Perpetual Futures Contracts and Cryptocurrency Market Quality

Abstract

We examine perpetual futures contracts' impact on cryptocurrency spot market quality. Using high-frequency order book data from 2017 to 2023, we document that spot market quality follows a U-shaped pattern over perpetual contracts' eight-hour funding cycles. Exploiting both the exogenous termination of perpetual trading at Huobi Exchange and 95 staggered contract introductions, we identify a seemingly puzzling liquidity pattern: perpetual contracts increase spot trading volume while widening quoted spreads. To resolve this puzzle, we demonstrate that this pattern reflects increased informed trading, particularly during funding settlement hours and periods of larger funding fee magnitudes. Market makers respond to heightened adverse selection risk by widening quoted spreads.

Keywords: Perpetual Futures Contracts, Funding Fee Mechanism, Cryptocurrency, Digital Finance, Market Quality

1 Introduction

Perpetual futures contracts, as conceptualized by Shiller (1993), are designed to continuously track underlying asset prices. These instruments are applicable to various non-tradable assets, including real estate, human capital, and economic indices like inflation rates, facilitating price discovery and effective hedging without requiring direct ownership or physical delivery. Cryptocurrency markets, underpinned by blockchain technology (Nakamoto, 2008), bring this conceptual contract to life under the name of perpetual contracts, serving as a "sandbox" for studying their effects on spot markets with findings that can illuminate their potential impact in other market applications.[1]

The cryptocurrency market, with its global and decentralized nature, enables 24/7 continuous trading. Such continuous trading offers several advantages that enhance the effectiveness of perpetual contracts. First, frequent price updates enable the contract price to closely track the underlying asset's price, reducing basis risk (the gap between futures and spot prices). Second, continuous trading enhances market liquidity by allowing participants to enter or exit positions at any time. Third, it mitigates counterparty risk through more frequent margin updates and liquidations, preventing the accumulation of large, unsustainable positions. However, continuous trading is not strictly necessary for their operation. The funding fee mechanism can function effectively within standard trading hours, and as shown in Shiller (1993), these contracts extend to non-tradeable assets, indicating their utility beyond continuously traded markets.

[Figure 1 about here.]

A key distinguishing feature of perpetual contracts from traditional futures is the absence of an expiration date, allowing investors to maintain positions indefinitely without contract rollovers. The funding fee mechanism, implemented by cryptocurrency exchanges, is crucial for maintaining perpetual prices' alignment with underlying cryptocurrency prices. This mechanism facilitates periodic payments between long and short position holders based on the perpetual-spot price differential. When perpetual prices exceed spot prices, long position holders pay funding fees to short position holders, and vice versa. This mechanism incentivizes traders to take positions that drive perpetual prices toward spot prices. Figure 1 illustrates how payment flows between long and short positions create convergence forces that maintain price alignment. Our data demonstrate that this mechanism effectively maintains price consistency between perpetual and spot markets.

[1]In addition to perpetual futures contracts, these instruments are sometimes referred to as "perpetual swap contracts" https://www.coindesk.com/learn/what-is-a-perpetual-swap-contract/. As a novel financial derivative innovation, market participants use different terminology to describe these instruments while also holding varying views on which traditional derivative instrument they most closely resemble.

Perpetual contracts exhibit lower basis risk (the price discrepancy between derivative and underlying asset) than traditional futures with expiration dates. Apart from perpetual contracts' ability to track underlying prices, they offer several benefits compared to direct trading in spot markets: lower transaction fees, faster execution without requiring on-chain verification, position leverage capabilities, and short-selling facilitation.

Since their 2016 introduction by BitMEX, perpetual contracts have gained significant traction in cryptocurrency markets, with substantial volume growth. According to Coinglass,[2] these contracts have generated over \$90 trillion in trading volume since 2020[3], surpassing underlying cryptocurrency volumes and representing 93% of the cryptocurrency futures market. This volume doubles the U.S. stock market's \$44 trillion in 2022.[4] At the individual contract level, Bitcoin's perpetual contract trading volume reached \$180 billion on February 28th, 2024, sextupling NVIDIA's \$30 billion daily volume, the highest among U.S. stocks. The Bitcoin perpetual futures market's trading volume parallels the aggregate trading volumes in gold or U.S. Treasury bills markets.[5] This phenomenal trading volume of perpetual contracts highlights its broader potential applications in other asset markets, such as real estate, human capital, and economic indices, as originally envisioned in Shiller (1993). Given the novelty and impact of perpetual contracts, it is both timely and relevant to discover their specific effects on the underlying spot market. The insight learned from this issue extends beyond cryptocurrency markets, offering broader economic implications for perpetual contract applications across various financial institution assets, which represent assets exceeding \$461 trillion,[6] particularly as asset tokenization gains momentum.[7]

Perpetual contracts are a novel financial instrument 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 applications of perpetual contracts and corresponding 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

[2]Perpetual Futures trading volume data at Coinglass. https://www.coinglass.com/pro/futures/ExVolume. Even after considering the estimated 70% wash trading in cryptocurrency spot markets documented in Cong, Li, Tang, and Yang (2023), this trading volume remains phenomenal.

[3]The trading volume of perpetual contracts represents the notional value of contracts traded. For example, if a trader enters a perpetual contract position of 1 Bitcoin (worth \$50,000) using \$5,000 as margin at 10x leverage, the trading volume is counted as \$50,000 (the full contract value).

[4]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.

[5]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.

[6]Source: https://www.statista.com/statistics/421060/global-financial-institutions-assets/.

[7]See discussions at https://chain.link/education/asset-tokenization.

cryptocurrencies. Factors such as the popularity or demand for certain cryptocurrencies may influence both the decision to introduce perpetual contracts and the overall market quality, making it difficult to isolate the true impact of perpetual contracts on the spot market. To surmount these challenges and establish a causal relationship, we implement identification strategies in different settings to tease out the causal effects of perpetual contracts on spot markets.

First, we investigate how the unique eight-hour funding cycle of perpetual contracts affects cryptocurrency spot market quality. We find that spot market trading volumes and percent quoted spreads exhibit a U-shaped pattern over the eight-hour funding cycle of perpetual contracts: around perpetual market funding times, both spot market trading volumes and percent quoted spreads are larger, while they are lower during normal hours. The funding time effects are both economically and statistically significant in our results. We also find this U-shaped pattern appearing in the perpetual contracts market itself. Given that this funding cycle is unique to perpetual contracts, it is unlikely that other forces drive the spot market systematically over this cycle, making our findings stand alone as causal evidence of perpetual contracts' impact on the spot market. Our finding sheds light on the interactions between perpetual and spot markets and may inform theoretical studies about perpetual contracts.

Second, we exploit a unique regulatory action in China that led to the uniform termination of perpetual contracts at Huobi Exchange in October 2021. This significant and unexpected regulatory action by the People's Bank of China aimed to ban cryptocurrency trading in Mainland China. In response, Huobi Exchange terminated perpetual contract trading in October 2021 while continuing spot market trading until December 2021. Meanwhile, other major cryptocurrency exchanges, including Binance, OKEX, Kucoin, and Bibox, whose headquarters are not in Mainland China, continued both perpetual and spot trading. This setting provides an ideal natural experiment for Difference-in-Difference analysis. We employ synthetic control methodology to construct the control group using these exchanges to ensure parallel trends. We find that following Huobi's termination of perpetual contract trading, the associated cryptocurrencies markets experience lower trading volume and narrower percent quoted spreads than their respective synthetic control group.

Third, we study the effects of staggered introductions of perpetual contracts on the spot market, implementing the staggered Differences-in-Differences (DiD) framework across 95 different cryptocurrencies in three major exchanges: Binance, OKEX, and Huobi, from December 2019 to September 2022. We employ the methodology in Callaway and Sant'Anna (2021) to obtain the estimates of our staggered DiD results. Following the introduction of perpetual contracts, we document increases in both spot market trading volume and percent quoted spreads with the results robust to the choice of the control group, be it the never treated or not yet treated token-exchange pairs. The effects of terminating and introducing perpetual contracts exactly mirror each other, adding credibility to our findings.

Our study reveals two primary effects associated with perpetual contracts: increased trading volume and widened percent quoted spreads following their introduction, with termination leading to opposite effects. To resolve this apparent paradox of higher volume but wider spreads, we investigate the mechanisms through the lens of information-based market microstructure theories. We find these effects concentrate during funding hours when arbitrage activity increases between perpetual and spot markets due to periodic funding payments. The funding fee serves as a powerful information aggregator, reflecting traders' willingness to pay and containing market information. Using the VPIN indicator proposed in Easley, L'opez de Prado, and O'Hara (2012), we confirm increased informed trading during funding hours. Furthermore, these effects strengthen with larger funding fee magnitudes, consistent with funding fees aggregating market information.

