after each funding time, 7 represents the last hour before each funding time. The bid-ask spread reflects the cost of immediate trade execution. This cost in spot markets seems to be higher around perpetual market funding times.

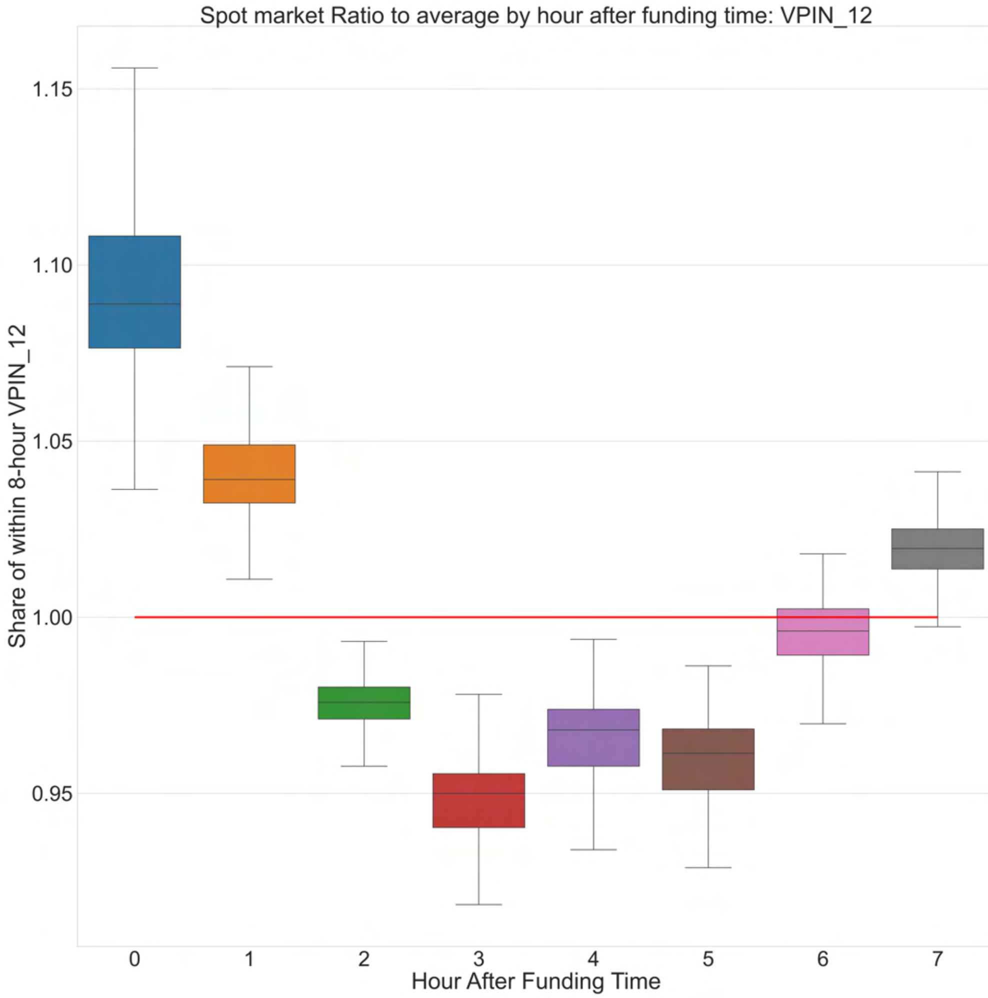


Figure 5: Spot Market $VPIN$ by Hour After Funding Time

Note: This figure illustrates the cross-sectional (across exchange-tokens) distribution of spot market Volume-Synchronized Probability of Informed Trading ($VPIN$) by hour after funding time relative to each respective 8-hour average, accompanied by a 99% confidence interval. 0 in the x-axis covers data points up to 1 hour after each funding time, 7 represents the last hour before each funding time. $VPIN$ estimates market toxicity and prevalence of informed trading in a market at time t. Probability of informed trading in spot markets increases substantially around perpetual market funding times.

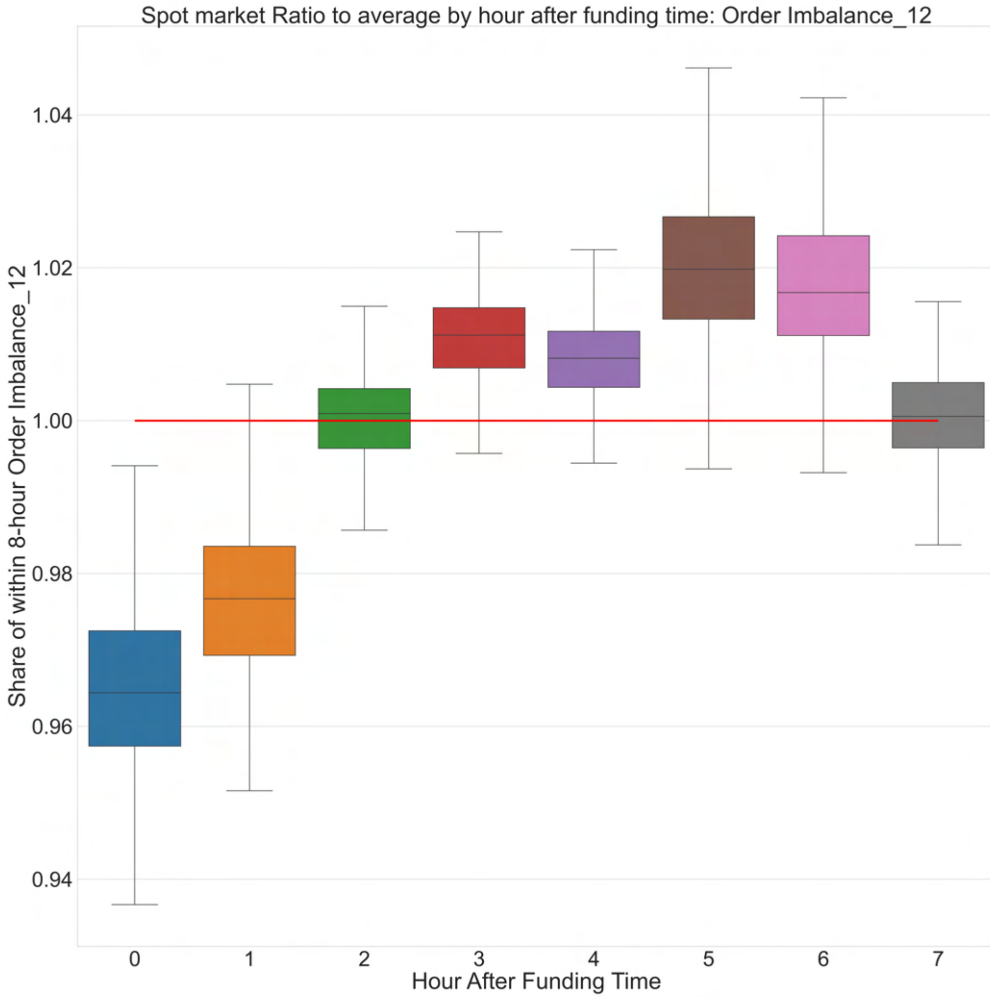
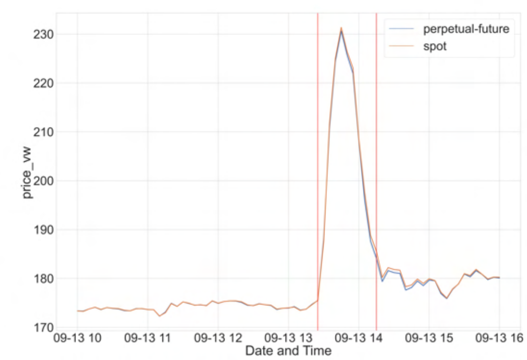
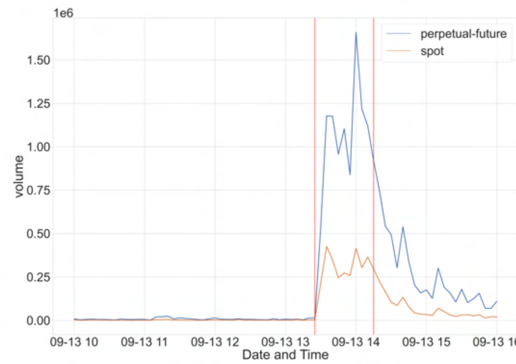


