Perpetual Futures Contracts and Cryptocurrency Market Quality *

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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. We explain our results through an information-based market microstructure model and find consistent effects in cryptocurrency markets around exogenous information shocks from pump-and-dump events.

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.” Our study uses cryptocurrency market as a “sandbox” to discover the effects of perpetual contracts on spot market, shedding light on their effects in potential broader applications.

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.

As a result, the trading volume of perpetuals are much higher than that of traditional futures, signifying the potential of wide applicaitons of perpetuals in other settings, including real estate, human capital, CPI index and more. this makes our economic insights learned from the cryptocurrency market generalizable and enhance the significance of our research. especially when tokenization of assets is gaining traction, having the perpetual futures as an option for hedging is essentail for the development in the space.

[Figure 1 about here.]

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. Figure 1 illustrates this funding mechanism, showing how the payment flows between long and short positions create convergence forces that maintain alignment between perpetual and spot prices.

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

[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.

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 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.

Our study uncovers the nuanced effects of perpetual markets on cryptocurrency market dynamics, highlighting that while they enhance trading volume, 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

Our paper connects to multiple streams of literature. First, we contribute to the literature on perpetual contracts. The concept originates from Shiller (1993), with implementation emerging in cryptocurrency trading. The existing work focuses on trading strategies, with Christin, Routledge, Soska, and Zetlin-Jones (2022) documenting carry-trade opportunities combining short perpetual positions with spot holdings. De Blasis and Webb (2022) analyze Bitcoin quarterly and perpetual futures prices at Binance, while Ackerer, Hugonnier, and Jermann (2023) and He, Manela, Ross, and von Wachter (2022) develop no-arbitrage pricing models under various market conditions. We identify the causal effects of perpetual contracts on spot markets, effects currently assumed away in theoretical models.

Our study extends the cryptocurrency and decentralized finance literature. Kogan, Makarov, Niessner, and Schoar (2024) document that cryptocurrency investors exhibit different beliefs and trading patterns from traditional market participants. Perpetual contracts represent one innovation from the cryptocurrency space, alongside peer-to-peer electronic payments (Nakamoto, 2008), smart contracts (Buterin et al., 2013; Cong and He, 2019), non-fungible tokens (Nadini, Alessandretti, Di Giacinto, Martino, Aiello, and Baronchelli, 2021), and automated market makers (Lehar and Parlour, 2021). The implementation of perpetual contracts demonstrates how cryptocurrency markets actualize theoretical financial concepts, offering a testing ground for understanding perpetual contracts' applications in real estate, human capital, and economic indicators, as proposed by Shiller (1993).

We contribute to research on the effects of derivatives on underlying markets. Perpetual contracts are a new innovation in the derivatives space, and their effects are not necessarily the same as those of traditional futures. More research is needed to uncover these effects, especially given that perpetual contracts are gaining traction in financial markets. Our research is, therefore, both timely and important. We stand out in the derivatives literature as the first paper to identify the causal effects of perpetual contracts. Moreover, we show that these effects differ from those of traditional futures studied in Augustin, Rubtsov, and Shin (2023) and prior research examining traditional futures on platforms such as 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). Technically, while Augustin et al. (2023) analyze a single BTC-USD futures pair, we examine data from Kaiko covering 100 cryptocurrencies across multiple exchanges. Our identification strategies exploit Huobi's perpetual contract termination and 95 contract introductions, implementing staggered Differences-in-Differences and synthetic control methods. The results show perpetual contracts increase trading volume while widening bid-ask spreads, differing from Augustin et al. (2023)'s aggregate liquidity measures. Our setting provides identification advantages. The funding mechanism creates predetermined cyclical shocks for causal analysis. The Huobi exchange's termination of perpetual contracts following regulatory changes, while other Chinese exchanges maintained operations, provides a natural experiment setting. These features enable identification of perpetual contracts' effects on market quality.

Our research adds to market microstructure literature. O'Hara and Ye (2011) examine market fragmentation effects on quality and efficiency, Holden and Jacobsen (2014) address liquidity measurement in fast markets, and Clark-Joseph, Ye, and Zi (2017) analyze Designated Market Makers' role. Comerton-Forde, Grégoire, and Zhong (2019) show how inverted exchange fee models affect liquidity and price accuracy. Our findings support information-based models (O'Hara, 1995; Easley, Kiefer, O'Hara, and Paperman, 1996), where informed trading leads to wider spreads through adverse selection. Glosten and Milgrom (1985) show bid-ask spreads reflect information asymmetry, while Easley and O'Hara (1992) model price adjustment processes. We document that perpetual contracts increase VPIN (Easley, L'opez de Prado, and O'Hara, 2012) and widen spreads, particularly during funding windows.

Our study connects to behavioral finance through analysis of market reactions to information shocks. Using pump-and-dump events (Li, Shin, and Wang, 2021), we document changes in price, volume, and market quality consistent with Fleming and Remolona (1999)'s findings on Treasury market responses to information. The results support Hong and Stein (1999)'s theory of market reactions and align with research on investor behavior and heterogeneous beliefs (Odean, 1999; Statman, Thorley, and Vorkink, 2006; Campbell, Grossman, and Wang, 1993).

2 The 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 pivotal 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 and the Volume-synchronized probability of informed trading (VPIN) (Easley et al., 2012). Dollar volume acts as a fundamental liquidity metric, 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 the transactions-based analysis, we further use order book snapshots to calculate percentage quoted spread, a measure of transaction costs. The equations for all the above measures are detailed in the Appendix A.1, ensuring transparency and reproducibility of our methodology.

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.

We link this observation to the higher adverse selection risks in perpetual markets and find that the probability of informed trading in perpetual markets exceeds that in spot markets by 31%. 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, may face higher adverse selection risks, leading to higher transaction costs for liquidity traders.

[Table 1 about here.]

4 The Impact of Perpetual Funding Times on Spot Market

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 investigation 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 dollar volume and informed trading (measured by VPIN) in 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 2 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 2 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 3-6 we can see that around the perpetual market funding time the following phenomena tend to be observed: 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 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:

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

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 2 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 2, 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. Our findings indicate that perpetual contracts affect their underlying cryptocurrency markets in several dimensions: we see increasing spot market trading volume with trading activity around funding times appearing more informed (Higher VPIN); we also see larger quoted percent bid-ask spreads, measuring direct transaction costs. The effects of funding times on the spot market are significant statistically and economically. We further reconcile the simultaneous increases of trading volume and quoted spread in the spot market using information-based market microstructure theories (Glosten and Milgrom, 1985; Easley et al., 1996). The robustness of these findings across chosen hyperparameters is confirmed (Internet Appendix A).

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:

$$FRate_{e,i,t} = \frac{P^{\text{perp}}_{e,i,t} - P^{\text{spot}}_{e,i,t}}{P^{\text{spot}}_{e,i,t}}, \tag{2}$$

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 3. 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:

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

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. 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 3 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:

$$Market\_Quality_{e,i,t} = \beta FRate_{e,i,t} + \gamma_{e,i} + \eta_t + \epsilon_{e,i,t}, \tag{4}$$

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 4 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 3, 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 significantly affect the 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 4 about here.]

5 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.

[Figure 7 about here.]

We present the timeline of events surrounding Huobi's termination of perpetual futures trading in response to Chinese regulatory actions in Figure 7. 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

[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.

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.

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 conditions, and establishes a more clean 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:

[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.

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

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-A4 in the Appendix. After collecting the treatment-control pairs and reshaping the data into a long form we run the following regressions:

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

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 5. 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 the percentage quoted spread.

6 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 per-

[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.

petual 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. In related literature, Martin et al. (2024) studies the real effects of centralized derivative markets using the staggered introduction of futures contracts for different steel products in the U.S.

To estimate the average effects of perpetual introduction on spot market quality, we take a monthly average of each outcome variable for each token-exchange and use 12 months before and after perpetual introduction as the analysis window. We employ the commonly used Callaway and Sant'Anna (2021) estimator using the R implementation provided by the authors (package 'did'). Our staggered DiD analyses reveal both economically and statistically (at 1%) significant findings: the introduction of perpetual contracts leads to an increase in spot market daily dollar volume by $98,248 or by 146% on average relative to the pre-treatment average of treated exchange-tokens. It also decreases order imbalance by 0.05

(or 9%), raises the probability of informed trading by 1.1 percentage points (or by 16%) and the percentage quoted spread by 0.85 percentage points (or 200%).

We plot dynamic Callaway and Sant'Anna (2021) effects for each outcome in Figures A5-A8 in the Appendix. Parallel trends between treated and never-treated units prior to introduction hold as indicated by insignificant effects prior to introduction. Effects are highly statistically significant immediately post-introduction as is apparent from the large jumps in average effects.

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 5 about here.]

[Table 6 about here.]

7 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.

7.1 Theoretical Model

In this section, we develop a theoretical model to analyze the impact of perpetual futures contracts on the cryptocurrency spot market. Our model demonstrates how the introduction of perpetual futures leads to increased trading volumes and wider bid-ask spreads in the spot market. We incorporate key features unique to perpetual futures, such as the funding fee mechanism, and examine the implications for different market participants.

Market Structure and Participants

Consider a discrete-time trading environment where time is indexed by $t = 1, 2, \ldots, T$. There are two financial instruments in the market:

1. *Spot Asset*: A cryptocurrency traded in the spot market at price S_t.
2. *Perpetual Futures Contract*: A futures contract with no expiration date, traded in the futures market at price F_t. The perpetual futures contract includes a funding fee mechanism designed to keep F_t aligned with S_t.

There are four types of market participants:

- *Informed Traders*: These traders possess private information about the fundamental value of the cryptocurrency. They aim to maximize their expected profits based on this information.
- *Noise Traders*: These traders buy or sell for reasons unrelated to fundamental information, such as liquidity needs or portfolio rebalancing. Their trades introduce randomness into the market.
- *Market Makers*: Market makers provide liquidity by continuously quoting bid and ask prices. They adjust these prices based on order flow to manage their exposure to adverse selection risk.
- *Arbitrageurs*: Arbitrageurs exploit price discrepancies between the futures and spot markets. Their trading activity helps align F_t with S_t.