We further examine the information channel by investigating pump-and-dump (PnD) activities, which constitute exogenous information shocks to cryptocurrency markets. Using the case of fake news about Walmart adopting Litecoin in September 2021, we find that following this event, trading volume increases, spot market spreads widen, and informed trading (measured by VPIN) rises. This pattern mirrors the effects of introducing perpetual contracts, providing robust evidence for the information channel. Our findings align with information-based microstructure theory, indicating that increased "toxic" trading volume leads market makers to widen spreads to protect against informed trading risks.

Our study is the first to identify the causal effects of perpetual markets on cryptocurrency market quality, documenting increased trading volume alongside wider spreads and higher informed trading in spot markets. These findings provide general economic insights about perpetual contracts, a novel derivative instrument that Robert Shiller envisioned could revolutionize risk management and price discovery across various assets, from real estate to human capital. Our findings lay the foundation for future theoretical studies and broader applications of perpetual contracts while informing regulatory considerations, particularly as these instruments extend beyond cryptocurrency markets to other financial assets.

1.1 Related Literature

Our paper connects to multiple strands of literature. First, we contribute to the literature that is specific to perpetual contracts. The concept of perpetual contracts 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 document the effects of perpetual contracts' 8-hour funding cycle on the spot market, and identify their causal impacts, which are currently assumed away in theoretical models. Our findings about these market interactions can inform future theoretical studies of perpetual contracts that incorporate spot market dynamics.

Our study extends the emerging cryptocurrency and decentralized finance literature. The cryptocurrency space has been a source of financial innovation, introducing patterns and instruments distinct from traditional financial markets. Kogan, Makarov, Niessner, and Schoar (2024) documents that cryptocurrency investors exhibit unique beliefs and trading patterns compared to traditional market participants. Perpetual contracts represent one such innovation, alongside other cryptocurrency developments including 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, providing a testing ground for understanding their potential 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. As evidenced by the trading volume of perpetual contracts being much larger than traditional futures, it is logical to expect their effects and economic significance to differ. 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 document the U-shaped funding cycle of perpetual contracts on the spot market and identify their causal effects. Moreover, we demonstrate that these effects differ from those of traditional futures with expiration dates 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). Our analysis offers several empirical advantages. While Augustin et al. (2023) analyze a single BTC-USD futures pair, we examine data from Kaiko covering 100 cryptocurrencies across multiple exchanges. Our setting provides three distinct identification advantages. First, the funding mechanism creates predetermined cyclical shocks every eight hours for causal analysis. Second, the Huobi exchange's termination of perpetual contract trading following Chinese regulatory changes, while other Chinese exchanges maintained operations, provides a natural experiment setting. Third, we analyze 95 perpetual contract introductions across different cryptocurrencies and exchanges. Methodologically, we implement a synthetic control method for the Huobi termination event following Chinese regulatory action in 2021, and a staggered differences-in-differences methodology for the 95 contract introductions. Across all three identification settings - the predetermined funding cycles, Huobi's termination, and contract introductions - we consistently find that perpetual contracts increase trading volume while widening percent quoted spreads, differing from Augustin et al. (2023)'s aggregate liquidity measures. This consistent pattern across multiple identification strategies provides new, robust, and nuanced understanding of perpetual contracts' effects on spot market quality and informed trading.

Our research adds to the literature on the factors affecting market microstructure. 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 volumes, widen spreads, and raise VPIN (Easley et al., 2012), with these effects particularly pronounced during funding windows. These findings contribute to our understanding of market microstructure determinants and demonstrate how these effects are driven by the informational channel, shedding new light on informed traders' venue choices (Easley, O'hara, and Srinivas, 1998; Chen, Lung, and Tay, 2005).

Our study connects to behavioral finance through analysis of market reactions to information shocks. We examine the pump-and-dump event (Li, Shin, and Wang, 2021) triggered by fake news of Walmart adopting Litecoin in September 2021. The documented changes in price, volume, and market quality are consistent with Fleming and Remolona (1999)'s findings on Treasury market responses to information. These 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 Funding Fee Mechanism: Design and Evidence

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.

The funding fee mechanism operates on an eight-hour cycle, during which perpetual contracts effectively "settle" by evaluating price differences between perpetual and spot markets. If the perpetual price exceeds the spot price, traders holding long positions pay a funding fee to those holding short positions; conversely, if the perpetual price falls below the spot price, long position traders receive a funding fee from short traders. The magnitude of the funding fee is proportional to the price deviation, creating financial incentives for traders to actively monitor and adjust their positions.

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. When traders are willing to pay higher funding fees to maintain long positions, it signals their strong conviction about future price appreciation based on their aggregate information. This premium reflects traders' collective assessment of market conditions, incorporating diverse information sets: fundamental factors such as network activity and adoption metrics, market sentiment derived from social media and news flows, technical indicators from trading patterns, and broader market conditions including liquidity and leverage conditions. For instance, during Bitcoin's bull run in early 2021, consistently positive funding rates reflected traders' willingness to pay premiums for long exposure, aggregating their positive outlook from technological advancement, institutional adoption, and favorable market sentiment.

According to data from Binance, the largest cryptocurrency exchange, funding rates across major exchanges average around 0.015%, translating to an annualized rate of approximately 16%. While typically positive, indicating the long side's leverage advantage, funding fees can turn negative during extreme market episodes, signaling that long traders require compensation for taking leveraged positions. This occurred during periods of negative market sentiment, such as the Terra/Luna meltdown, Three Arrows Capital (3AC) bankruptcy, and the FTX collapse.

While perpetual contracts generally track underlying cryptocurrency prices effectively, significant decoupling events have occurred. During the COVID-19-induced market crash on March 12, 2020, BitMEX perpetual contract prices for Bitcoin traded at discounts of up to 15% compared to Coinbase spot prices, while discounts reached 12% on Binance and 10% on Huobi. Conversely, during the Bitcoin bull run on January 4, 2021, perpetual contracts traded at premiums of 5.4% on Binance and 4.8% on Huobi relative to spot prices. These decoupling episodes, typically short-lived, demonstrate how extreme market conditions can temporarily impact the alignment mechanism, though prices tend to quickly realign as markets stabilize.

The economic significance of funding fees, their effectiveness in price alignment, and their role as information aggregators underscore the importance of understanding this mechanism in cryptocurrency markets. This understanding becomes particularly relevant as we examine the broader effects of perpetual contracts on market quality.

3 Data

We use high-frequency trading data and order book snapshots from Kaiko, covering more than 100 cryptocurrency pairs denominated in USDT (Tether) across 10 major exchanges including Coinbase, Binance, Huobi, OKEX, ByBit, KuCoin, Bibox, BitFinex, BitMex, and HitBTC from July 2017 to July 2023.

Using transaction data at millisecond frequency, we construct several market quality measures. We compute dollar volume as a fundamental liquidity metric and estimate the Volume-synchronized Probability of INformed trading (VPIN, Easley et al. (2012)) to assess order flow toxicity. VPIN, particularly suitable for high-frequency cryptocurrency markets, measures the probability that an order comes from an informed trader. We follow Easley et al. (2012) in constructing the VPIN measure. This measure captures the intensity of informed trading, with higher values indicating greater adverse selection risk for market makers.

The dataset's trade direction identifier enables the calculation of signed volume estimates, V_t^S and V_t^B, for order imbalance analysis. Following Easley, López de Prado, O'Hara, and Zhang (2021), we partition data into 5-minute intervals and calculate moving averages using window sizes W of {5, 12, 24}, corresponding to 25 minutes, 1 hour, and 2 hours. We supplement transaction-based measures with order book snapshots to compute percentage quoted spreads. Detailed variable definitions are provided in Appendix A.1.

Table 1 compares spot and perpetual markets across exchange-token pairs with active perpetual contracts. Perpetual markets exhibit substantially higher trading volumes, averaging $8.8 million per exchange-token-hour compared to $128,000 in spot markets. However, despite this 69-fold volume difference, perpetual markets exhibit 14% wider percentage quoted spreads. This pattern aligns with our finding of 31% higher informed trading probability in perpetual markets than in spot, as measured by VPIN, suggesting that increased adverse selection risk leads market makers to maintain wider spreads despite higher trading activity.

[Table 1 about here.]