Figure 6: Spot Market Order Imbalance by Hour After Funding Time

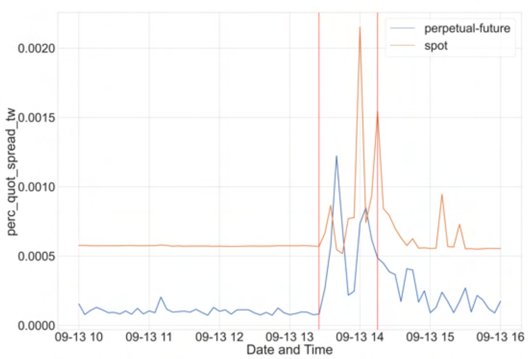
Note: This figure depicts the cross-sectional (across exchange-tokens) distribution of spot market order imbalance by hour after funding time relative to each respective 8-hour average, accompanied by a 99% confidence interval. 0 in the x-axis covers data points up to 1 hour after each funding time, 7 represents the last hour before each funding time. Order imbalance measures the degree to which a market is subject to a particular negative or positive sentiment. Spot market order imbalances are eased around perpetual market funding times. This means that the necessary liquidity that spot markets lacked before funding times enters the markets around funding times and gets executed against the prevailing outstanding volume.



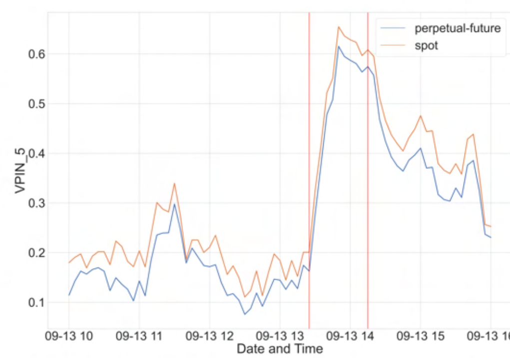
(a) Volume-weighted average price of Litecoin around the Walmart-Litecoin PD event. The vertical red lines indicate the time of the fake announcement.



(b) Trading volume of Litecoin around the Walmart-Litecoin PD event. The vertical red lines indicate the time of the fake announcement.



(c) Percentage quoted spread (time-weighted) of Litecoin around the Walmart-Litecoin PD event. The vertical red lines indicate the time of the fake announcement.



(d) Volume-Synchronized Probability of Informed Trading (VPIN) of Litecoin around the Walmart-Litecoin PD event, calculated using a 5-bucket approach (25-minute rolling average). The vertical red lines indicate the time of the fake announcement.

Figure 7: Market dynamics of Litecoin around the Walmart-Litecoin pump-and-dump event in September 2021. The figure presents the volume-weighted average price, trading volume, percentage quoted spread, and VPIN of Litecoin, with the vertical red lines indicating the time of the fake announcement. The graphs demonstrate a sharp increase in price, volume, percentage quoted spread, and informed trading probability following the announcement, followed by a rapid reversal as the news is revealed to be false.

APPENDIX

A.1 Variables Definitions

Denote a 5-minute interval as τ, with price changes represented by $\Delta p_t = p_t - p_{t-1}$ and 5-minute returns by r_τ. The indicator b_t is set to 1 for buyer-initiated trades and -1 for seller-initiated trades. The trading volume for interval τ, V_τ, aggregates the dollar volume of transactions, expressed in USDT, within the 5-minute period. Bid and ask prices at time t are p_t^b and p_t^a, respectively, with their midpoint calculated as $m_t = 0.5(p_t^a + p_t^b)$.

- Roll measure

$$R_\tau = 2\sqrt{|autocov\left(\{\Delta p_t\}_{t\in\tau}\right)|}$$

- Amihud's measure

$$\lambda^A_{\tau,W} = \frac{1}{W}\sum_{i=\tau-W+1}^{\tau}\frac{|r_i|}{p_i V_i}, \quad W \in \{5, 12, 24\}$$

- Volume-synchronized probability of informed trading ($VPIN$)

$$VPIN_{\tau,W} = \frac{1}{W}\sum_{i=\tau-W+1}^{\tau}\frac{|\hat{V_i^S} - \hat{V_i^B}|}{V_i}, \quad W \in \{5, 12, 24\}$$

  where $\hat{V_i^S} = V_i\, t_{CDF}\left(\frac{\Delta p_\tau}{\sigma_{\Delta p_\tau}}, df\right)$ and $\hat{V_i^B} = V_i - \hat{V_i^S}$. As our baseline we set $df = 0.25$ as in Easley et al. (2021).

- Order Imbalance

$$OrderImbalance_{\tau,W} = \frac{1}{W}\sum_{i=\tau-W+1}^{\tau}\frac{|V_i^S - V_i^B|}{V_i}, \quad W \in \{5, 12, 24\}$$