The fundamental value of the cryptocurrency is denoted by v, which is realized at time $t = 0$ and remains constant over time. Informed traders know the true value v, while uninformed participants believe that v is a random variable with distribution $v \sim \mathcal{N}(\mu_v, \sigma_v^2)$.

Funding Fee Mechanism

A key feature of perpetual futures contracts is the funding fee mechanism, which ensures that the futures price F_t remains tethered to the spot price S_t. The funding fee is calculated at regular intervals (e.g., every eight hours) and is given by:

$$f_t = \kappa(F_t - S_t), \tag{6}$$

where $\kappa > 0$ is the funding rate coefficient set by the exchange. If $F_t > S_t$, traders holding long positions in the futures contract pay the funding fee to traders holding short positions. Conversely, if $F_t < S_t$, short position holders pay the funding fee to long position holders. This mechanism incentivizes traders to take positions that drive F_t toward S_t, thus aligning the two prices.

Trading Process

At each time t, the net demand in the spot market, q_t^S, and the futures market, q_t^F, are determined by the aggregate actions of all market participants.

In the spot market, the net demand is:

$$q_t^S = x_t^S + u_t^S, \tag{7}$$

where x_t^S is the net demand from informed traders, and u_t^S is the net demand from noise traders. We assume that u_t^S follows a normal distribution with mean zero and variance σ_u^2, i.e., $u_t^S \sim \mathcal{N}(0, \sigma_u^2)$.

In the futures market, the net demand is:

$$q_t^F = x_t^F + u_t^F + a_t^F, \tag{8}$$

where x_t^F is the net demand from informed traders, $u_t^F \sim \mathcal{N}(0, \sigma_u^2)$ is the net demand from noise traders, and a_t^F is the net demand from arbitrageurs.

Arbitrageurs act to eliminate price discrepancies between the futures and spot markets. Their net demand is modeled as:

$$a_t^F = -\theta(F_t - S_t), \tag{9}$$

where $\theta > 0$ represents the intensity of arbitrage activity. A higher θ implies that arbitrageurs are more aggressive in correcting mispricings between F_t and S_t.

Price Formation and Market Clearing

Market makers set prices in both markets to clear the net demand while managing their exposure to adverse selection risk. The spot market clears when the total net demand equals zero:

$$q_t^S = x_t^S + u_t^S = 0. \tag{10}$$

The spot price is then determined by:

$$S_t = \mu_v + \lambda_S q_t^S, \tag{11}$$

where λ_S is the price impact coefficient in the spot market, capturing how sensitive the price is to changes in net demand.

Similarly, the futures market clears when:

$$q_t^F = x_t^F + u_t^F + a_t^F = 0. \tag{12}$$

The futures price is set as:

$$F_t = \mu_v + \lambda_F q_t^F, \tag{13}$$

where λ_F is the price impact coefficient in the futures market.

Informed Traders' Optimization Problem

Informed traders aim to maximize their expected profits from trading in both the spot and futures markets, taking into account the funding fee and the impact of their trades on prices.

Their expected profit is given by:

$$\Pi_t = E\left[(v - S_t)x_t^S + (v - F_t)x_t^F - f_t x_t^F\right] - \frac{\gamma}{2}\left((x_t^S)^2 + (x_t^F)^2\right), \tag{14}$$

where $\gamma > 0$ represents a risk aversion or transaction cost parameter. The term $f_t x_t^F$ accounts for the funding fee paid or received in the futures market.

Informed traders face the following constraints:

1. *Capital Constraint*:

$$|x_t^S S_t + x_t^F F_t| \leq K, \tag{15}$$

where K is the maximum capital available for trading.

2. *Short-Sale Constraint*:

$$x_t^S \geq -L, \quad x_t^F \geq -L, \tag{16}$$

where L is the limit on short positions.

Equilibrium Analysis

To analyze the equilibrium, we consider the case where arbitrage activity is strong (i.e., θ is large). In this scenario, arbitrageurs effectively eliminate price discrepancies between the futures and spot markets, resulting in $F_t \approx S_t$. Consequently, the funding fee f_t becomes negligible, and the futures market offers little profit opportunity for informed traders. As a result, informed traders concentrate their trading activity in the spot market.

The expected profit from spot trading simplifies to:

$$\Pi_t^S = (v - S_t)x_t^S - \frac{\gamma}{2}(x_t^S)^2. \tag{17}$$

Substituting the expression for S_t, we have:

$$\Pi_t^S = \left(v - \mu_v - \lambda_S x_t^S\right) x_t^S - \frac{\gamma}{2}(x_t^S)^2. \tag{18}$$

The first-order condition for maximizing Π_t^S with respect to x_t^S is:

$$\frac{\partial \Pi_t^S}{\partial x_t^S} = (v - \mu_v) - (2\lambda_S + \gamma)x_t^S = 0. \tag{19}$$

Solving for the optimal trade size, we obtain:

$$x_t^{S*} = \frac{v - \mu_v}{2\lambda_S + \gamma}. \tag{20}$$

This expression shows that the optimal trade size increases with the information advantage $(v - \mu_v)$ and decreases with the total price impact and transaction cost parameter $(2\lambda_S + \gamma)$.

Bid-Ask Spread and Trading Volume in the Spot Market

Market makers adjust the bid-ask spread to manage adverse selection risk from informed traders. Following the framework of Glosten and Milgrom (1985), the bid-ask spread is set to cover the expected loss from trading with informed traders.

The expected absolute value of informed traders' net demand is:

$$E\left[|x_t^{S*}|\right] = \frac{\sigma_v}{\sqrt{2\pi}(2\lambda_S + \gamma)}, \tag{21}$$

where we assume that $(v - \mu_v) \sim \mathcal{N}(0, \sigma_v^2)$.

The bid-ask spread in the spot market is then:

$$s_t = 2\lambda_S E\left[|x_t^{S*}|\right] = \frac{2\lambda_S \sigma_v}{\sqrt{2\pi}(2\lambda_S + \gamma)}. \tag{22}$$

This expression shows that the bid-ask spread increases with the price impact coefficient λ_S and the volatility of the fundamental value σ_v.

The total trading volume in the spot market is the sum of the expected trading volumes from informed and noise traders:

$$V_t^S = E\left[|x_t^{S*}|\right] + E\left[|u_t^S|\right] = \frac{\sigma_v}{\sqrt{2\pi}(2\lambda_S + \gamma)} + \frac{\sigma_u}{\sqrt{2/\pi}}, \tag{23}$$

where $E\left[|u_t^S|\right] = \sigma_u\sqrt{2/\pi}$.

Impact of Perpetual Futures Introduction

Our model demonstrates two key empirical predictions regarding the impact of perpetual futures contracts on the cryptocurrency spot market. First, we predict an increase in spot market trading volume. This occurs because informed traders, finding limited profit opportunities in the futures market due to the effective arbitrage mechanism, concentrate their trading activity in the spot market. Specifically, our model shows that the total trading volume in the spot market (V_t^S) increases by a factor proportional to the informed traders' information advantage (σ_v):

$$V_t^S = \frac{\sigma_v}{\sqrt{2\pi}(2\lambda_S + \gamma)} + \frac{\sigma_u}{\sqrt{2/\pi}}. \tag{24}$$

Second, we predict wider bid-ask spreads in the spot market. This occurs because market makers, facing increased adverse selection risk from the concentration of informed trading, must protect themselves by widening their quoted spreads. The bid-ask spread (s_t) increases proportionally with both the price impact coefficient (λ_S) and the volatility of the fundamental value (σ_v):

$$s_t = \frac{2\lambda_S \sigma_v}{\sqrt{2\pi}(2\lambda_S + \gamma)}. \tag{25}$$

These theoretical predictions arise from the unique features of perpetual futures contracts, particularly their funding fee mechanism which keeps futures prices tightly aligned with spot prices. This alignment effectively forces informed traders to concentrate their information-based trading in the spot market, leading to the observed changes in market quality metrics.

Distribution of Economic Benefits and Costs

The introduction of perpetual futures contracts creates a redistribution of economic benefits and costs among market participants. Our model identifies three primary beneficiaries of this market innovation. First, informed traders gain significant advantages as they can now leverage their information more effectively in the spot market, leading to higher trading profits. The concentration of their trading activity in the spot market allows them to better exploit their information advantage, as shown by their optimal trading size $x_t^{S*} = \frac{v-\mu_v}{2\lambda_S+\gamma}$. Second, arbitrageurs benefit from new profit opportunities arising from the need to maintain price alignment between futures and spot markets, earning the spread between these markets while contributing to price efficiency. Third, the overall market benefits from improved price discovery and efficiency, as informed trading more quickly incorporates fundamental information into prices.

However, these benefits come at substantial costs to other market participants. Noise traders, who trade for liquidity or portfolio rebalancing reasons, bear the greatest burden through increased transaction costs from wider bid-ask spreads. Our model shows that these spreads widen proportionally with both market makers' price impact coefficient and fundamental value volatility. Market makers also face challenges, as they must commit more capital to manage the increased adverse selection risk from concentrated informed trading. This higher risk exposure can lead to reduced market-making capacity or requirements for higher compensation through wider spreads.

The net effect on market quality is mixed. While overall trading volume increases and price discovery improves, the wider bid-ask spreads may create barriers to market participation, particularly for smaller or less sophisticated traders. This tradeoff between improved price efficiency and higher transaction costs represents a fundamental tension in the market's evolution following the introduction of perpetual futures.

7.2 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 8 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 8 about here.]

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 (%)
Dollar Volume	8,807,518	127,597	6,803***
Order Imbalance	0.33	0.39	-16***
Percentage Quoted Spread (%)	0.13	0.12	14***
VPIN (%)	13	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 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), and VPIN (volume-synchronized probability of informed trading, averaged over the last 12 five-minute windows). 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.