4 The Effects of Funding Times

We examine how perpetual contracts affect spot market quality through their eight-hour funding cycle. This predetermined mechanism provides clean identification of perpetual contracts' effects on spot markets for two reasons. First, funding times occur at fixed eight-hour intervals regardless of market conditions, making them exogenous to market quality. Second, this funding cycle is unique to perpetual contracts, minimizing the likelihood that other systematic factors drive market quality at these specific times. The funding cycle also enables us to investigate the high-frequency dynamics of perpetual contracts' effects, complementing our analysis of contract introductions and terminations.

The funding mechanism operates through periodic settlements that incentivize price convergence between perpetual and spot markets: when perpetual prices exceed spot prices, long position holders pay funding fees to short position holders, and vice versa. This mechanism creates two distinct channels affecting trading behavior. The first channel operates through arbitrage and informed trading: sophisticated traders engage in strategic trading around funding times, either to arbitrage the price discrepancies that arise from funding pressures or to optimize their positions before funding settlements. For instance, when funding rates are significantly positive, indicating perpetual prices exceed spot prices, informed traders may simultaneously reduce perpetual longs and increase spot positions to earn the funding payment while maintaining their desired exposure. The second channel works through forced trading and position management: traders need to execute spot market transactions to cover funding payments or maintain their desired exposure after funding transfers. These automatic settlements can trigger trading cascades as positions are adjusted across markets.

These economic channels generate two testable predictions. First, if funding settlements significantly influence trading behavior through these channels, we should observe systematic U-shaped patterns in market activity around funding times, reflecting anticipatory trading before and adjustment trading after settlements. Second, if these effects operate primarily through informed trading, we should observe increased adverse selection risk alongside higher volume, manifesting as elevated VPIN and wider spreads when the market makers protect themselves against the informed order flow.

Our analysis begins with perpetual markets themselves. Figure 2 reveals a pronounced U-shaped pattern in trading volume within each eight-hour cycle, with activity increasing by more than 50% one hour before and after funding times compared to mid-cycle periods. A Cressie-Read power divergence test formally rejects that the trading pattern follows a uniform distribution at the 1% level, confirming systematic bunching around settlements.

[Figure 2 about here.]

[Figure 3 about here.]

[Figure 4 about here.]

[Figure 5 about here.]

[Figure 6 about here.]

Most importantly, this perpetual market funding cycle significantly impacts spot markets as well. Figures 3-6 show the measures of market quality over the funding cycle, including dollar volume, spread, VPIN, and order imbalance. The results support our predictions. Spot market dollar volume exhibits a U-shaped pattern around perpetual market funding times (Figure 3), with spot market activity increasing by over 50% during settlement hours. This elevated trading coincides with wider bid-ask spreads (Figure 4), which increase by 3.2%, and higher VPIN (Figure 5), rising by 17.4%. These patterns strongly suggest increased informed trading around funding settlements. Moreover, the reduction in order imbalances (Figure 6) indicates that funding-driven trading provides the needed liquidity to the market, helping resolve existing imbalances through informed arbitrage activity.

We formally quantify these effects through panel treatment effect regressions:

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

where $Market\_Quality_{e,i,t}$ measures hourly outcomes relative to pre-funding averages, $\gamma_{e,i}$ captures exchange-token fixed effects, and η_t represents eight-hour window fixed effects. The treatment indicator D_t identifies observations around funding times, with standard errors clustered at the exchange-token level. This specification isolates funding time effects while controlling for token-specific and time-varying market conditions.

Table 2 presents our results of the effects of perpetual contracts' funding times on spot market quality. The effects of funding times on spot market quality are both statistically and economically significant: the 50% increase in trading volume represents millions of dollars in additional trading activity per token-exchange-hour, while the 3.2% wider spreads translate to substantially higher transaction costs for liquidity traders. The 17.4% rise in VPIN indicates a marked increase in adverse selection risk. These magnitudes remain robust across different time windows around funding settlements and align with theoretical predictions from information-based market microstructure models (Glosten and Milgrom, 1985; O'Hara, 1995; Easley et al., 1996). Our sample's global nature helps address potential time-of-day effects, as exchanges operate primarily in different time zones relative to UTC. While we acknowledge time-varying exchange-token characteristics as potential confounders (Augustin et al., 2023), three features strengthen the robustness of our findings. First, we document consistent effects across multiple settings: exchange terminations, contract introductions, and funding cycles. Second, our results hold at different time frequencies, from hourly to daily observations. Third, we demonstrate strong parallel trends in our difference-in-differences analyses. This triangulation of evidence across various empirical settings and frequencies lends credibility to our estimates, suggesting they capture the true effects of perpetual contracts on spot market quality.

[Table 2 about here.]

5 The Effects of Terminating Perpetual Contracts

While our analysis of funding cycles provides initial evidence of perpetual contracts' effects on spot markets, identifying broader causal effects is challenging. The key difficulty arises from the endogenous nature of exchanges' decisions to introduce or terminate these contracts, which typically correlate with the underlying cryptocurrencies' market quality. To address this challenge, we exploit a unique and exogenous event: Huobi's unanticipated termination of perpetual trading in October 2021, triggered by an unexpected and significant regulatory directive issued by China.

[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 illegal.[8] Huobi, a prominent cryptocurrency exchange, promptly responded to these new regulations. On October 1, 2021, Huobi announced a detailed compliance plan, including the unwinding and settlement of all derivative contracts by October 28, 2021, and complete termination of derivative trading.[9] Meanwhile, spot market trading continued until 3:00 UTC of December 15, 2021, when spot trading for Mainland China users was disabled.[10]

Three features establish the exogeneity of Huobi's termination event. Prior to this regulatory action, Huobi had experienced significant and growing trends in perpetual contracts and spot market trading volumes, along with the bullish sentiment in the cryptocurrency market, with no indications of disruption. The regulatory changes in Mainland China were unanticipated by cryptocurrency markets and led to a uniform termination of all perpetual contract trading on Huobi, regardless of individual contract performance or profitability. In contrast, other major exchanges, such as Binance, OKEX, Bibox, and KuCoin, continued their perpetual trading operations. This combination - an unanticipated regulatory shock, uniform termination of all contracts, and the presence of unaffected peer exchanges - constitutes a natural experiment for identifying the specific effects of perpetual contracts on spot market quality.

We take the classical approach to constructing the synthetic control and following well-established literature (Abadie, Diamond, and Hainmueller, 2010, 2015; Abadie and L'Hour, 2021). We pair this synthetic control with factual Huobi observations to identify the causal effects of terminating perpetual contracts trading on spot market microstructure in a Differences-in-Differences (DiD) framework.

[8] 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.

[9] 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.

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

More specifically, using one month before the 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:

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

The synthetic control for token pair i is then estimated as $\hat{Y}_i^c = \sum_{j=1}^{n} W_{i,j}^* Y_j^c$. 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 demonstrated in 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:

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

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 token-treatment-group level.

[Table 3 about here.]

To establish robustness, we analyze the effects of Huobi's perpetual contract termination across multiple horizons: 1, 3, 7, 14, and 30 days post-termination. Table 3 presents the synthetic control estimates of perpetual contract termination on spot market quality. Following termination, Huobi's spot markets experience significant decreases in both trading volume and percent quoted spreads relative to the synthetic control group. These results present an apparent paradox in market quality measures: while decreased trading volume typically indicates lower liquidity, narrower percentage quoted spreads—a standard liquidity measure (Holden and Jacobsen, 2014)—suggests improved market liquidity.

We interpret these findings through the lens of informed trading. Prior to termination, perpetual contracts attracted informed traders through their key features: higher leverage, lower trading costs, and short-selling capabilities. The termination of these contracts reduced informed traders' participation in Huobi's ecosystem, thereby decreasing adverse selection risk in the spot market.

Professional market makers in cryptocurrency markets, including firms like Wintermute and DWF Lab,[11] respond to this reduced adverse selection risk by narrowing their bid-ask spreads. With fewer informed traders in the market, market makers face lower risks of adverse selection, allowing them to set tighter spreads while still maintaining profitability - the gains from providing liquidity to uninformed traders can more easily cover the reduced losses to informed traders. This economic mechanism reconciles the simultaneous decrease in trading volume and spreads: while the removal of perpetual contracts reduces overall trading activity by deterring informed traders, it improves spot market liquidity through tighter spreads as market makers adjust their optimal pricing strategy to the new information environment.