- Bid-Ask Spread

$$BAS_t = p_t^a - p_t^b$$

- Percentage Quoted Spread

$$PQS_t = \frac{BAS_t}{m_t}$$

- Temporary Price Impact

$$TempPI_t = 2b_t(p_t - m_{t+5})$$

- Permanent Price Impact

$$PermPI_t = 2b_t(m_{t+5} - m_t)$$

- Total Price Impact

$$TPI_t = 2b_t(p_t - m_t)$$

A.2 Perpetual Contract Trading Termination: Synthetic Control

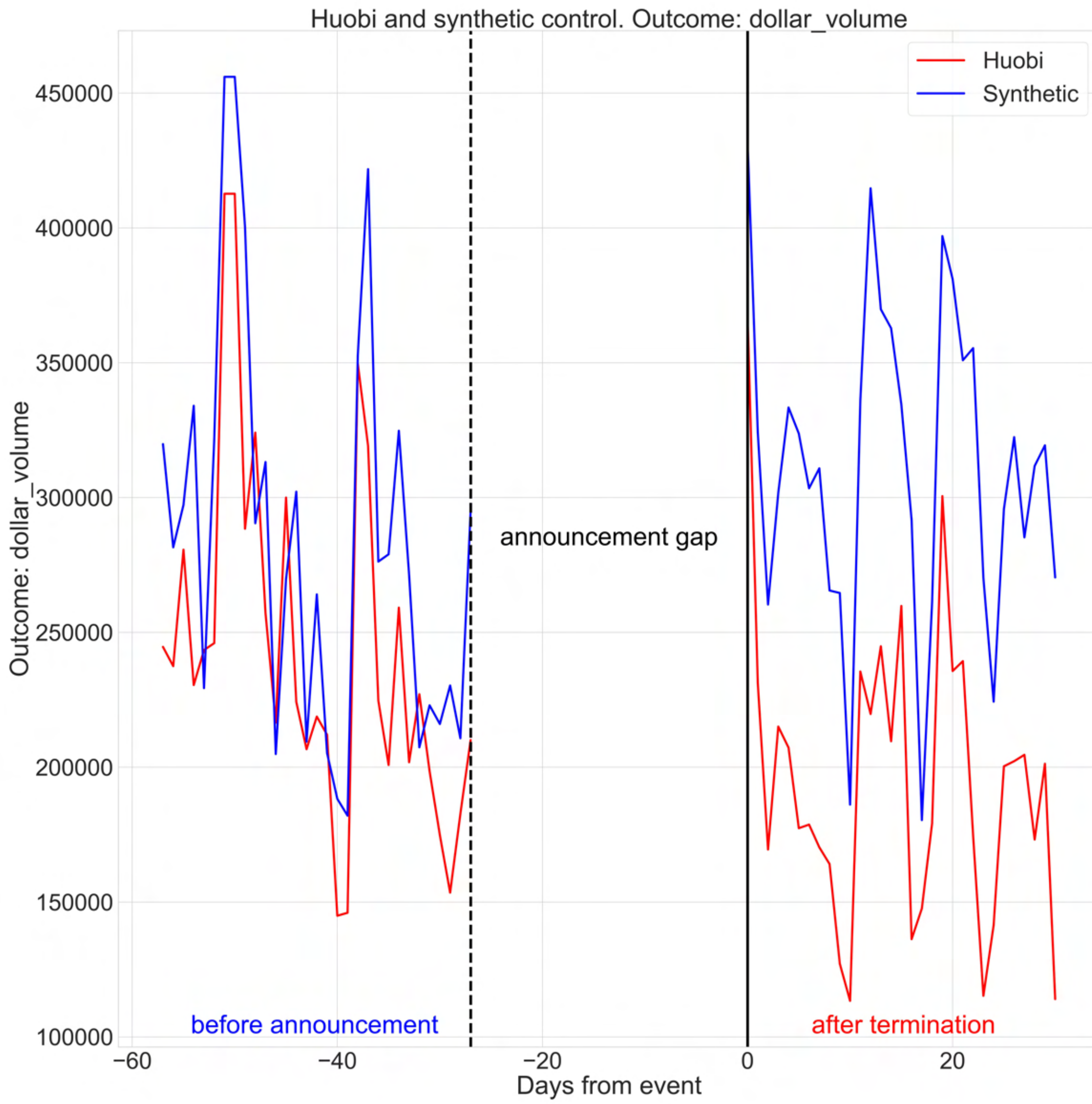


Figure A1: Huobi and synthetic control trading Volume around Huobi perpetual trading termination.

Note: This figure displays the trading volume for Huobi and its synthetic control. The control is fit using token pairs on other exchanges in the 1 month prior to perpetual trading termination announcement on Huobi. The Differences-in-Differences part discards the period between announcement and actual termination and compares post-termination outcomes to those before announcement. The first dashed black vertical line depicts the announcement date, the second black line is the termination date.

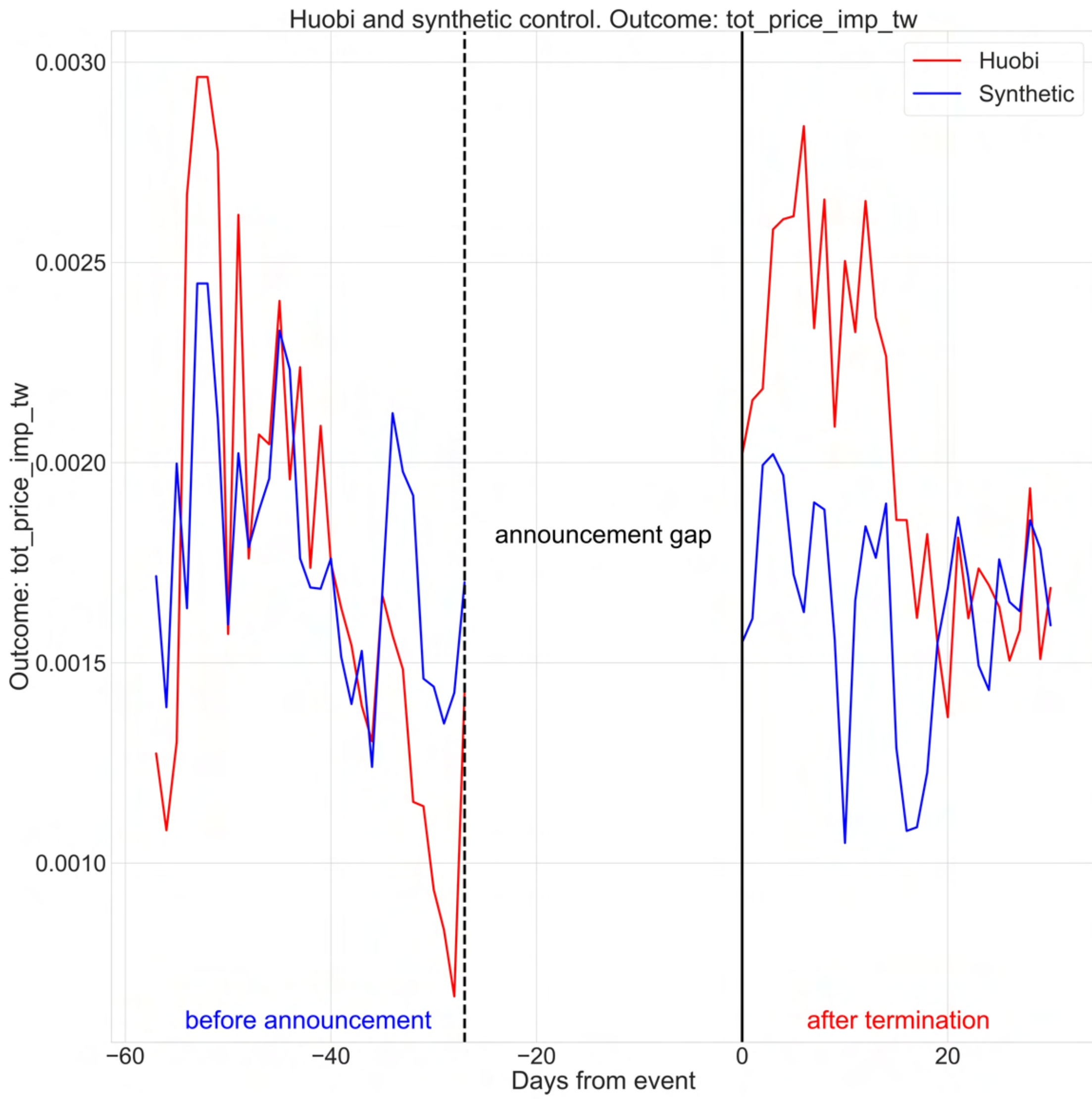


Figure A2: Huobi and synthetic control total price impact around Huobi perpetual trading termination.