Table 2: Funding time outcome percentage change relative to non-funding time period immediately prior

Outcome	Hour 1	[-1, 1]	[-2, 2]
Dollar Volume	50.4***	37.3***	37.8***
	46.6	48.6	36.7
Order Imbalance 5	-4.5***	-2.7***	-1.2***
	-31.4	-20.0	-5.80
Order Imbalance 12	-3.4***	-1.6***	-0.7***
	-24.7	-9.02	-4.06
Percentage Quoted Spread	3.1***	2.4***	3.0***
	15.9	12.4	9.7
VPIN 5	17.4***	12.1***	11.4***
	35.2	24.7	18.5
VPIN 12	13.6***	10.1***	10.9***
	36.7	19.8	17.2

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. 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.

Table 3: Spot Market Funding Time Effect by Contemporary Funding Rate Proxy Quintile

Outcome	Q1	Q2	Q3	Q4	Q5
Dollar Volume	60.4***	45.6***	46.2***	48.3***	49.8***
	28.4	32.4	32.4	43.2	44.2
Order Imbalance 5	-4.8***	-5.0***	-4.8***	-4.5***	-4.3***
	-36.9	-29.8	-31.5	-25.5	-20.0
Order Imbalance 12	-3.6***	-3.7***	-3.6***	-3.3***	-3.1***
	-29.0	-22.8	-30.0	-20.8	-18.2
Percentage Quoted Spread	3.3***	2.1***	2.2***	2.1***	4.1***
	21.9	11.6	4.3	3.3	13.8
VPIN 5	17.8***	17.0***	18.0***	18.6***	15.4***
	23.4	21.6	29.0	33.2	22.6
VPIN 12	14.0***	13.1***	13.9***	14.5***	12.0***
	24.8	23.3	29.1	30.4	21.5

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: 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. 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. 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.

Table 4: Funding Time Effect with Average Fee Proxy Before Funding Time as Treatment Dosage

Market Quality Measure	$FRate$	R^2	$\|FRate\|$	R^2
Dollar Volume	-9.61***		15.97***	
	-5.27	0.0003	6.13	0.0003
Order Imbalance 5	1.335***		-1.37***	
	4.65	0.0001	-3.55	0.0001
Order Imbalance 12	0.96***		-1.26***	
	3.47	0.0005	-4.28	0.0001
Percentage Quoted Spread	-2.731***		5.19***	
	-5.64	0.0001	7.92	0.0002
VPIN 5	-5.28***		5.33***	
	-7.74	0.0006	5.50	0.0001
VPIN 12	-4.89***		4.99***	
	-8.02	0.0007	5.39	0.0001

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. The sample size is 1 million observations randomly sampled from the dataset.

Variable Definitions: 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. 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. 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.

Table 5: Effect of Huobi Perpetual Trading Termination on Spot Market Microstructure: DiD with a Synthetic Control

Outcome	[-1,1]	[-3,3]	[-7,7]	[-14,14]	[-30,30]
Dollar Volume	-87679*	-64266***	-109008***	-106369***	-113484***
	-3.6	-3.47	-5.65	-5.67	-8.7
Order Imbalance 5	0.046**	0.063***	0.065***	0.049***	0.035***
	6.94	4.92	7.73	7.29	7.17
Order Imbalance 12	0.046**	0.064***	0.065***	0.049***	0.032***
	5.57	4.91	7.77	7.43	6.42
Percentage Quoted Spread	-0.017***	-0.031***	-0.015**	-0.009**	-0.008***
	-6.75	-9.63	-2.19	-2.08	-3.18
VPIN 5	-0.001	0.003	0.007***	0.009***	0.013***
	-0.06	1.2	3.8	7.34	13.61
VPIN 12	-0.001	0.003	0.007***	0.009***	0.013***
	-0.03	1.08	3.64	7.19	13.16

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

Outcome	Coefficient	t-statistic
Dollar Volume	98248***	4.33
Order Imbalance 5	-0.05***	4.21
Order Imbalance 12	-0.05***	4.22
Percentage Quoted Spread (%)	0.85***	2.93
VPIN 5 (%)	1.1***	2.50
VPIN 12 (%)	1.1***	2.50

Notes: This table presents the causal effect of perpetual contract introduction on various spot market microstructure outcomes. Each line reports a separate regression using the Callaway and Sant'Anna (2021) estimator for multi-period fixed effects with 12028 monthly observations in each regression. Percentage Quoted Spread is computed via time-weighted averaging that adjusts for the temporal distribution of trading activity. Significance levels are denoted by asterisks: *** p<0.01, ** p<0.05, * p<0.1.

Variable Definitions: 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 reflects transaction costs; VPIN quantifies the probability of informed trading.

Figures

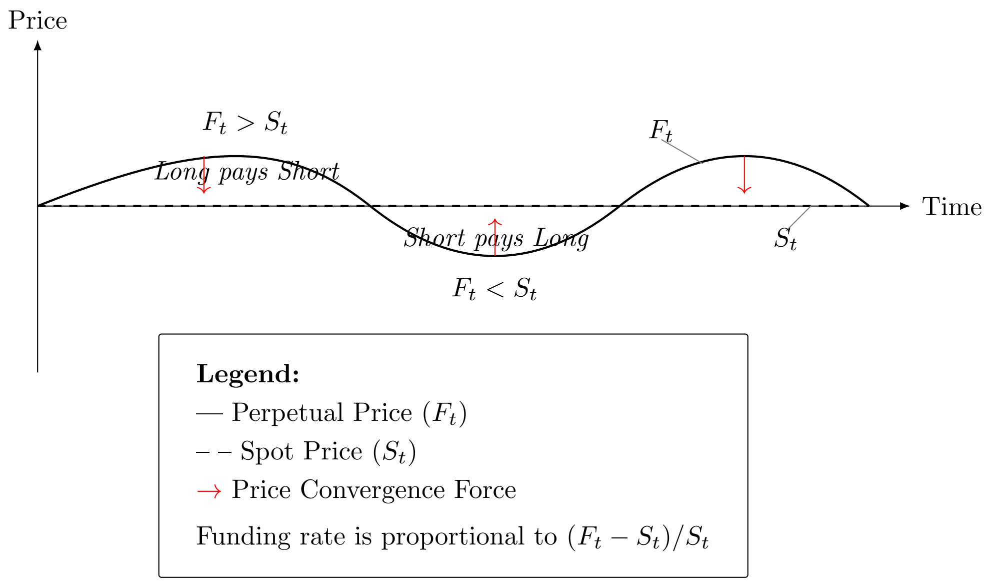


Figure 1: Perpetual Futures Funding Rate Mechanism

Notes: This figure illustrates how the funding rate mechanism maintains price convergence between perpetual futures (F_t) and spot prices (S_t). When $F_t > S_t$, long position holders pay funding fees to short position holders, creating downward pressure on perpetual prices. When $F_t < S_t$, the payment flow reverses, creating upward pressure. The funding rate is proportional to the percentage price difference between perpetual and spot prices.

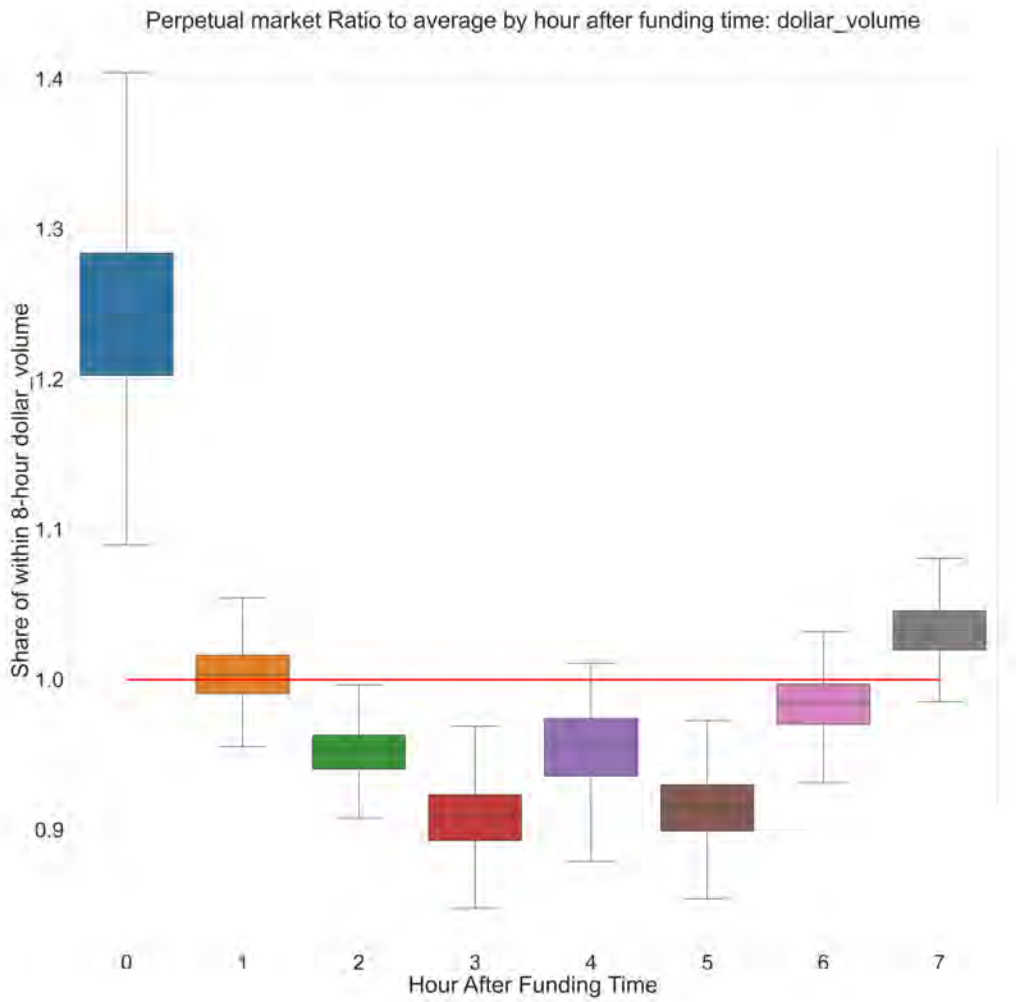


Figure 2: Hourly Trading Volume Ratios to 8-Hour Average in Perpetual Markets

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.