6 The Effects of Introducing Perpetual Contracts

Complementary to Huobi's termination of perpetual contracts, we investigate the impact of perpetual contract introduction on spot market quality. We hypothesize that introducing perpetual contract has the opposite effects of terminating perpetual contracts: increased trading volume and wider percent quoted spreads. To test this hypothesis, we collect data of 95 introduction events of perpetual contracts for 75 token pairs across three major exchanges: Binance, Huobi, and OKEX. This research sample represents the complete set of events in our research sample with available order book data, addressing potential sample selection concerns. The timing of the perpetual contract introduction spans from December 2019 to September 2022, covering various market conditions including bull runs and bear markets. Table A1 lists all 95 perpetual contract introduction events and provides information on the exchange, introduction date, and trading pair.

The introduction of perpetual contracts may be endogenous to market quality, as exchanges may strategically choose to introduce these contracts for cryptocurrencies with larger trading volumes to maximize transaction fee revenues. To address these endogeneity concerns, we carefully construct our control group. For each introduction event, we consider control groups both of tokens with future introductions ("not-yet-treated") and of those that never received treatment during our sample period ("never-treated"). Exchanges like Coinbase, which lacked perpetual contract trading throughout our study period, serve as a "never-treated" control. The inclusion of never-treated units provides a baseline for market evolution in the absence of perpetual contracts, while the "not-yet-treated" group helps control for selection into treatment. Additionally, comparing the same tokens

[11] 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.

across exchanges with different perpetual contract status enables us to isolate the effects specifically attributable to perpetual contracts, as the underlying token characteristics remain constant.

Methodologically, regarding the effectiveness of staggered Differences-in-Differences (DiD) method, Baker, Larcker, and Wang (2022) emphasize that non-staggered DiD is applicable for analyzing both homogeneous and heterogeneous treatment effects, which applies to our analyses of Huobi's sudden 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 and tokens. Baker et al. (2022) argue that consistent results across diverse empirical settings enhance the credibility of the results of staggered DiD. Aligning with this perspective, our findings demonstrate consistency across different settings, including perpetual trading termination, staggered introductions, and the funding time experiment. We investigate the causal effect of perpetual contract trading on spot market quality from multiple angles with various methodologies, and arrive at consistent conclusions, confirming the robustness of our findings. 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 US, highlighting the effectiveness of staggered DiD methodology in our study.

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 methodology in Callaway and Sant'Anna (2021) to obtain the estimates of our staggered DiD results.[12]

We present the results of our staggered DiD analyses in Table 4. The effects of introducing perpetual contracts on the spot market quality are both economically and statistically (at 1%) significant. The introduction of perpetual contracts is associated with 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. Perpetual contract introductions also decrease order imbalance by 0.05 (or 9% of the level), raises the probability of informed trading by 1.1 percentage points (or by 16%) and the relative spread by 0.85 percentage points (or 200%) in the spot market.

[Table 4 about here.]

We present the dynamic effects of introducing perpetual contracts on the spot market in Figures A5-A8, using estimates in Callaway and Sant'Anna (2021) for each outcome. The results provide

[12]Technically, we use the R implementation provided by the authors (package 'did').

compelling evidence supporting our identification strategy and main findings. First, our market measures (trading volume, percent quoted spread, order imbalance, and VPIN) demonstrate parallel trends prior to introduction of perpetual contracts, with coefficients statistically indistinguishable from zero in the pre-treatment period. Second, they show immediate and persistent treatment effects following introduction. Figure A5 shows a sharp increase in trading volume that persists throughout the post-treatment period. Figure A7 reveals an immediate uptick in informed trading probability, suggesting that perpetual contracts attract sophisticated traders. Figure A8 documents a significant widening of percentage quoted spreads, consistent with market makers' response to increased informed trading risk. These dynamic patterns confirm our hypothesis that introducing perpetual contracts has effects exactly opposite to those observed following termination, leading to simultaneous increases in trading volume and percentage quoted spreads.

7 Examining the Information Channel

Our findings reveal a consistent pattern—higher trading volume and wider bid-ask spreads in spot markets following the introduction of perpetual contracts, and their decline upon contract termination. This pattern may appear puzzling since higher trading volume typically suggests increased liquidity, while wider spreads indicate higher transaction costs and reduced liquidity. Drawing upon information-based microstructure theory (Glosten and Milgrom, 1985; O'Hara, 1995; Easley et al., 1996), we explain this apparent paradox: increases in informed, or "toxic," trading volume can lead to wider bid-ask spreads. We argue that perpetual contracts increase informed trading in the spot market, making the increased volume more "toxic." Consequently, market makers optimally widen bid-ask spreads to protect against adverse selection.

Based on this framework, we develop two testable hypotheses. First, we hypothesize that larger funding fee magnitudes strengthen perpetual contracts' impact on spot markets, as the funding fee magnitude reflects market information revealed through traders' willingness to pay. When informed traders possess stronger information advantages, informed trading increases, leading market makers to widen bid-ask spreads. Second, we leverage pump-and-dump events as independent information shocks to test our channel. Since these events involve exogenous misinformation distribution to markets, they temporarily increase certain traders' information advantages. If our information channel hypothesis is valid, pump-and-dump events should generate effects consistent with perpetual contract introductions—increased spot market volume, wider spreads, and higher VPIN. In Appendix A.4, we formalize these intuitions in a market microstructure model.

7.1 Perpetual Funding Rates and Spot Market Quality

We examine how funding rate magnitudes affect the U-shaped pattern of volumes, spreads, and VPIN in spot markets. Given funding rates' role as the price of holding cryptocurrencies and a powerful aggregator of market supply and demand information, as emphasized in Section 2, we anticipate that perpetual contracts' impact intensifies with larger funding fee magnitudes. Larger funding fees attract more arbitrage activities and reflect more market information, 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.

To measure funding fees, we construct a proxy for each exchange-token pair:

$$FRate_{e,i,t} = \frac{P^{\text{perp}}_{e,i,t} - P^{\text{spot}}_{e,i,t}}{P^{\text{spot}}_{e,i,t}}, \tag{3}$$

where $P^{\text{perp}}_{e,i,t}$ denotes the perpetual futures contract price and $P^{\text{spot}}_{e,i,t}$ refers to the spot price for token i on exchange e at hour t. This proxy captures the perpetual-spot price deviation, which fundamentally drives the funding fee mechanism. When positive, long position holders pay funding fees to short position holders; when negative, the payment flows in the opposite direction.

We employ two analyses to investigate how the funding time cycle relates to funding rates. First, we examine funding time effects across funding rate proxy quintiles to uncover potential nonlinear patterns. Second, we implement a treatment effect regression using the funding rate proxy prior to a funding time (or its absolute value) as the treatment intensity. Within each funding rate quintile, we estimate:

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

where $Market\_Quality_{e,i,t}$ measures hourly outcomes relative to pre-funding averages, $\gamma_{e,i}$ captures exchange-token fixed effects, and η_t represents eight-hour window fixed effects. The treatment indicator D_t identifies observations within the funding time window, with a focus on the first hour after funding time. Standard errors are clustered at the exchange-token level.

We find a nonlinear relationship between funding rates and spot market effects, with Q1 (lowest rates) and Q5 (highest rates) showing stronger effects on trading volume and percentage quoted spreads compared to Q3 (median rates). This U-shaped pattern intensifies with larger funding rate magnitudes, supporting our information channel hypothesis that larger price deviations reflect more information content and lead to more pronounced spot market effects through increased informed trading.

[Table 5 about here.]

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

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

where $Market\_Quality_{e,i,t}$ denotes the outcome at time t for token i on exchange e, $\gamma_{e,i}$ captures exchange-token fixed effects, and η_t represents 8-hour window fixed effects. $FRate_{e,i,t}$ equals zero during non-funding hours and takes the average funding rate proxy (or its absolute value) from the previous 8-hour window during funding times. Standard errors are clustered at the exchange-token level.

[Table 6 about here.]

Table 6 presents these results. Both the funding rate and its magnitude are positively associated with funding time effects on spot trading volume, percentage quoted spread, and VPIN. A one percentage point increase in funding rate magnitude is associated with 3.9 and 12.2 percentage point increases in informed trading probability and spread width, respectively, significant at the 1% level. The absolute value of funding rates shows stronger effects than raw funding rates, consistent with the nonlinear pattern in Table 5 where extreme quintiles (Q1 and Q5) exhibit the most pronounced effects. Additionally, the information effect is stronger the higher the spot price relative to the perpetual market price emphasizing the role short-selling and access to leverage inherent in perpetual markets play in price discovery. These findings further support our information channel hypothesis.

7.2 The Effects of Pump-and-Dump Events

To complement our funding rate analysis, we examine pump-and-dump (P&D) events as exogenous information shocks to test our information channel hypothesis. While funding rates provide indirect evidence of information flows, P&D events offer a unique advantage: they create clear, measurable episodes of information asymmetry through the mechanical distribution of misinformation. This setting allows us to observe how market quality measures respond to well-identified information advantages, providing an independent validation of our findings on perpetual contracts' effects.