Note: This figure displays the total price impact for Huobi and its synthetic control. The control is fit using token pairs on other exchanges in the 1 month prior to perpetual trading termination announcement on Huobi. The Differences-in-Differences part discards the period between announcement and actual termination and compares post-termination outcomes to those before announcement. The first dashed black vertical line depicts the announcement date, the second black line is the termination date.

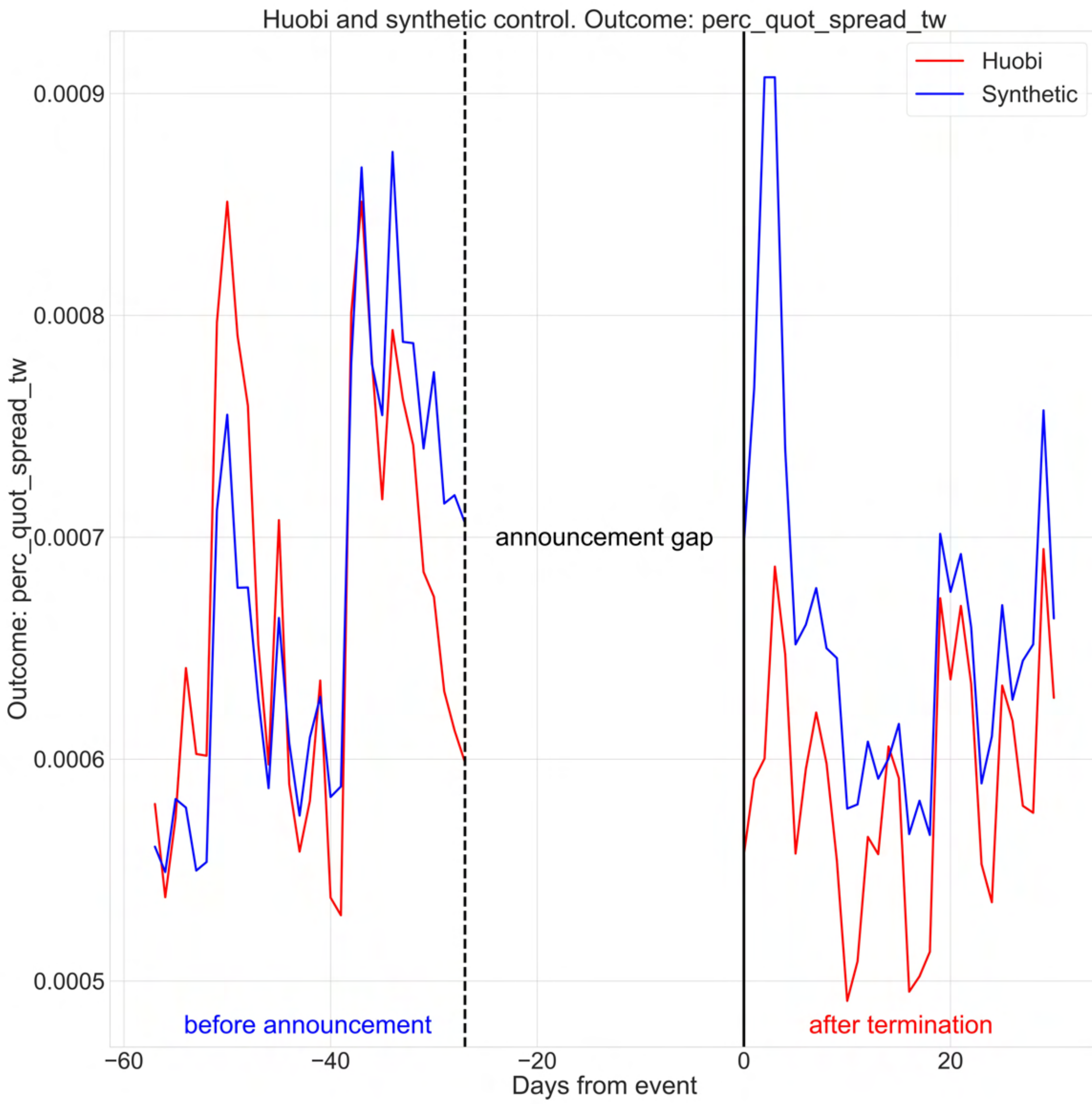


Figure A3: Huobi and synthetic control Percentage Quoted Spread around Huobi perpetual trading termination.

Note: This figure displays the percentage quoted spread for Huobi and its synthetic control. The control is fit using token pairs on other exchanges in the 1 month prior to perpetual trading termination announcement on Huobi. The Differences-in-Differences part discards the period between announcement and actual termination and compares post-termination outcomes to those before announcement. The first dashed black vertical line depicts the announcement date, the second black line is the termination date.