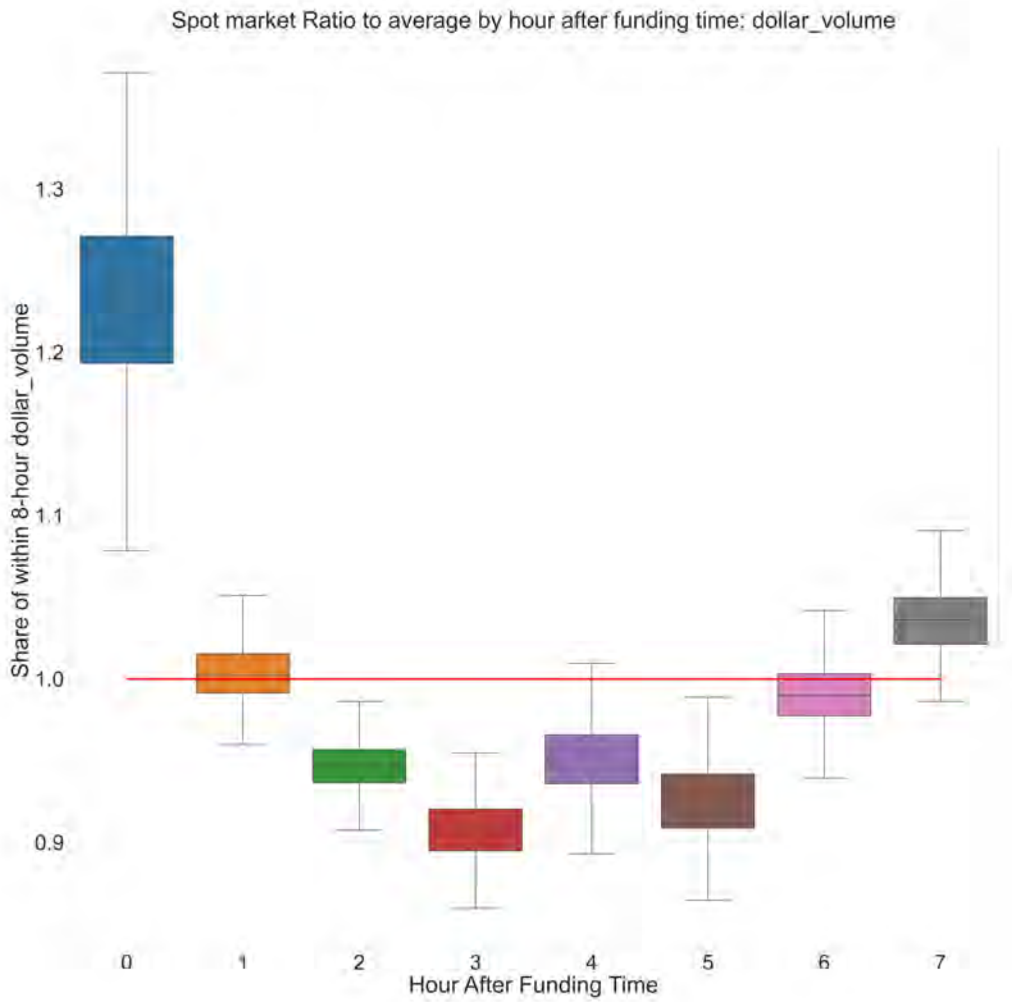


Figure 3: Spot Market Dollar Volume by Hour After Funding Time

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.

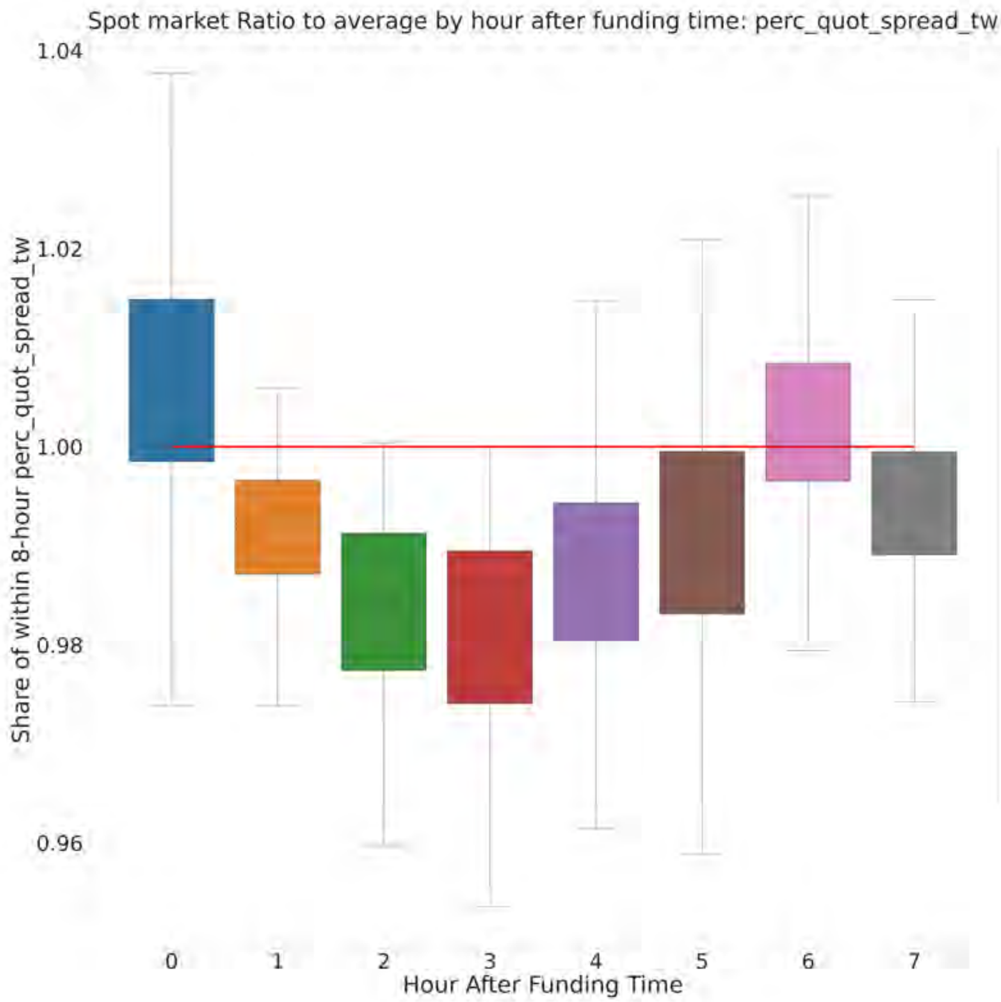


Figure 4: Spot Market Percentage Quoted Spread by Hour After Funding Time

Note: This figure depicts the cross-sectional (across exchange-tokens) distribution of spot market percentage quoted 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.

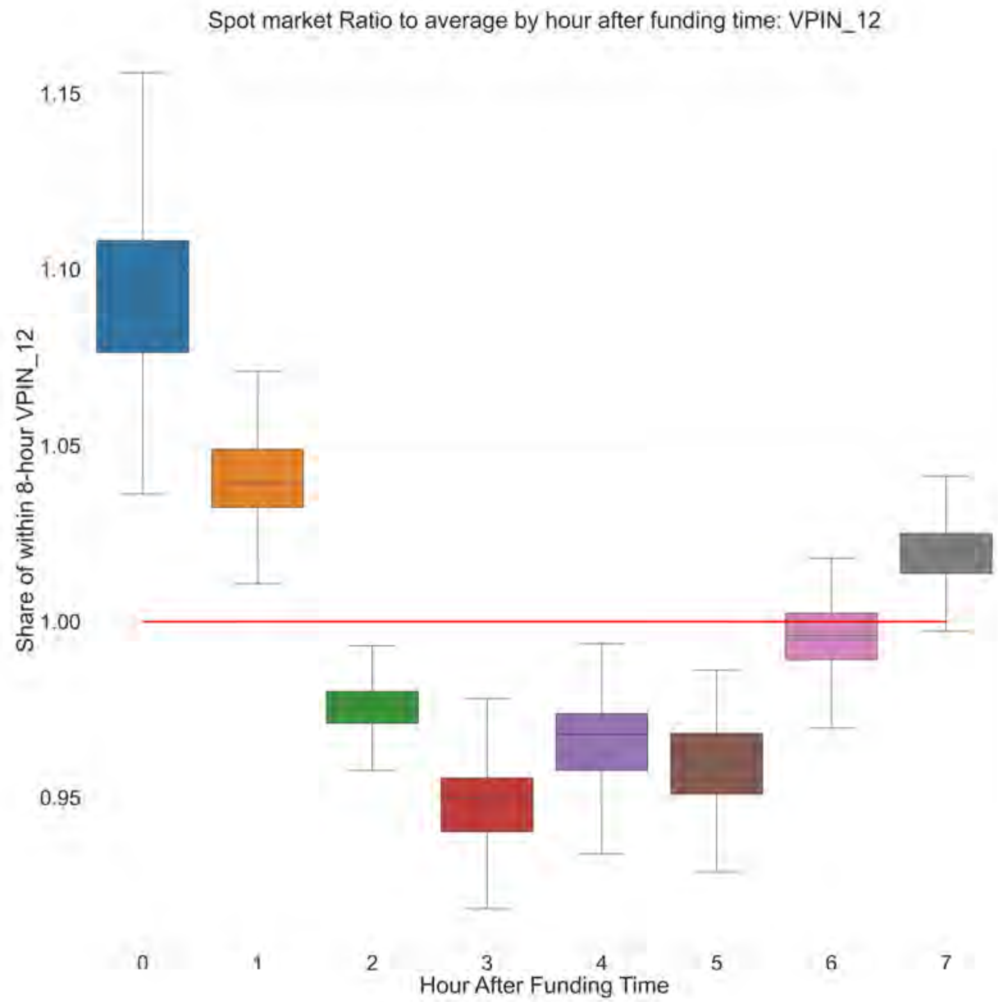


Figure 5: Spot Market $VPIN$ by Hour After Funding Time

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.