P&D schemes in cryptocurrency markets typically involve coordinated dissemination of fake news to artificially inflate prices. The market's relatively weak regulatory framework makes these events particularly prevalent, creating natural experiments for studying information shocks. If our hypothesis that perpetual contracts affect spot markets through an information channel is valid, P&D events should generate similar effects: increased trading volumes, wider spreads, and higher VPIN, as both settings enhance traders' ability to profit from information advantages.

We examine the September 2021 Litecoin-Walmart incident as a significant case. On September 13, 2021, a fake press release claimed Walmart had partnered with Litecoin, generating substantial price movement before being debunked. This event represents an ideal natural experiment as it creates a clear, unanticipated shock to information asymmetry, where certain traders temporarily possessed definitive information advantages regarding the news's falsity.

Figure 8 documents market quality dynamics around this event. Panel (a) shows Litecoin's volume-weighted average price spike and subsequent decline. Trading volume (Panel b) increases significantly, while percentage quoted spreads widen (Panel c), indicating deteriorating liquidity. The VPIN metric (Panel d), calculated using 5-bucket, 25-minute rolling averages, shows elevated informed trading levels.

These P&D effects mirror our findings on perpetual contract introductions, with both settings demonstrating how enhanced information advantages affect market quality. In P&D events, certain traders gain information advantages through access to fake news distribution, while perpetual contracts provide traders with enhanced capabilities to exploit their information through leverage, short-selling, and faster execution. Despite the different sources of information advantage–artificial creation in P&D events versus improved utilization in perpetual contracts–both scenarios lead to similar market outcomes. In each case, the enhanced ability to profit from information advantages increases informed trading, prompting market makers to widen spreads against heightened adverse selection risk while simultaneously generating higher trading volume as informed traders actively exploit their advantages.

Together, our analyses of funding rates and P&D events provide consistent evidence for an information-based explanation of perpetual contracts' effects. Larger funding rates intensify funding cycle effects on spot markets, while P&D events generate parallel patterns of increased volume, wider spreads, and elevated VPIN. These complementary findings support our central hypothesis that perpetual contracts increase informed trading, leading market makers to optimally widen spreads against heightened adverse selection risks.

[Figure 8 about here.]

8 Conclusion

Perpetual contracts represent a novel financial innovation implemented in cryptocurrency markets. As depicted in Shiller (1993), these contracts have potential applications beyond cryptocurrency markets, extending to non-tradeable assets such as real estate, human capital, and economic indicators like CPI. Leveraging high-frequency order book data from cryptocurrency exchanges, we discover significant effects of perpetual contracts' eight-hour funding cycle on spot market quality. We document a U-shaped pattern in trading volumes and percent quoted spreads over this funding cycle, with effects that are both economically and statistically significant. This finding carries causal interpretation since the eight-hour funding cycle is a unique feature of perpetual contracts and unlikely to be driven by other factors systematically across exchanges, tokens, and time periods.

Our study provides the first identification of perpetual contracts' causal effects on spot markets through multiple approaches. We leverage Huobi's termination of perpetual contract trading in October 2021 (while maintaining spot market trading) as a natural experiment, establishing a Difference-in-Difference strategy with a carefully constructed control group comprising Binance, OKEX, Kucoin, and Bibox, which maintained both perpetual and spot trading. Following the termination of perpetual contract trading, Huobi's cryptocurrency spot markets experienced decreased trading volume and narrower percentage quoted spreads compared to the control group. Furthermore, employing a staggered Difference-in-Difference methodology to study perpetual contract introductions, we find increased spot market trading volume and wider percentage quoted spreads—effects exactly opposite to those observed following termination.

These findings present an apparent paradox: higher trading volume typically indicates improved liquidity, while wider spreads suggest higher transaction costs and reduced liquidity. To reconcile this, we turn to information-based market microstructure theories, proposing that these dual effects arise from increased informed trading in the spot market. Market makers, facing higher adverse selection risks, optimally widen bid-ask spreads to ensure profits from noise traders can offset losses to informed traders. We test this framework through two hypotheses: first, that funding cycle effects intensify with larger funding rate magnitudes, reflecting greater information content; and second, that pump-and-dump events, as exogenous information shocks, generate similar patterns of increased trading volume, wider spreads, and more informed trading. Our empirical evidence supports both hypotheses, validating our information-based explanation.

Our study takes initiative in understanding the mechanisms underlying perpetual contracts and provides the first direct causal evidence of their impact on spot markets. The findings offer general economic insights about perpetual contracts, whose potential extends far beyond their current implementation in cryptocurrency markets. Their implementation across these diverse assets could significantly enhance price discovery and hedging effectiveness, contributing to broader social welfare. Given the novelty of perpetual contracts, our insights into their effects on spot markets can inform theoretical studies, guide their implementation in other contexts, and shape regulatory policies.

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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 reports hourly market quality measures for perpetual and spot markets. Dollar Volume represents total transaction value in five-minute bins. Order Imbalance measures the normalized difference between buy and sell volumes over 12 five-minute windows. Percentage Quoted Spread is the time-weighted bid-ask spread relative to midpoint price. VPIN (Volume-synchronized Probability of INformed trading) estimates informed trading probability using volume-bucketed trade imbalances over 12 five-minute windows, with higher values indicating greater adverse selection risk. The sample includes up to 104 million observations. Asterisks (***, **, *) denote significance at 1%, 5%, and 10% using heteroskedasticity and autocorrelation consistent standard errors.

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. The sample size is 1 million observations with 8-hour windows randomly sampled from the dataset.

Table 3: Effect of Huobi Perpetual Trading Termination on Spot Market Quality: DiD with a Synthetic Control

Outcome	[-1,1]	[-3,3]	[-7,7]	[-14,14]	[-30,30]
Dollar Volume	-21,881	-47,555	-102,173***	-98,927**	-110,367**
	(-0.26)	(-0.89)	(-2.62)	(-2.08)	(-2.20)
Order Imbalance 5	0.034**	0.046***	0.049**	0.036*	0.026
	(2.23)	(2.66)	(2.50)	(1.90)	(1.48)
Order Imbalance 12	0.033**	0.044**	0.047**	0.035*	0.025
	(2.16)	(2.55)	(2.40)	(1.82)	(1.44)
Percentage Quoted Spread (%)	-0.020***	-0.024***	-0.013***	-0.008**	-0.005
	(-2.70)	(-3.19)	(-3.66)	(-2.47)	(-1.47)
VPIN 5 (%)	0.27	0.86	1.10	1.03	1.45
	(0.37)	(0.76)	(1.03)	(0.90)	(1.17)
VPIN 12 (%)	0.30	0.88	1.08	1.00	1.42
	(0.41)	(0.79)	(1.01)	(0.88)	(1.15)

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 token-treatment-group level. Sample sizes are 78, 182, 390, 754 and 1586 observations for each window size respectively.

Table 4: Staggered Differences-in-Differences: Causal Effect of Perpetual Contract Introduction on Spot Market Quality

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 12,028 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.

Table 5: 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. The sample is 560,191 observations.

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

Market Quality Measure	$FRate$	$\|FRate\|$
Dollar Volume	-9.61***	5.97***
	-5.27	6.13
Order Imbalance 5	1.335***	-1.37***
	4.65	-3.55
Order Imbalance 12	0.96***	-1.26***
	3.47	-4.28
Percentage Quoted Spread	-2.731***	5.19***
	-5.64	7.92
VPIN 5	-5.28***	5.33***
	-7.74	5.50
VPIN 12	-4.89***	4.99***
	-8.02	5.39

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. The sample size is 1 million observations with 8-hour windows randomly sampled from the dataset.