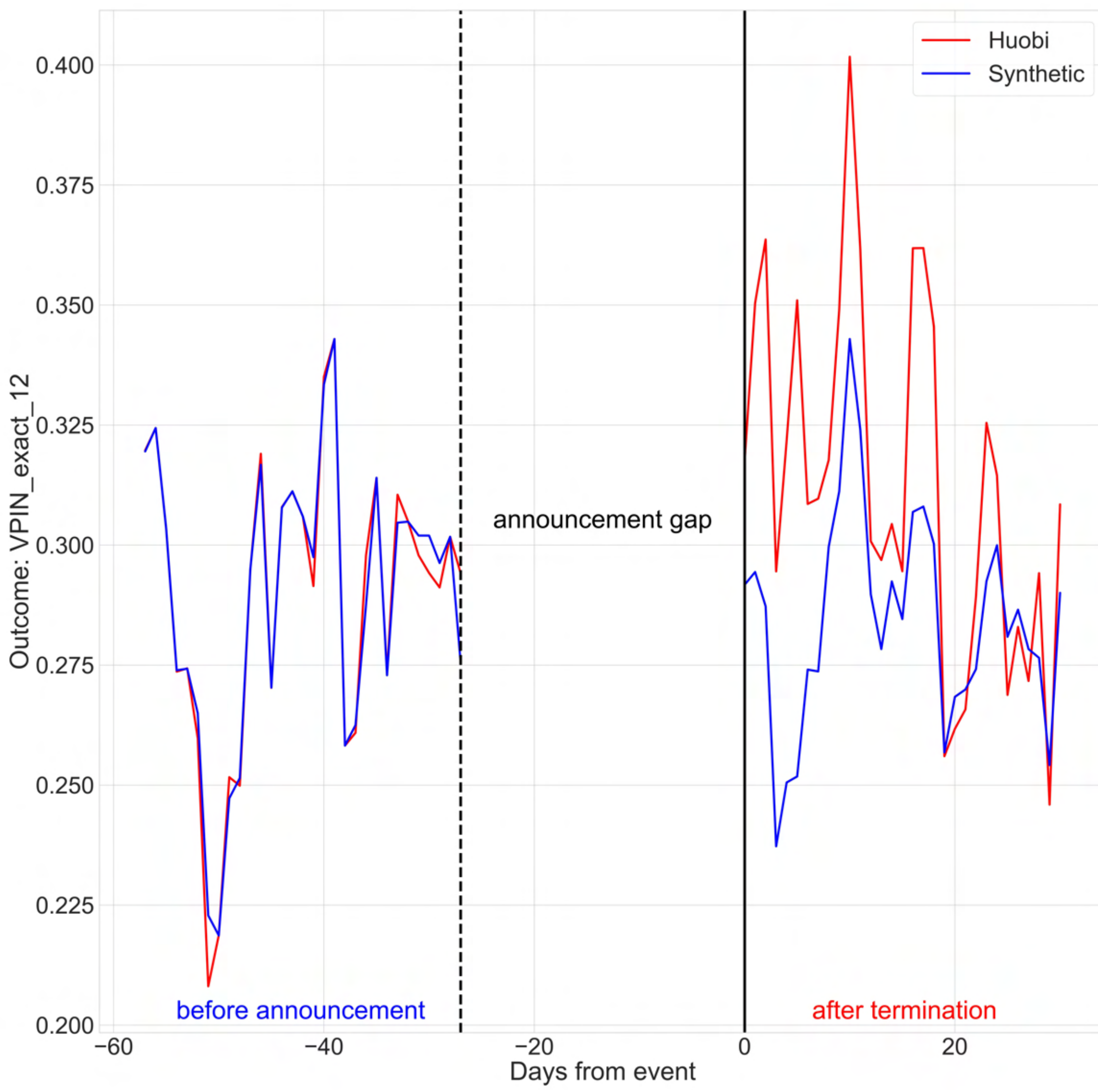


Figure A4: Huobi and synthetic control Order Imbalance (12) around Huobi perpetual trading termination.

Note: This figure displays the order imbalance for Huobi and its synthetic control. The control is fit using token pairs on other exchanges in the 1 month prior to perpetual trading termination announcement on Huobi. The Differences-in-Differences part discards the period between announcement and actual termination and compares post-termination outcomes to those before announcement. The first dashed black vertical line depicts the announcement date, the second black line is the termination date.

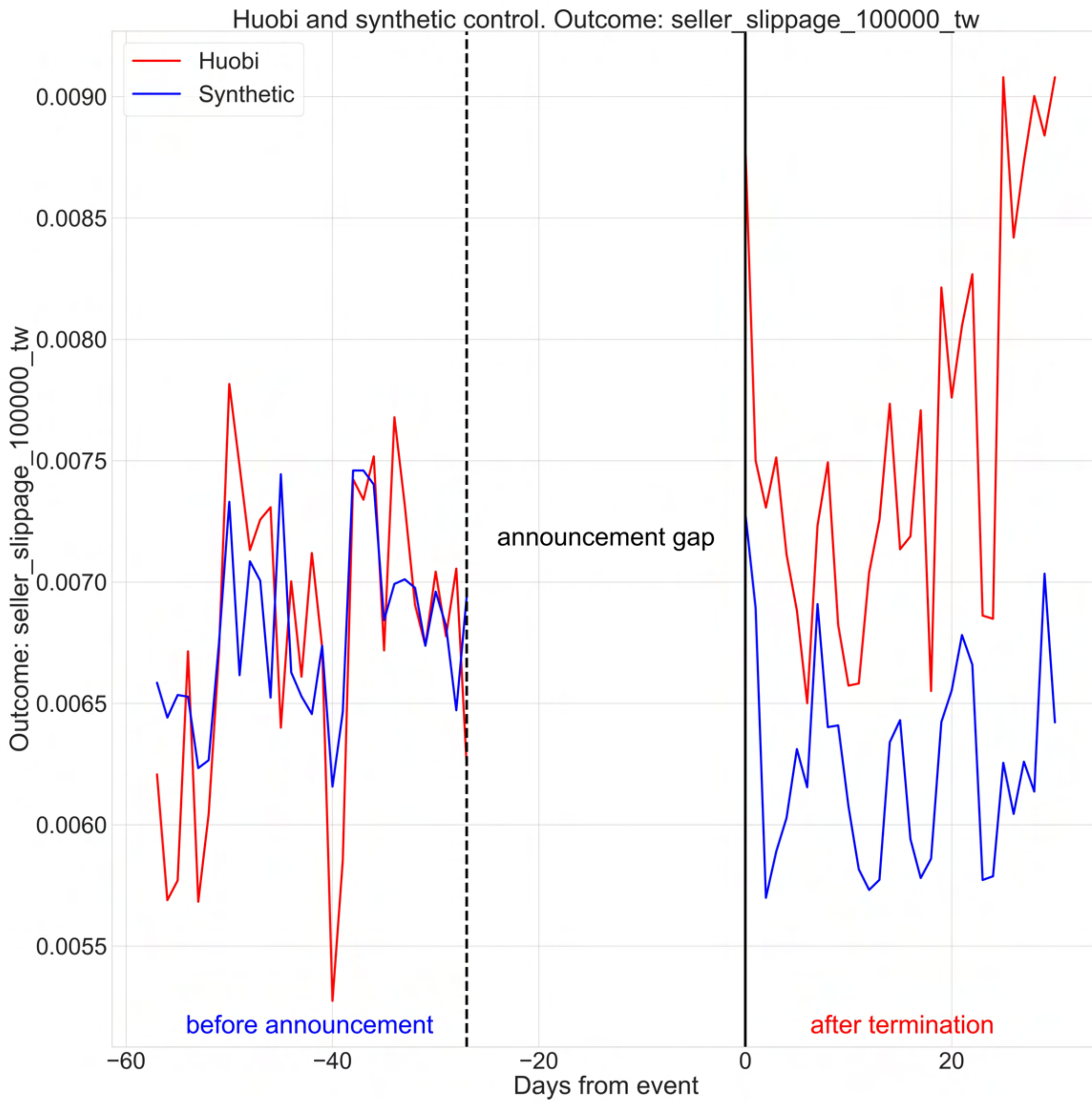


Figure A5: Huobi and synthetic control seller slippage ($100,000) around Huobi perpetual trading termination.

Note: This figure displays the seller slippage for a position of size $100,000 for Huobi and its synthetic control. The control is fit using token pairs on other exchanges in the 1 month prior to perpetual trading termination announcement on Huobi. The Differences-in-Differences part discards the period between announcement and actual termination and compares post-termination outcomes to those before announcement. The first dashed black vertical line depicts the announcement date, the second black line is the termination date.