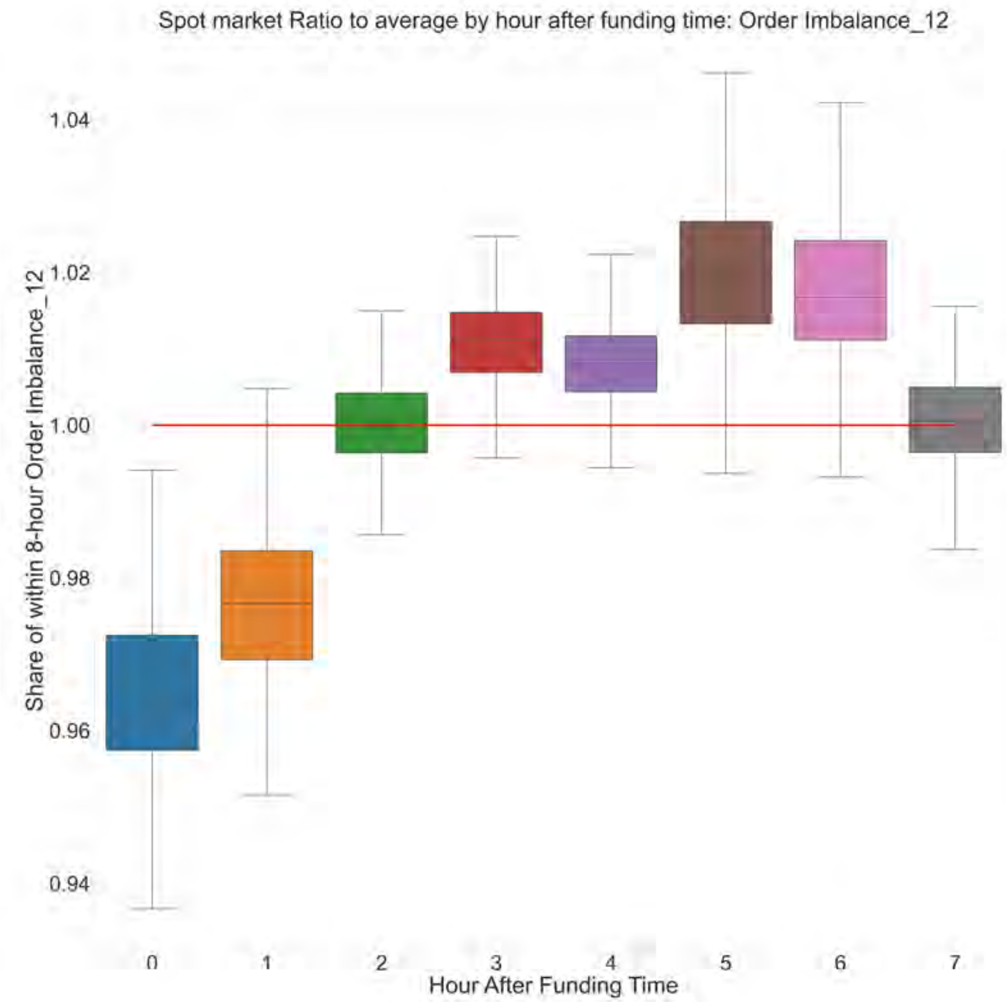


Figure 6: Spot Market Order Imbalance by Hour After Funding Time

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.

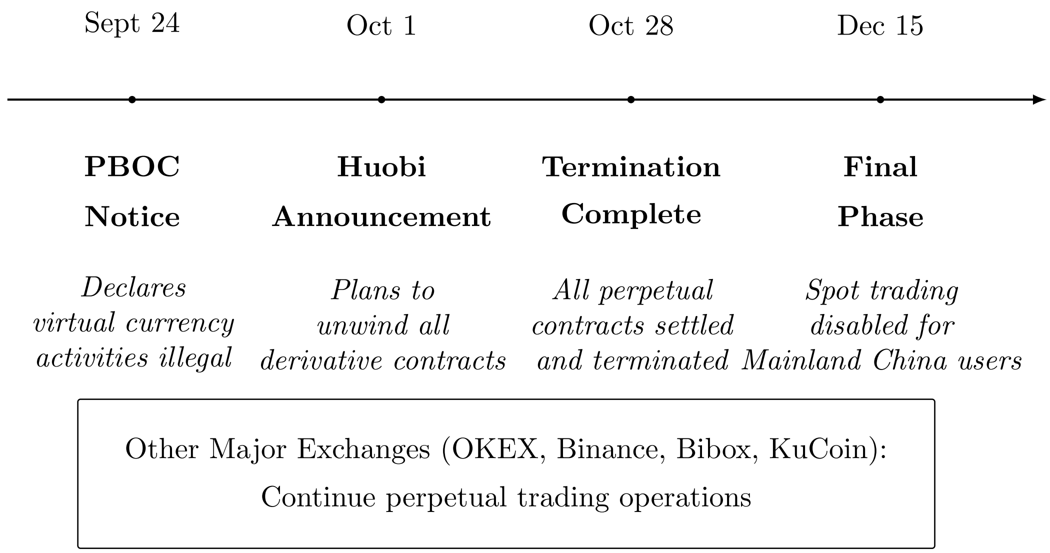
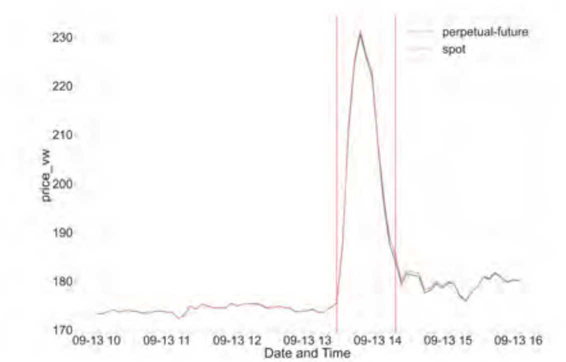
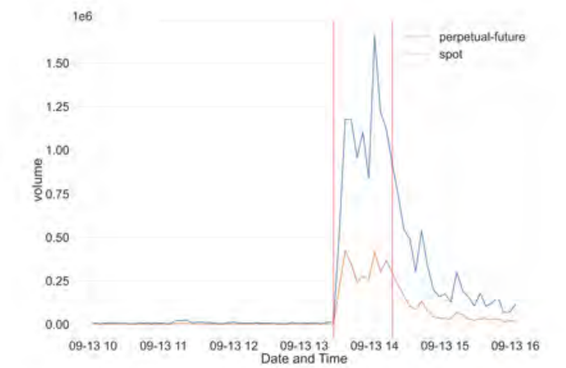


Figure 7: Timeline of Regulatory Events and Huobi's Response

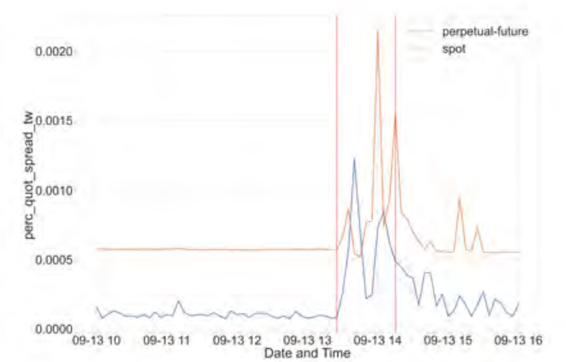
Notes: This figure illustrates the timeline of events surrounding Huobi's termination of perpetual futures trading in response to Chinese regulatory actions in 2021. Other major exchanges maintained their perpetual trading operations during this period.



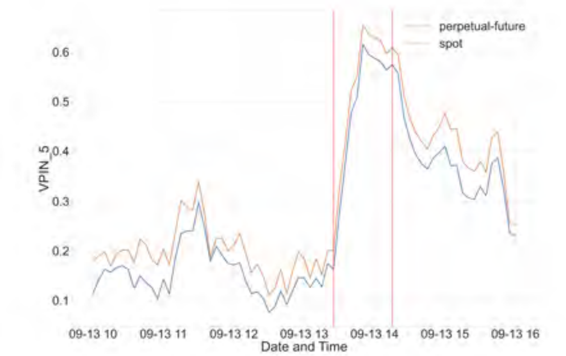
(a) Volume-weighted average price of Litecoin around the Walmart-Litecoin PD event. The vertical red lines indicate the time of the fake announcement.



(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 8: 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 $m_t = 0.5(p_t^a + p_t^b)$.