Figures

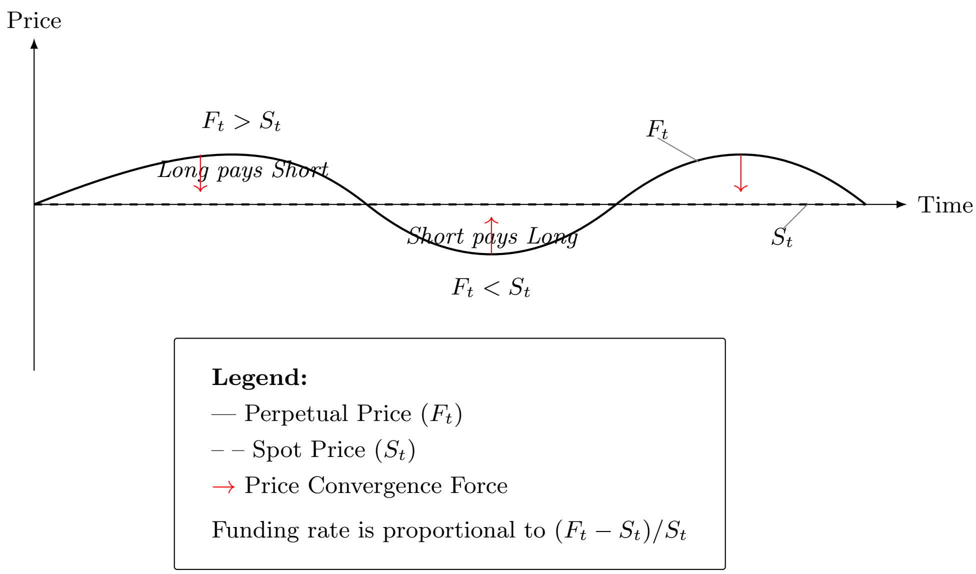


Figure 1: Perpetual Futures Funding Rate Mechanism

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.

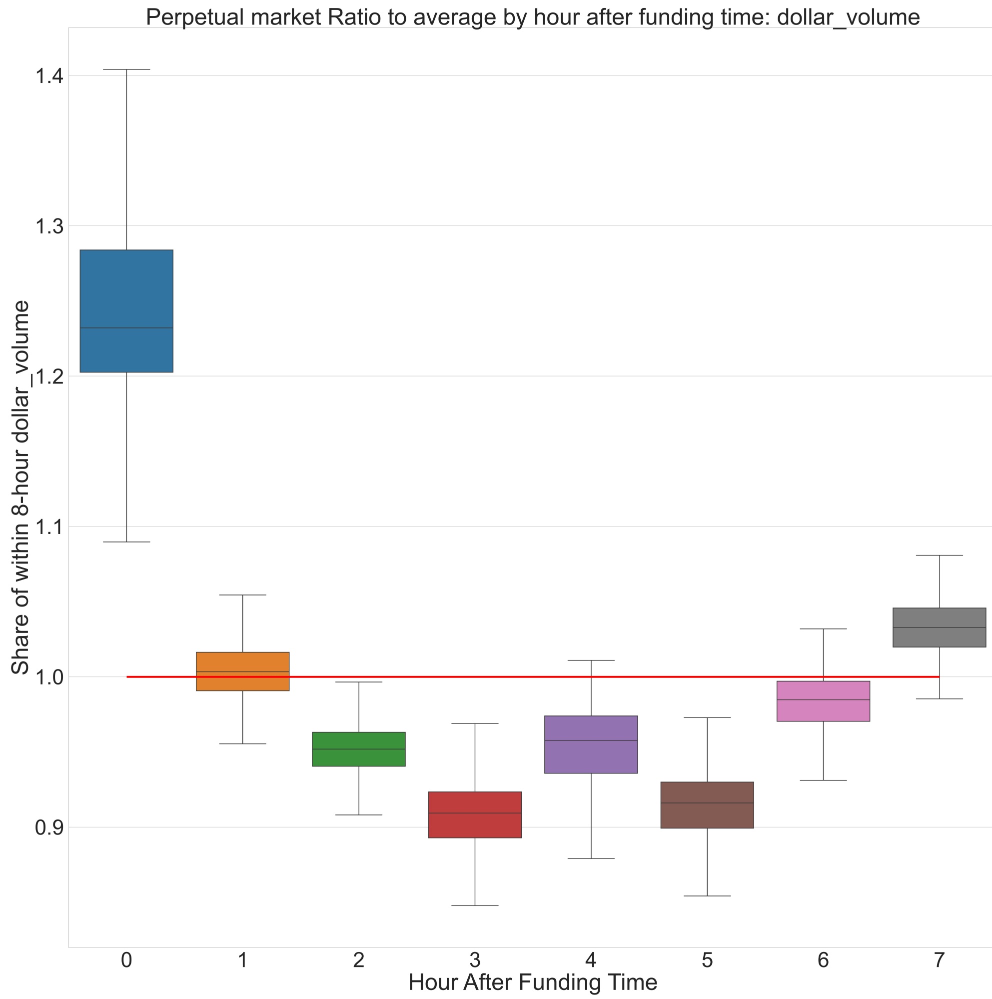


Figure 2: Hourly Trading Volume Ratios to 8-Hour Average in Perpetual Markets

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.

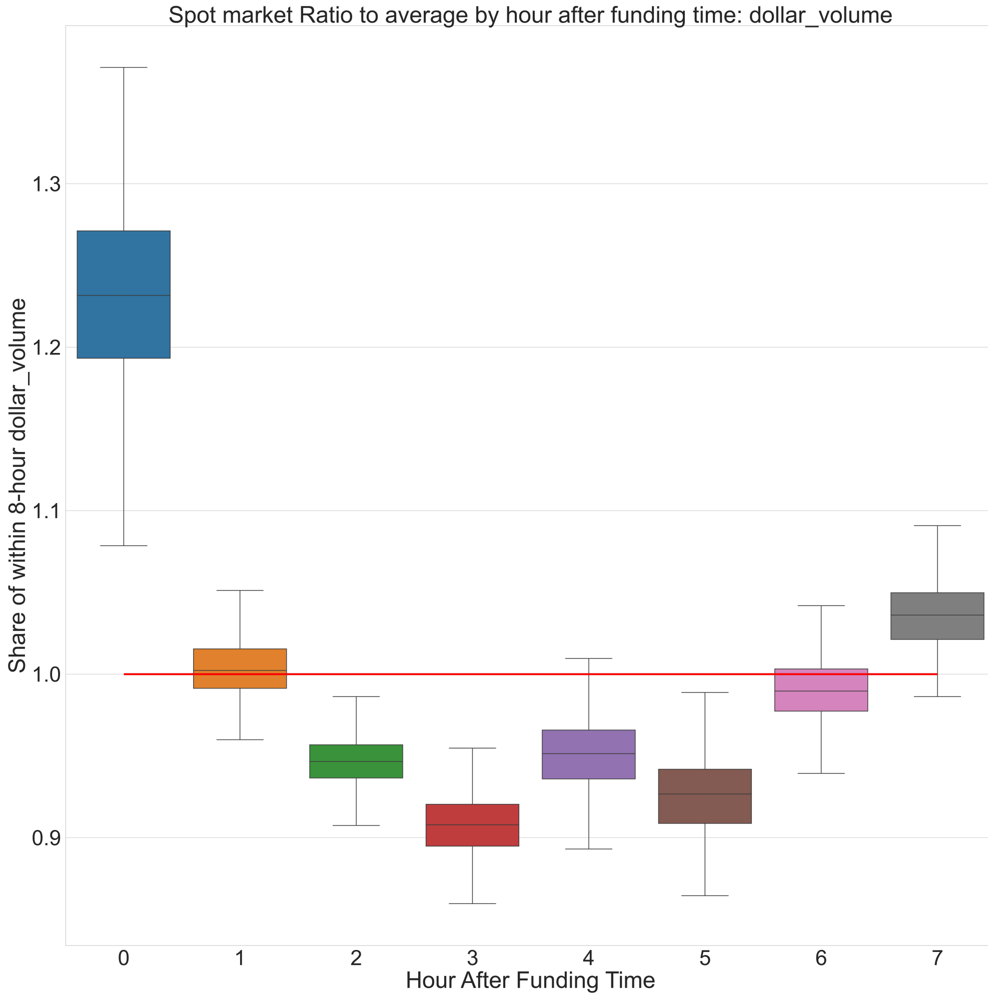


Figure 3: Spot Market Dollar Volume by Hour After Funding Time

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.