A.3 Perpetual Contract Introduction Events

Table A1: Perpetual Contract Introduction Events

Exchange	Introduction Date	Trading Pair
Binance	2021-04-10	ADA-USDT
Binance	2021-04-10	BTS-USDT
Binance	2021-04-10	CELR-USDT
Binance	2021-04-10	CVC-USDT
Binance	2021-04-10	DOGE-USDT
Binance	2021-04-10	LINK-USDT
Binance	2021-04-10	MATIC-USDT
Binance	2021-04-10	REN-USDT
Binance	2021-04-10	XEM-USDT
Binance	2021-04-10	XRP-USDT
Binance	2021-08-31	ATA-USDT
Binance	2021-10-12	KLAY-USDT
Binance	2021-11-11	LPT-USDT
Binance	2022-01-07	DUSK-USDT
Binance	2022-02-10	FLOW-USDT
Binance	2022-04-01	BNX-USDT
Binance	2022-04-01	INJ-USDT
Binance	2022-04-01	QNT-USDT
Binance	2022-04-01	SPELL-USDT
Binance	2022-09-22	LDO-USDT
Huobi	2020-11-06	BTC-USDT
Huobi	2020-11-06	ETH-USDT
Huobi	2020-11-06	UNI-USDT
Huobi	2020-11-06	YFI-USDT
Huobi	2020-11-11	EOS-USDT
Huobi	2020-11-11	XRP-USDT
Huobi	2020-11-11	YFII-USDT
Huobi	2020-11-20	AAVE-USDT
Huobi	2020-11-20	ADA-USDT
Huobi	2020-11-20	CRV-USDT

Note: This table presents a comprehensive list of perpetual contract introduction events based on our dataset with order-book measures. For each event, the exchange, introduction date, and trading pair are provided. The trading pairs are denoted in the format of "Base Currency-Quote Currency". USDT refers to Tether, a stablecoin pegged to the value of the US Dollar. The introduction events span multiple major cryptocurrency exchanges and cover various prominent cryptocurrencies traded against USDT. The data is ranked first by exchange and then by introduction date.

Exchange	Introduction Date	Trading Pair
Huobi	2020-11-26	RSR-USDT
Huobi	2020-11-26	WAVES-USDT
Huobi	2020-12-04	XTZ-USDT
Huobi	2020-12-05	ALGO-USDT
Huobi	2020-12-18	KSM-USDT
Huobi	2020-12-18	OMG-USDT
Huobi	2020-12-18	THETA-USDT
Huobi	2020-12-18	XEM-USDT
Huobi	2020-12-23	BAND-USDT
Huobi	2020-12-23	ONT-USDT
Huobi	2020-12-23	SNX-USDT
Huobi	2021-01-13	DOGE-USDT
Huobi	2021-01-13	IOTA-USDT
Huobi	2021-01-13	LRC-USDT
Huobi	2021-01-13	SOL-USDT
Huobi	2021-01-20	BAT-USDT
Huobi	2021-01-20	CVC-USDT
Huobi	2021-01-20	KNC-USDT
Huobi	2021-01-20	MKR-USDT
Huobi	2021-01-29	AKRO-USDT
Huobi	2021-01-29	BAL-USDT
Huobi	2021-01-29	MANA-USDT
Huobi	2021-01-29	SAND-USDT
Huobi	2021-02-23	FRONT-USDT
Huobi	2021-03-04	WOO-USDT
Huobi	2021-03-12	BLZ-USDT
Huobi	2021-03-12	UMA-USDT
Huobi	2021-03-19	HBAR-USDT
Huobi	2021-04-09	MASK-USDT
Huobi	2021-04-09	OGN-USDT
Huobi	2021-05-18	CHR-USDT
Huobi	2021-08-13	IOTX-USDT
Huobi	2021-08-17	CTSI-USDT
OKEx	2019-12-27	BTC-USDT
OKEx	2019-12-27	ETH-USDT
OKEx	2019-12-30	XRP-USDT
OKEx	2020-03-05	NEO-USDT
OKEx	2020-03-11	DASH-USDT
OKEx	2020-04-29	ADA-USDT
OKEx	2020-05-06	ATOM-USDT
OKEx	2020-05-06	ONT-USDT

Exchange	Introduction Date	Trading Pair
OKEx	2020-05-11	QTUM-USDT
OKEx	2020-05-11	XLM-USDT
OKEx	2020-05-18	IOTA-USDT
OKEx	2020-06-15	THETA-USDT
OKEx	2020-06-17	KNC-USDT
OKEx	2020-07-10	DOGE-USDT
OKEx	2020-08-21	MKR-USDT
OKEx	2020-08-22	ZRX-USDT
OKEx	2020-08-29	BAT-USDT
OKEx	2020-08-29	LEND-USDT
OKEx	2020-09-09	BAL-USDT
OKEx	2020-09-09	BTM-USDT
OKEx	2020-09-09	STORJ-USDT
OKEx	2021-03-12	MANA-USDT
OKEx	2021-03-18	FTM-USDT
OKEx	2021-04-01	ENJ-USDT
OKEx	2021-04-08	SC-USDT
OKEx	2021-04-08	XEM-USDT
OKEx	2021-04-23	RVN-USDT
OKEx	2021-04-29	MATIC-USDT
OKEx	2021-09-24	CELO-USDT
OKEx	2021-11-05	KISHU-USDT
OKEx	2022-03-03	API3-USDT
OKEx	2022-04-14	ASTR-USDT

INTERNET APPENDIX

A Funding Time Results

Table IA1: Perpetual Market Funding Time Treatment Effect on Spot Market Microstructure

Outcome	[0]	[7, 0]	[6, 7, 0, 1]
Amihud Measure 5	-3.5***	-0.4	5.6***
Amihud Measure 12	-0.1	4.0***	10.0***
Amihud Measure 24	5.9***	10.1***	13.3***
Ask Max QuoteQty SA	1.1***	0.9***	1.2***
Ask Max QuoteQty TW	1.2***	0.9***	1.3***
Bid Max QuoteQty SA	0.5***	0.4***	0.5***
Bid Max QuoteQty TW	0.5***	0.4***	0.5***
Bid-Ask Spread SA	3.2***	2.5***	3.1***
Bid-Ask Spread TW	3.2***	2.4***	3.1***
Buyer Slippage 10000 SA	5.0***	4.0***	4.8***
Buyer Slippage 10000 TW	4.9***	4.0***	4.8***
Buyer Slippage 100000 SA	4.1***	2.9***	3.5***
Buyer Slippage 100000 TW	4.0***	2.9***	3.5***
Buyer Slippage 1000000 SA	2.8***	2.0***	2.5***
Buyer Slippage 1000000 TW	2.7***	2.0***	2.5***
Dollar Volume	50.4***	37.3***	37.8***
Order Imbalance 5	-4.5***	-2.7***	-1.2***
Order Imbalance 12	-3.4***	-1.6***	-0.7***
Order Imbalance 24	-1.4***	0.2***	0.2***
Percentage Quoted Spread SA	3.2***	2.4***	3.0***
Percentage Quoted Spread TW	3.1***	2.4***	3.0***
Permanent Price Impact SA	24.0***	17.5***	19.5***
Permanent Price Impact TW	23.6***	17.1***	19.1***
Roll Measure	2.8***	2.5***	3.4***
Seller Slippage 10000 SA	4.5***	3.5***	4.1***
Seller Slippage 10000 TW	4.4***	3.5***	4.1***
Seller Slippage 100000 SA	3.5***	2.6***	2.8***
Seller Slippage 100000 TW	3.3***	2.5***	2.8***
Seller Slippage 1000000 SA	2.1***	1.6***	1.8***
Seller Slippage 1000000 TW	2.0***	1.6***	1.8***
Temporary Price Impact SA	-31.8***	-33.9***	-50.5***
Temporary Price Impact TW	-32.9***	-35.2***	-52.6***
Total Price Impact SA	15.3***	10.6***	10.7***
Total Price Impact TW	14.9***	10.4***	10.5***
VPIN 5	17.4***	12.1***	11.4***
VPIN 12	13.6***	10.1***	10.9***
VPIN 24	9.0***	6.7***	8.4***

Note: This table examines the impact of perpetual market funding times on spot market microstructure. Time intervals [0], [7, 0], and [6, 7, 0, 1] represent the hour of funding, 7 hours before to the hour of funding, and 6 hours before to 1 hour after funding, respectively. Asterisks (***) denote significance at the 1% level. Variables with “SA” are simple averages and those with “TW” are time-weighted averages, reflecting the dynamic nature of market responses to funding events. All regressions include time and exchange-token fixed effects.