- 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

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

- Percentage Quoted Spread

$$PQS_t = \frac{p_t^a - p_t^b}{m_t}$$

A.2 Perpetual Contract Trading Termination: Synthetic Control

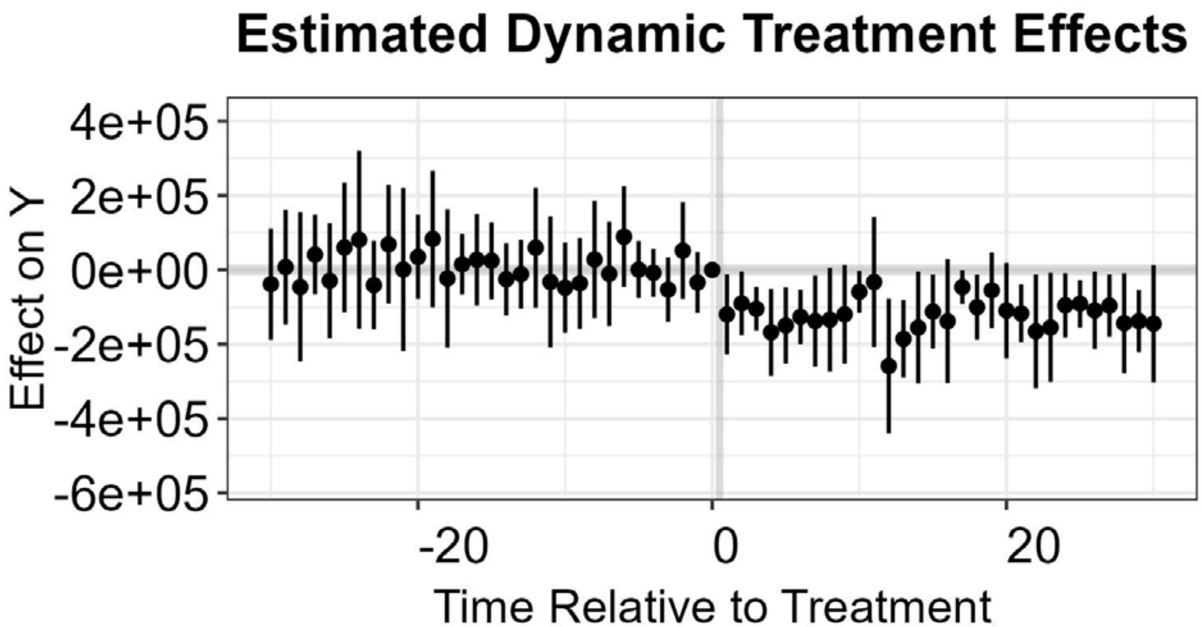


Figure A1: Dynamic Effects: Huobi and synthetic control trading Volume around Huobi perpetual trading termination.

Note: This figure displays the dynamic effects with trading volume for Huobi and its synthetic control as outcome. The control is fit using token pairs on other exchanges in the 1 month prior to restriction announcement in China. The Differences-in-Differences part discards the period between announcement and actual termination and compares post-termination outcomes to those before announcement.

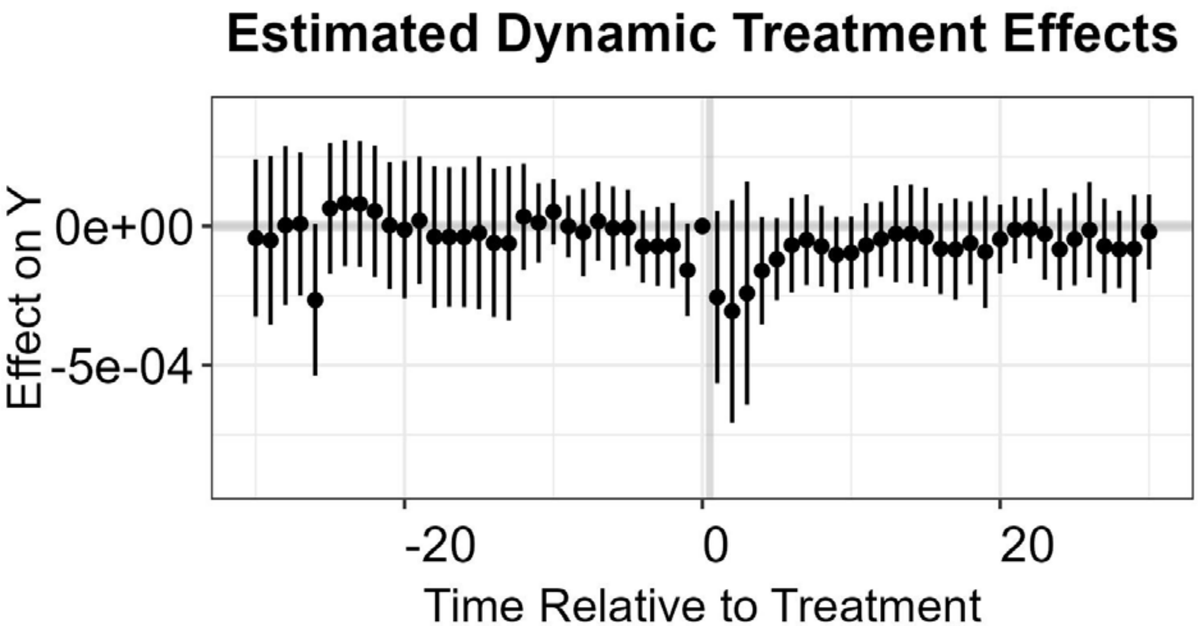


Figure A2: Dynamic Effects: Huobi and synthetic control Percentage Quoted Spread around Huobi perpetual trading termination.

Note: This figure displays the dynamic effects with percentage quoted spread for Huobi and its synthetic control as outcome. The control is fit using token pairs on other exchanges in the 1 month prior to restriction announcement in China. The Differences-in-Differences part discards the period between announcement and actual termination and compares post-termination outcomes to those before announcement.

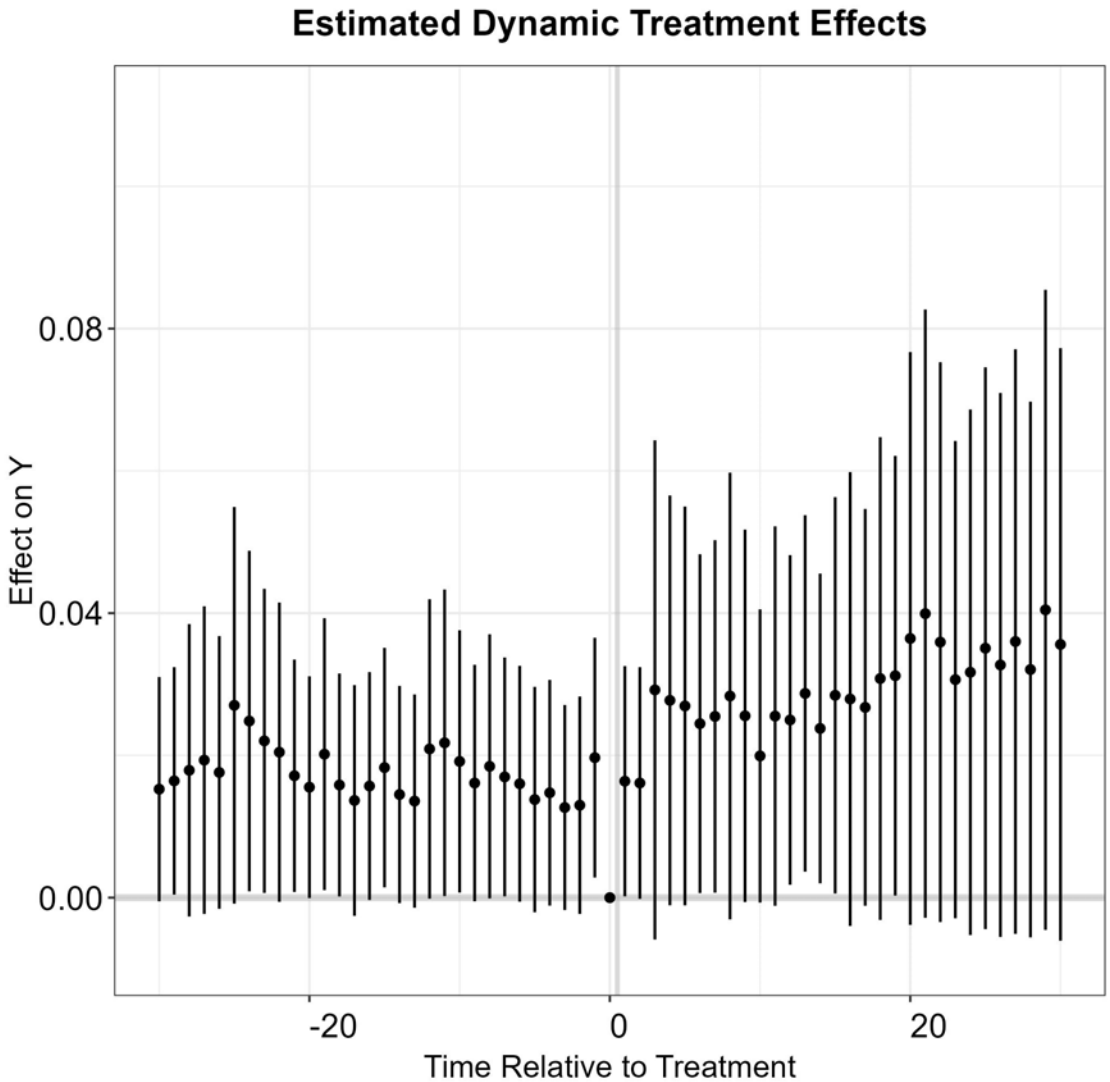


Figure A3: Dynamic Effects: Huobi and synthetic control Probability of Informed Trading (VPIN) around Huobi perpetual trading termination.

Note: This figure displays the dynamic effects with probability of informed trading for Huobi and its synthetic control as outcome. The control is fit using token pairs on other exchanges in the 1 month prior to restriction announcement in China. The Differences-in-Differences part discards the period between announcement and actual termination and compares post-termination outcomes to those before announcement.