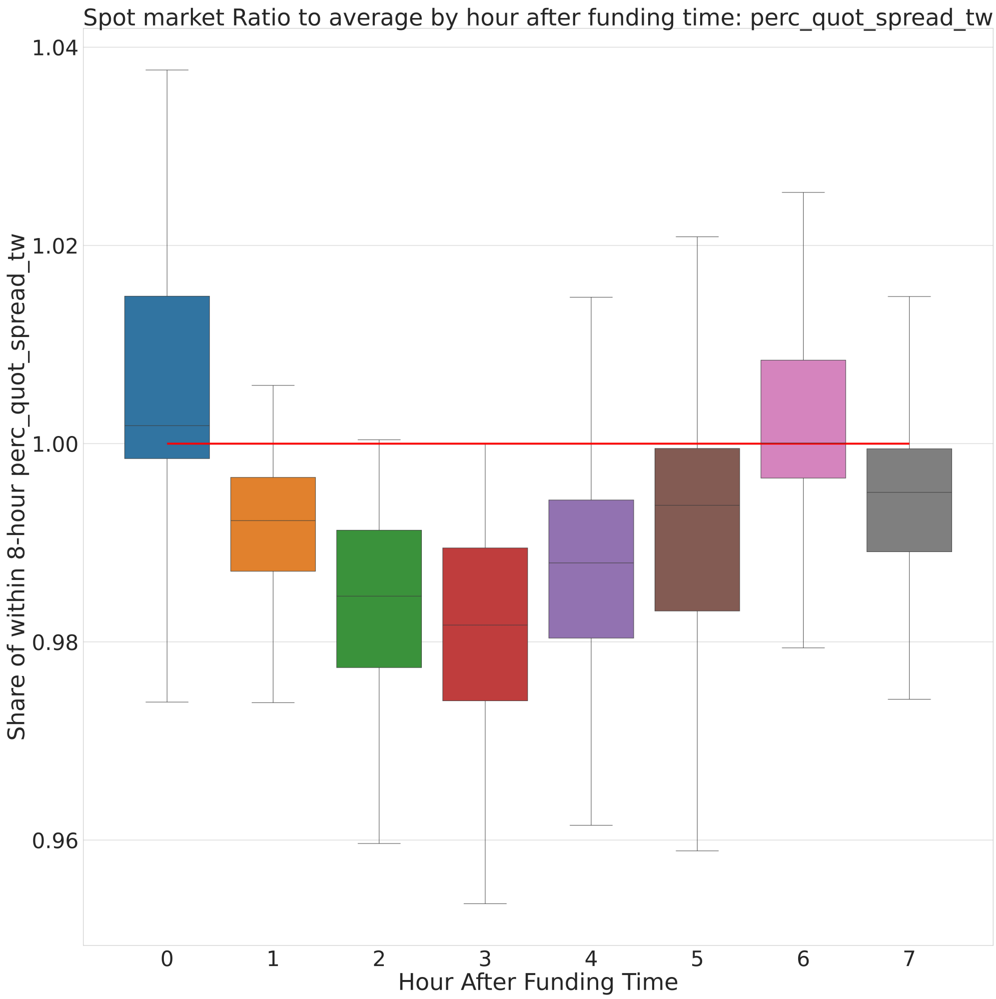


Figure 4: Spot Market Percentage Quoted Spread by Hour After Funding Time

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.

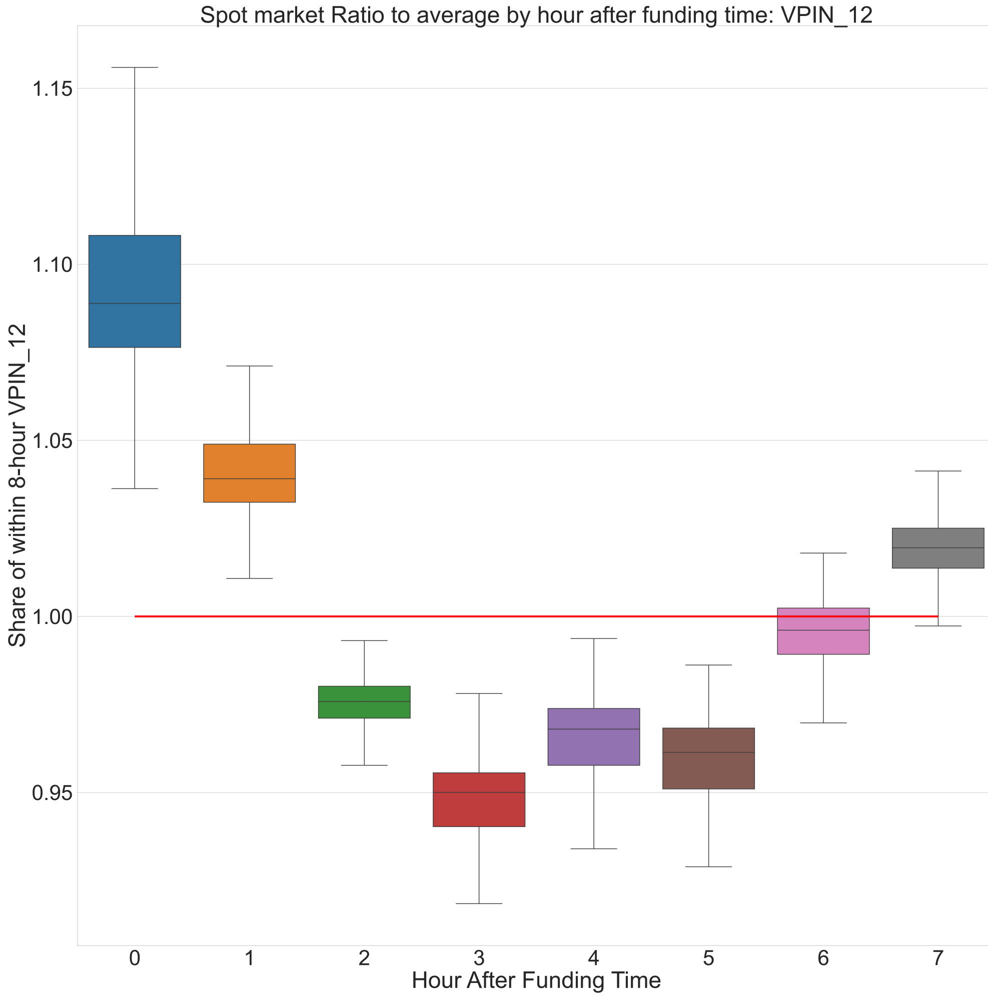


Figure 5: Spot Market $VPIN$ by Hour After Funding Time

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.

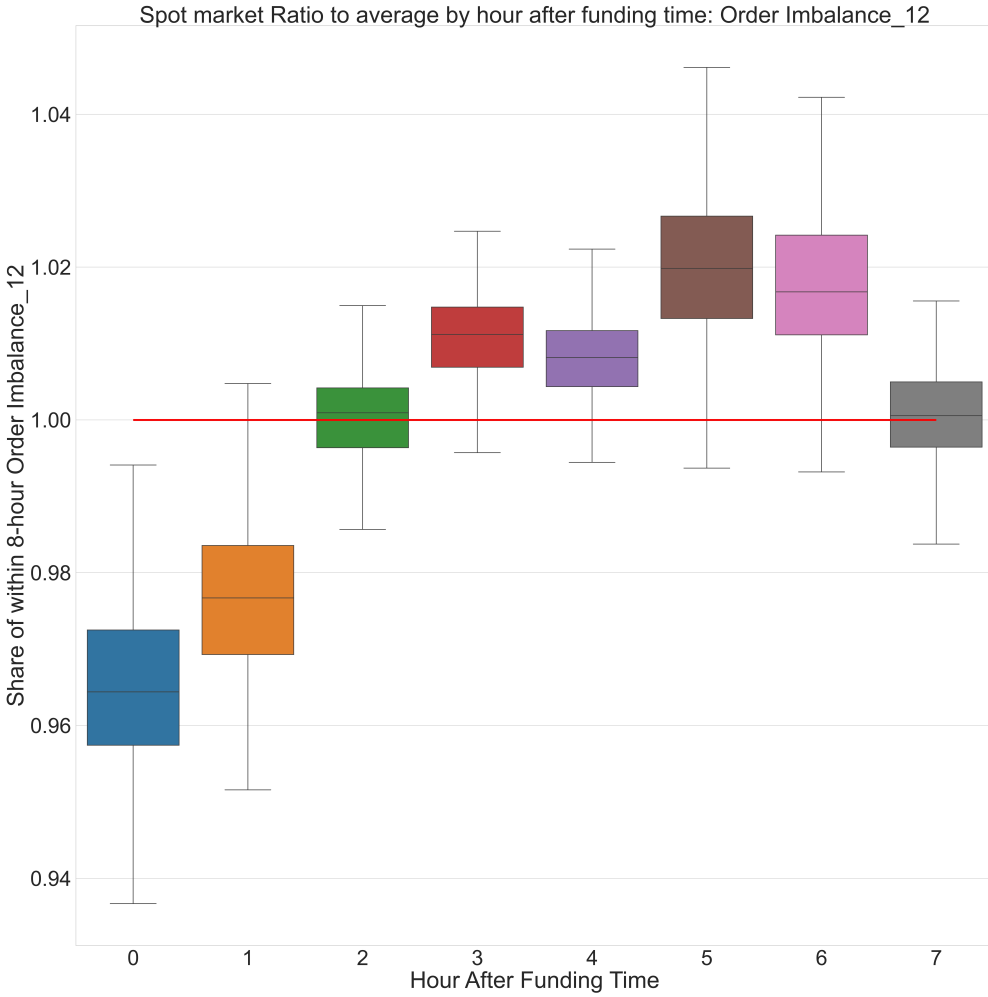


Figure 6: Spot Market Order Imbalance by Hour After Funding Time

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.