Table IA2: Perpetual Market Funding Time Treatment Effect on Spot Market Microstructure on Business Days and Weekends

Outcome	Business Days	Weekends
Amihud Measure 5	-3.5***	-3.6***
Amihud Measure 12	-0.5	0.3
Amihud Measure 24	5.5***	7.1***
Bid-Ask Spread SA	3.3***	3.0***
Bid-Ask Spread TW	3.3***	3.0***
Buyer Slippage 10000 SA	5.2***	4.6***
Buyer Slippage 10000 TW	5.1***	4.5***
Buyer Slippage 100000 SA	4.3***	3.4***
Buyer Slippage 100000 TW	4.2***	3.3***
Buyer Slippage 1000000 SA	3.0***	2.3***
Buyer Slippage 1000000 TW	2.9***	2.2***
Dollar Volume	49.5***	51.8***
Order Imbalance 5	-4.6***	-4.2***
Order Imbalance 12	-3.4***	-3.1***
Order Imbalance 24	-1.5***	-0.9***
Percentage Quoted Spread SA	3.3***	2.9***
Percentage Quoted Spread TW	3.2***	2.9***
Permanent Price Impact SA	23.1***	26.0***
Permanent Price Impact TW	22.9***	25.2***
Realized Volatility SA	4.3***	4.0***
Realized Volatility TW	4.5***	4.1***
Roll Measure	3.1***	2.9***
Seller Slippage 10000 SA	4.7***	4.0***
Seller Slippage 10000 TW	4.6***	3.9***
Seller Slippage 100000 SA	3.6***	3.2***
Seller Slippage 100000 TW	3.5***	3.0***
Seller Slippage 1000000 SA	2.2***	2.0***
Seller Slippage 1000000 TW	2.1***	1.9***
Temporary Price Impact SA	-31.7***	-32.1***
Temporary Price Impact TW	-34.2***	-29.6***
Total Price Impact SA	15.1***	15.9***
Total Price Impact TW	14.7***	15.6***
VPIN 5	17.4***	17.2***
VPIN 12	13.6***	13.4***
VPIN 24	9.0***	8.4***

Note: This table showcases the effect of perpetual market funding times on the microstructure of the spot market, differentiated between business days and weekends. The "SA" denotes simple averages, and "TW" denotes time-weighted averages, highlighting the nuanced impacts of funding events across different market conditions. Asterisks (***) signify significance at the 1% level. All regressions include time and exchange-token fixed effects.

Table IA3: Spot Market Funding Time Effect by Contemporary Funding Rate Proxy Quintile

Outcome	Q1	Q2	Q3	Q4	Q5
Amihud Measure 5	-5.2***	-4.0***	-4.3***	-4.3***	-1.9***
Amihud Measure 12	-2.7***	-1.6***	-2.3***	-1.6***	3.8***
Amihud Measure 24	2.8***	3.9***	3.9***	5.2***	12.0***
Ask Max QuoteQty SA	1.6***	0.6***	0.5***	0.5***	0.8***
Ask Max QuoteQty TW	1.6***	0.6***	0.6***	0.6***	0.9***
Bid-Ask Spread SA	4.0***	2.5***	2.4***	2.4***	3.4***
Bid-Ask Spread TW	4.2***	2.2***	2.3***	2.2***	3.3***
Bid Max QuoteQty SA	0.2***	0.1	0	0.1	0.5***
Bid Max QuoteQty TW	0.3***	0.2**	0	0.2*	0.5***
Buyer Slippage 10000 SA	5.0***	4.4***	4.5***	4.9***	7.0***
Buyer Slippage 10000 TW	4.8***	4.2***	4.4***	4.8***	6.8***
Buyer Slippage 100000 SA	3.9***	3.5***	3.8***	3.8***	5.7***
Buyer Slippage 100000 TW	3.8***	3.4***	3.6***	3.6***	5.6***
Buyer Slippage 1000000 SA	2.5***	2.3***	2.4***	2.4***	3.9***
Buyer Slippage 1000000 TW	2.5***	2.2***	2.3***	2.4***	3.9***
Dollar Volume	49.8***	48.3***	46.2***	45.6***	60.4***
Order Imbalance 5	-4.3***	-4.5***	-4.8***	-5.0***	-4.8***
Order Imbalance 12	-3.1***	-3.3***	-3.6***	-3.7***	-3.6***
Order Imbalance 24	-0.9***	-1.2***	-1.5***	-1.7***	-1.9***
Percentage Quoted Spread SA	4.2***	2.5***	2.4***	2.3***	3.3***
Percentage Quoted Spread TW	4.1***	2.1***	2.2***	2.1***	3.3***
Roll Measure	5.0***	2.4***	1.5***	1.0***	3.4***
Seller Slippage 10000 SA	5.0***	3.9***	4.0***	4.6***	5.4***
Seller Slippage 10000 TW	4.9***	3.7***	3.9***	4.5***	5.3***
Seller Slippage 100000 SA	3.7***	3.3***	3.5***	3.3***	3.6***
Seller Slippage 100000 TW	3.5***	3.1***	3.3***	3.1***	3.4***
Seller Slippage 1000000 SA	2.0***	1.8***	2.0***	2.0***	2.1***
Seller Slippage 1000000 TW	1.9***	1.7***	1.9***	1.9***	2.1***
VPIN 5	15.4***	18.6***	18.0***	17.0***	17.8***
VPIN 12	12.0***	14.5***	13.9***	13.1***	14.0***
VPIN 24	7.0***	9.0***	9.3***	9.2***	10.1***

Note: This table shows the effect of funding times on spot market microstructure across different quintiles (Q1-Q5) of contemporary funding rate proxy. Significance levels: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Variables with "SA" are calculated as simple averages, and those with "TW" are time-weighted to reflect more recent data. Definitions include Amihud Measure (liquidity indicator), Bid-Ask Spread (market efficiency measure), Buyer and Seller Slippage (impact of trade size on price), Dollar Volume (total transaction value), Order Imbalance (difference between buy and sell orders), Percentage Quoted Spread (relative bid-ask spread), Permanent and Temporary Price Impacts (long-term and short-term price effects of trades), Roll Measure (effective bid-ask spread estimate), and VPIN (volume-synchronized probability of informed trading, indicating market order flow imbalance).