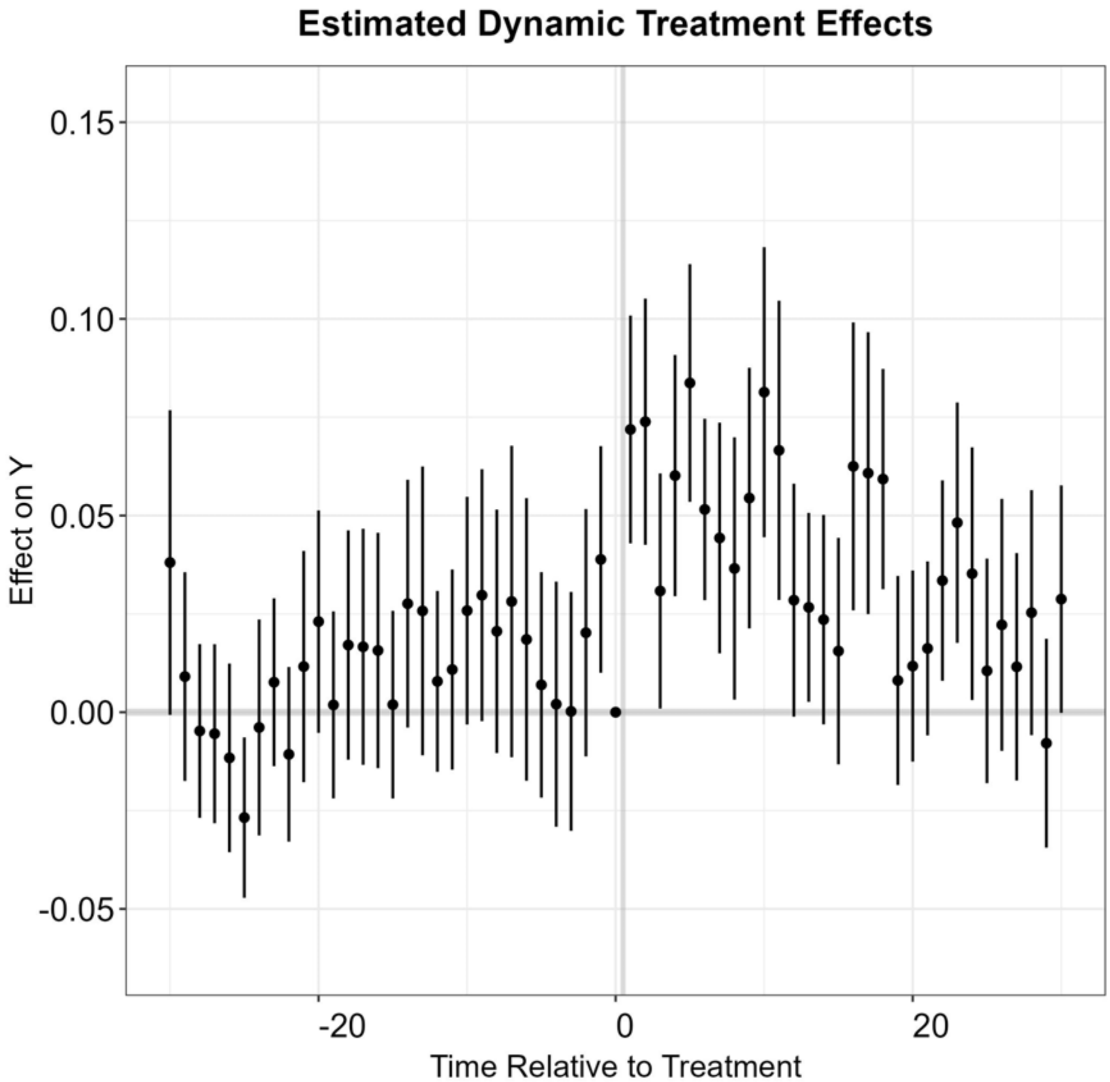


Figure A4: Dynamic Effects: Huobi and synthetic control Order Imbalance (12) around Huobi perpetual trading termination.

Note: This figure displays the dynamic effects with order imbalance for Huobi and its synthetic control as outcome. The control is fit using token pairs on other exchanges in the 1 month prior to restriction announcement in China. The Differences-in-Differences part discards the period between announcement and actual termination and compares post-termination outcomes to those before announcement

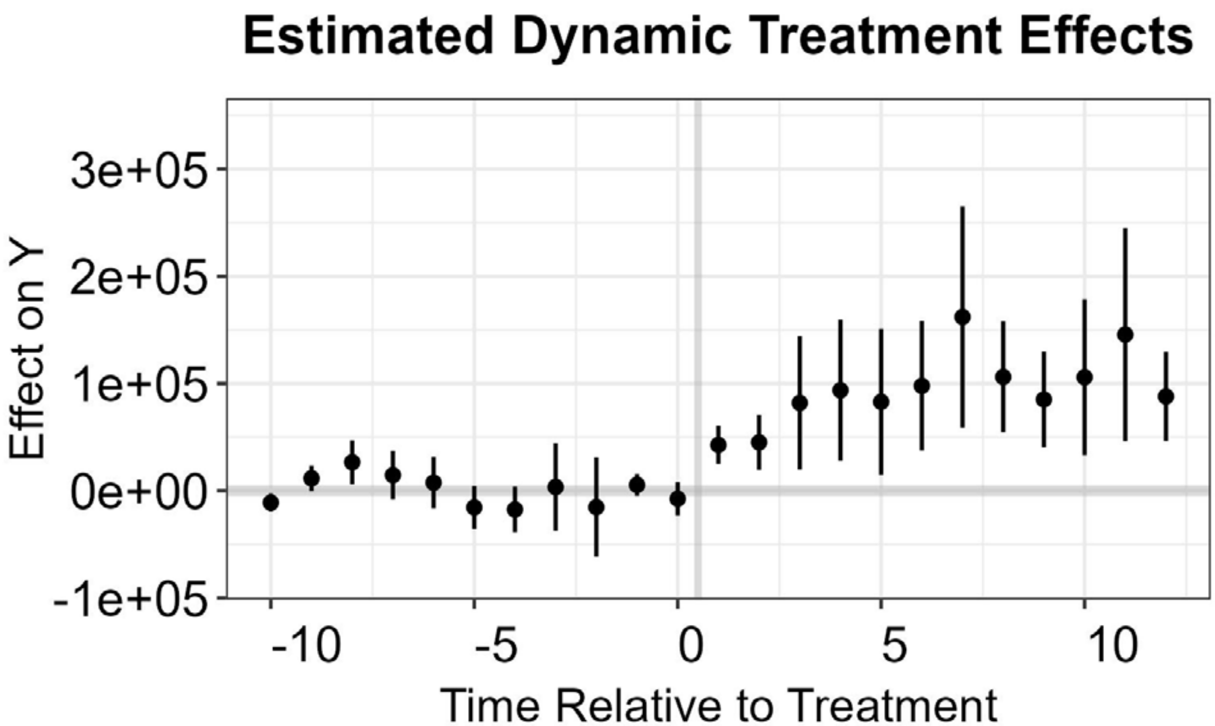


Figure A5: Perpetual introduction dollar volume Callaway and Sant'Anna (2021) dynamic effects.

Note: This figure displays the dynamic effects for spot market dollar volume by time relative to perpetual contract introduction using the Callaway and Sant'Anna (2021) estimator. Observations are at a monthly frequency computed as within month daily averages.

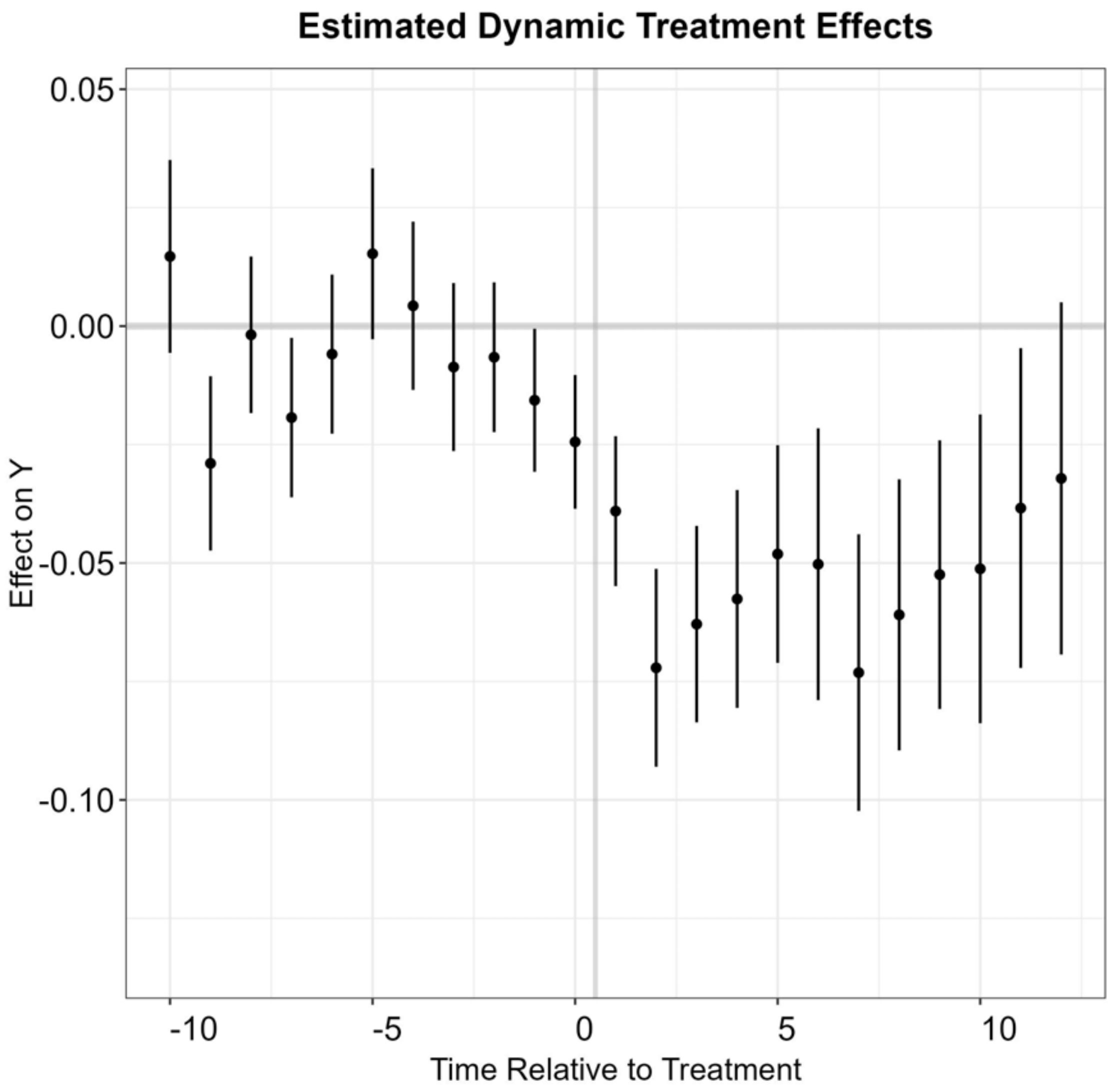


Figure A6: Perpetual introduction order imbalance volume Callaway and Sant'Anna (2021) dynamic effects.

Note: This figure displays the dynamic effects for spot market order imbalance by time relative to perpetual contract introduction using the Callaway and Sant'Anna (2021) estimator. Observations are at a monthly frequency computed as within month daily averages.

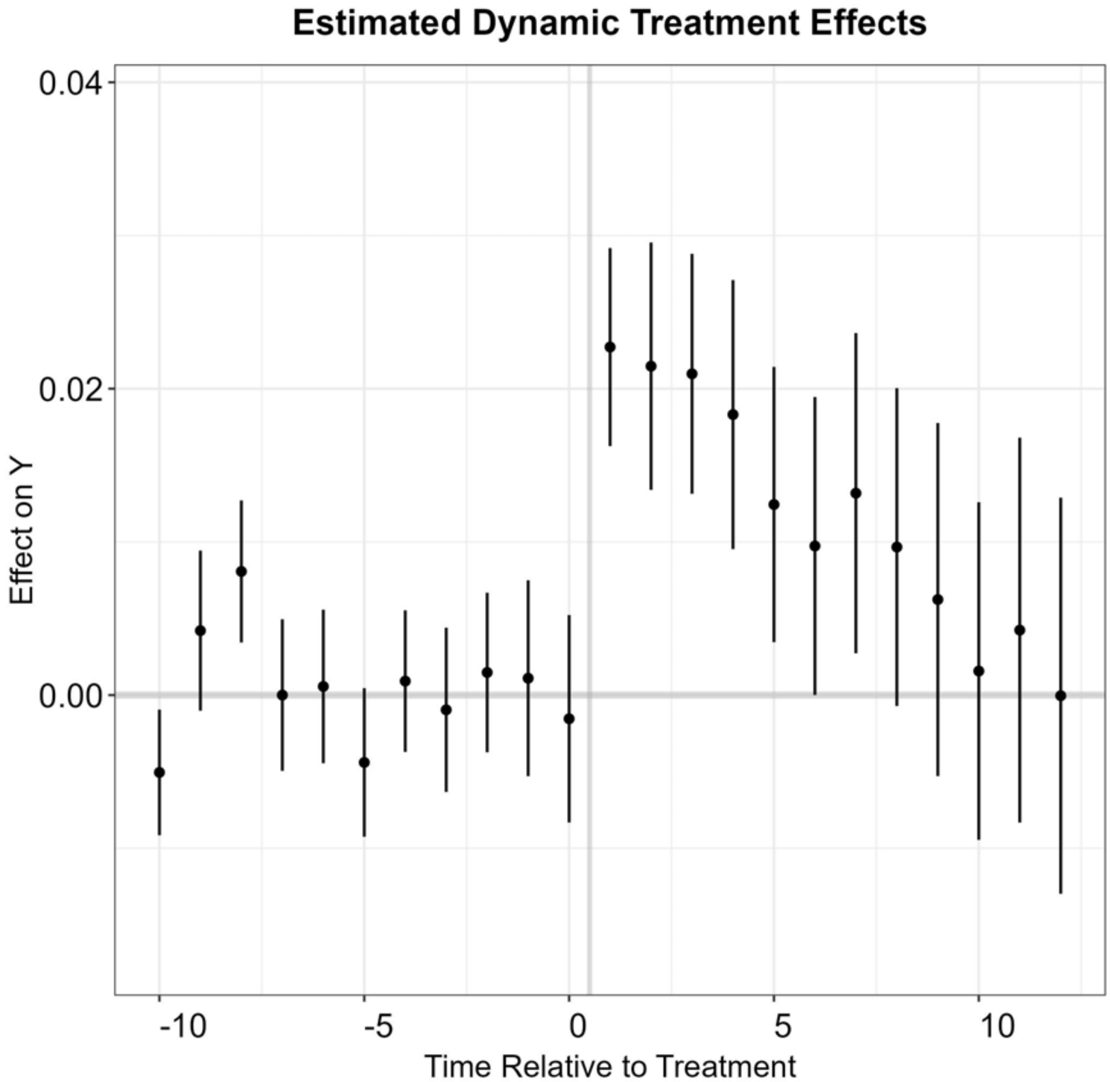


Figure A7: Perpetual introduction probability of informed trading (VPIN 5) Callaway and Sant'Anna (2021) dynamic effects.

Note: This figure displays the dynamic effects for spot market probability of informed trading (VPIN 5) by time relative to perpetual contract introduction using the Callaway and Sant'Anna (2021) estimator. Observations are at a monthly frequency computed as within month daily averages.

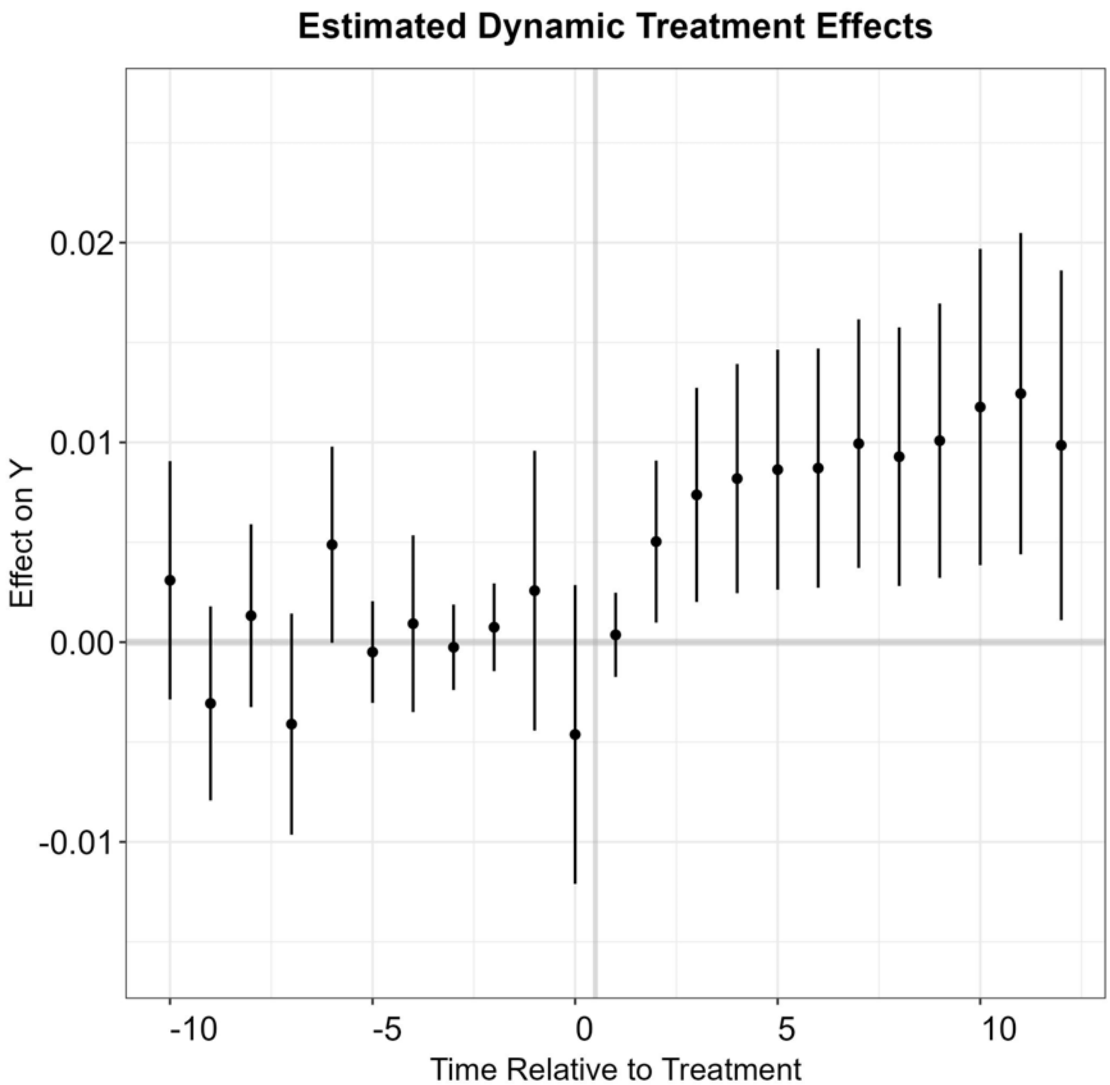


Figure A8: Perpetual introduction percentage quoted spread Callaway and Sant'Anna (2021) dynamic effects.

Note: This figure displays the dynamic effects for spot market percentage quoted spread by time relative to perpetual contract introduction using the Callaway and Sant'Anna (2021) estimator. Observations are at a monthly frequency computed as within month daily averages.

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]
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***
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
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***
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
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***
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 Dollar Volume (total transaction value), Order Imbalance (difference between buy and sell orders), Percentage Quoted Spread (relative bid-ask spread), and VPIN (volume-synchronized probability of informed trading, indicating market order flow imbalance).