B Role of Perpetual Markets in Wash Trading

Wash trading represents a significant challenge in the cryptocurrency market, affecting its overall quality and integrity. This practice involves executing simultaneous buy and sell orders for the same asset to artificially inflate trading volumes. It's a tactic employed by some cryptocurrency exchanges to falsely enhance their market activity, thereby attracting new users through the appearance of high liquidity and increased transaction fee revenues. The issue is so prevalent that even leading platforms, such as Binance, have faced accusations from regulatory bodies like the Securities and Exchange Commission (SEC) for participating in such schemes.

In this context, perpetual contracts emerge as a potential countermeasure against wash trading. These financial derivatives, distinct for their lack of expiration date and mechanism for tethering the contract price to the underlying asset's spot price, introduce a layer of market efficiency and transparency absent in traditional spot markets. The continuous price alignment, facilitated by funding rates, discourages the artificial manipulation of trading volumes by imposing financial disincentives on unprofitable trades, including those executed with the intent of wash trading.

The impact of perpetual contracts on wash trading is a subject of keen scholarly interest. Investigating this relationship sheds light on the broader effects of financial derivatives on market manipulation and artificial volume creation in cryptocurrency spot markets. Specifically, this research aims to explore whether the presence of perpetual contracts can deter wash trading activities by making them less economically viable and by promoting a shift in trading volume from spot to derivatives markets, where trading activities are often subject to more stringent oversight and involve more sophisticated market participants.

Furthermore, the potential of perpetual contracts to redistribute trading volume from more manipulation-prone spot markets to derivatives markets suggests a pathway to enhancing market quality. By deterring wash trading, these derivatives could foster genuine liquidity and more accurate price discovery, contributing to the overall integrity and efficiency of the cryptocurrency market.

This section of our study delves into the mechanics of perpetual contracts and their theoretical capability to mitigate wash trading practices. By examining empirical data and theoretical frameworks, we aim to provide comprehensive insights into how financial derivatives can influence trading behavior and market dynamics, offering implications for regulators, exchanges, and market participants in the cryptocurrency ecosystem.

We investigate whether perpetual contracts facilitate or hinder wash trading and whether wash trading makes perpetual contract introduction more or less likely. We also examine the relationship between wash trading and perpetual contract introduction effects on spot market microstructure.

Benford's law has been widely used in fraud detection in social sciences. First significant digits of the transaction sizes are expected to follow Benford's law to a reasonable extent. We follow Cong et al. (2023) in constructing the measures of adherence to a natural order flow with several key differences. We compute each measure for hundreds of tokens on dozens of exchanges on a monthly basis. Instead of offering a single exchange-level estimate we thus produce a time-varying exchange-token-level measure of adherence to Benford's law. We use a random sampling approach with a fixed sample size in computing the χ^2-statistic. This makes each measure somewhat comparable over time and across exchange-tokens. We further use this measure to answer the questions listed above.

Let us start by comparing average wash trading measures in spot and perpetual markets. Average wash trading χ^2-statistic is 87 and 91 for spot and perpetual markets respectively (for samples matched on exchange, token and date). This difference is statistically significant at 1%. This is some evidence that wash trading may be more common in perpetual markets than spot markets.

Next, we answer the following question: does wash trading measure increase or decrease after perpetual contract introduction? We run a Staggered Differences-in-Differences regression with exchange-token fixed effects and the χ^2-statistic as the outcome. The average pre-treatment level of the χ^2-statistic for the treated exchange-tokens is 196. Our results indicate that at the 5% significance level on average the χ^2-statistic increased by 93 or 47% after perpetual introduction. We therefore have evidence that wash trading is exacerbated by a perpetual contract introduction.

We further investigate whether wash trading makes specific exchange-tokens more or less likely to adopt a perpetual contract in the future or to have a Pump-and-Dump event. In Table IA4 we present results of two logit regressions modelling the probability of a next month Pump-and-Dump or Perpetual Adoption event. Our wash trading measure is statistically significant in both regressions at 1% and 5% significance level respectively. The coefficients indicate that a 1 standard deviation increase in the wash trading measure increases odds of a Pump-and-Dump event by 1.06 and decreases odds of a Perpetual Adoption event next month by 0.51.

Finally, we investigate how wash trading levels affect the microstructure benefits from perpetual contract introduction for an underlying spot market. More specifically, we run a regression of exchange-token level treatment effect from perpetual introduction for each outcome on our measure of wash trading in the month before introduction and exchange,

Table IA4: Logit Regressions of a Next Month Pump-and-Dump Event or Perpetual Adoption

	Pump-and-Dump		Perpetual Adoption	
Variable	Coefficient	Odds	Coefficient	Odds
Constant	-1.010***	0.36	-6.315***	0.00
Perpetual Dummy	-0.872***	0.42		
Number of PnD			-0.205**	0.81
Chi2 Stat	0.054***	1.06	-0.707**	0.49
Dollar Volume (Previous Month)	0.012	1.01	0	1.00
BBSP	0	1.00	0	1.00
BFNX	-0.719***	0.49	0.605	1.83
BINC	-0.524***	0.59	1.645***	5.18
BTMX	0.197	1.22	0	1.00
HITB	0.678***	1.97	-1.719***	0.18
KCON	-0.448***	0.64	-1.688***	0.18
OKEX	0.027	1.03	1.199***	3.32
Exchange	-0.510**	0.60	0	1.00
Gaming	-0.203	0.82	0	1.00
General Payment	-1.205***	0.30	1.127***	3.09
Meme	-0.754***	0.47	0	1.00
Platform	-1.169***	0.31	1.150***	3.16
Privacy	-1.759***	0.17	0	1.00
Stablecoin	-1.101***	0.33	0	1.00
Tokenized Asset	-0.772***	0.46	0	1.00
Utility	-0.622***	0.54	0.708**	2.03

Note: This table presents logit regression outcomes for the likelihood of a pump-and-dump event or the adoption of perpetual contracts in the following month, with significance levels denoted by asterisks: *** $p<0.01$, ** $p<0.05$. Variables include constants, a perpetual dummy, the number of previous pump-and-dump events, Chi2 statistics, and categories reflecting different aspects of cryptocurrency markets and exchange characteristics. Odds ratios provide a measure of the effect size for each coefficient.

token fixed effects. We find at a 1% significance level that a 1 standard deviation increase in the measure of wash trading is associated with a 62% higher illiquidity, a 127 percentage point smaller increase in dollar volume in the spot market following a perpetual contract introduction. At a 10% significance level, probability of informed trading ($VPIN$) is also smaller by 0.3 percentage points per 1 standard deviation of increase in wash trading. We can thus see that spot markets of tokens and exchanges subject to wash trading do not benefit from perpetual contract introduction as much and gain less (if not lose) in informational efficiency and liquidity from such an introduction.

In summary, we have established that perpetual markets seem to be involved in wash trading more than spot markets, that perpetual contract introduction increases wash trading activity in underlying spot markets. We also find that exchange-tokens with a large wash trading component do not benefit from a perpetual contract introduction in terms of their microstructure quality. Such exchange-tokens are also more likely to have Pump-and-Dump events and be less likely to adopt a perpetual contract in the future.