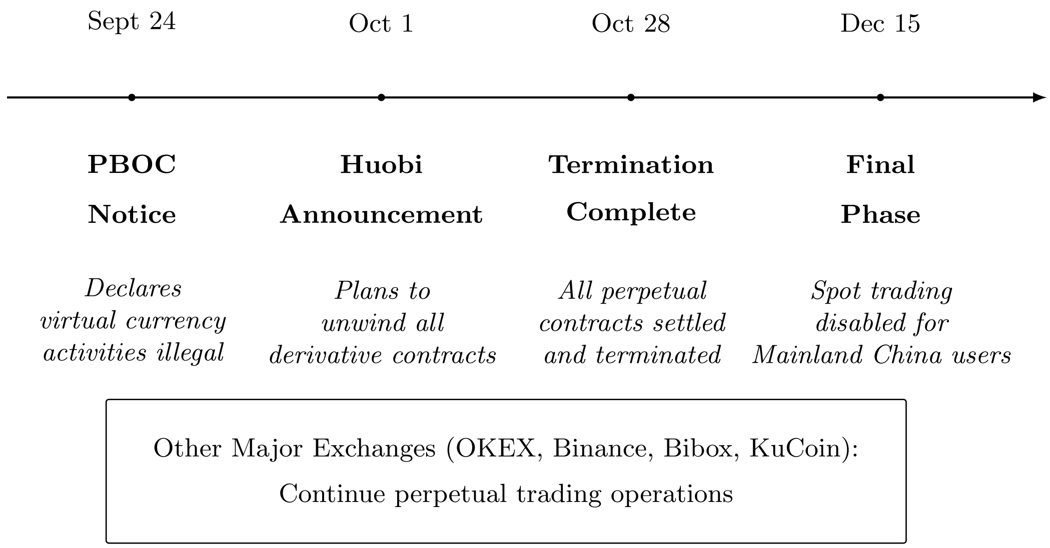
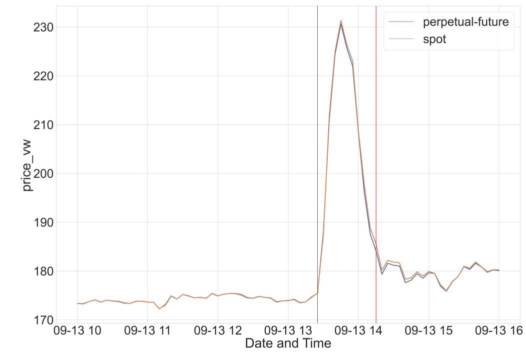
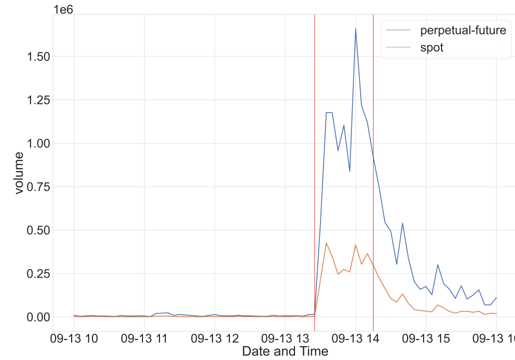


Figure 7: Timeline of Regulatory Events and Huobi's Response

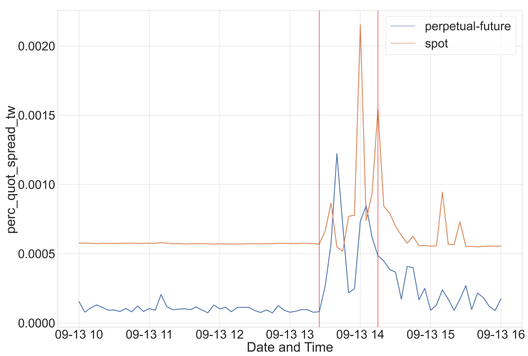
Notes: This figure illustrates the timeline of events surrounding Huobi's termination of perpetual futures trading in response to Chinese regulatory actions in 2021. Other major exchanges maintained their perpetual trading operations during this period.



(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

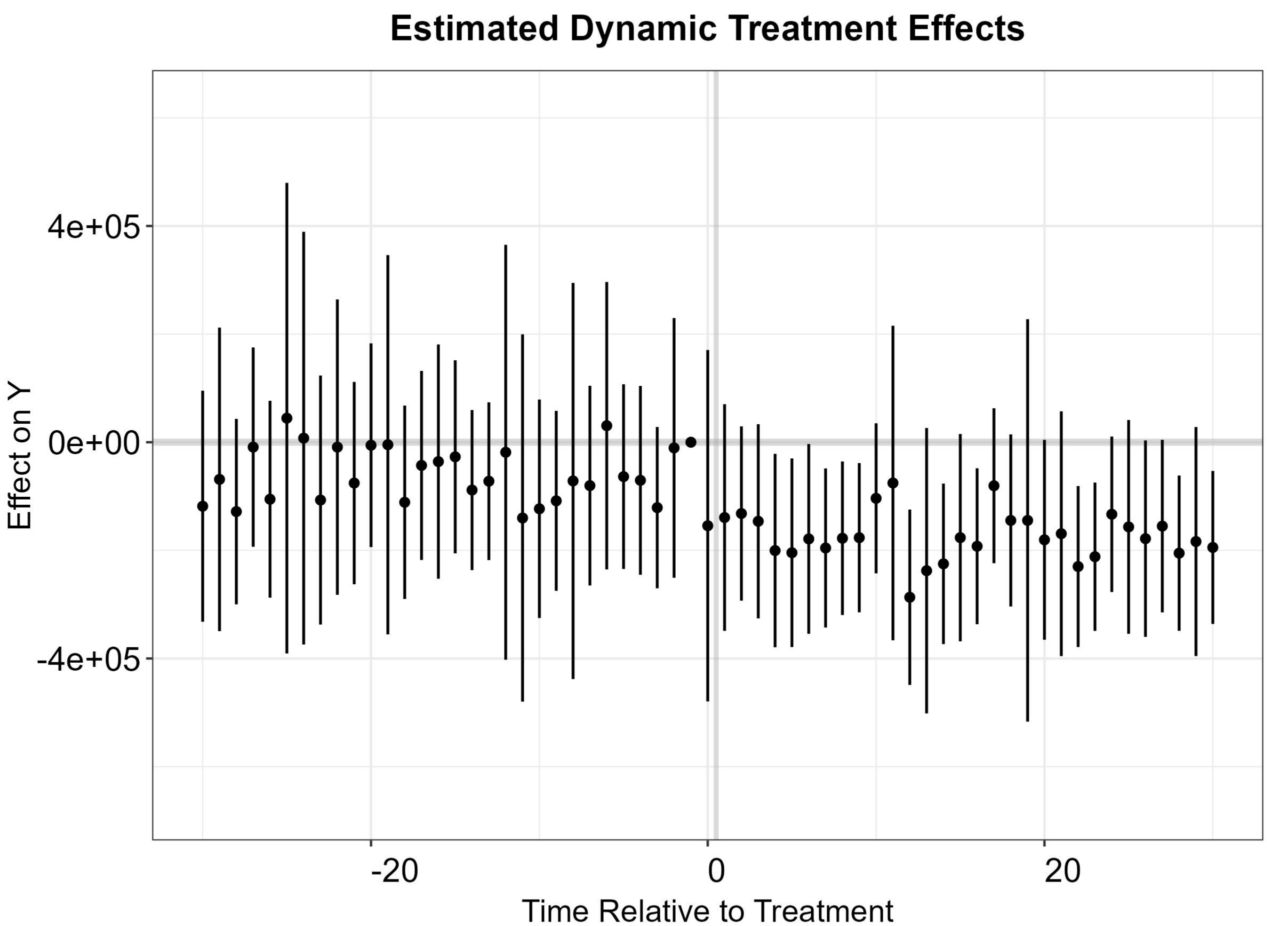


Figure A1: Dynamic Effects: Huobi and synthetic control trading Volume around Huobi perpetual trading termination.

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.

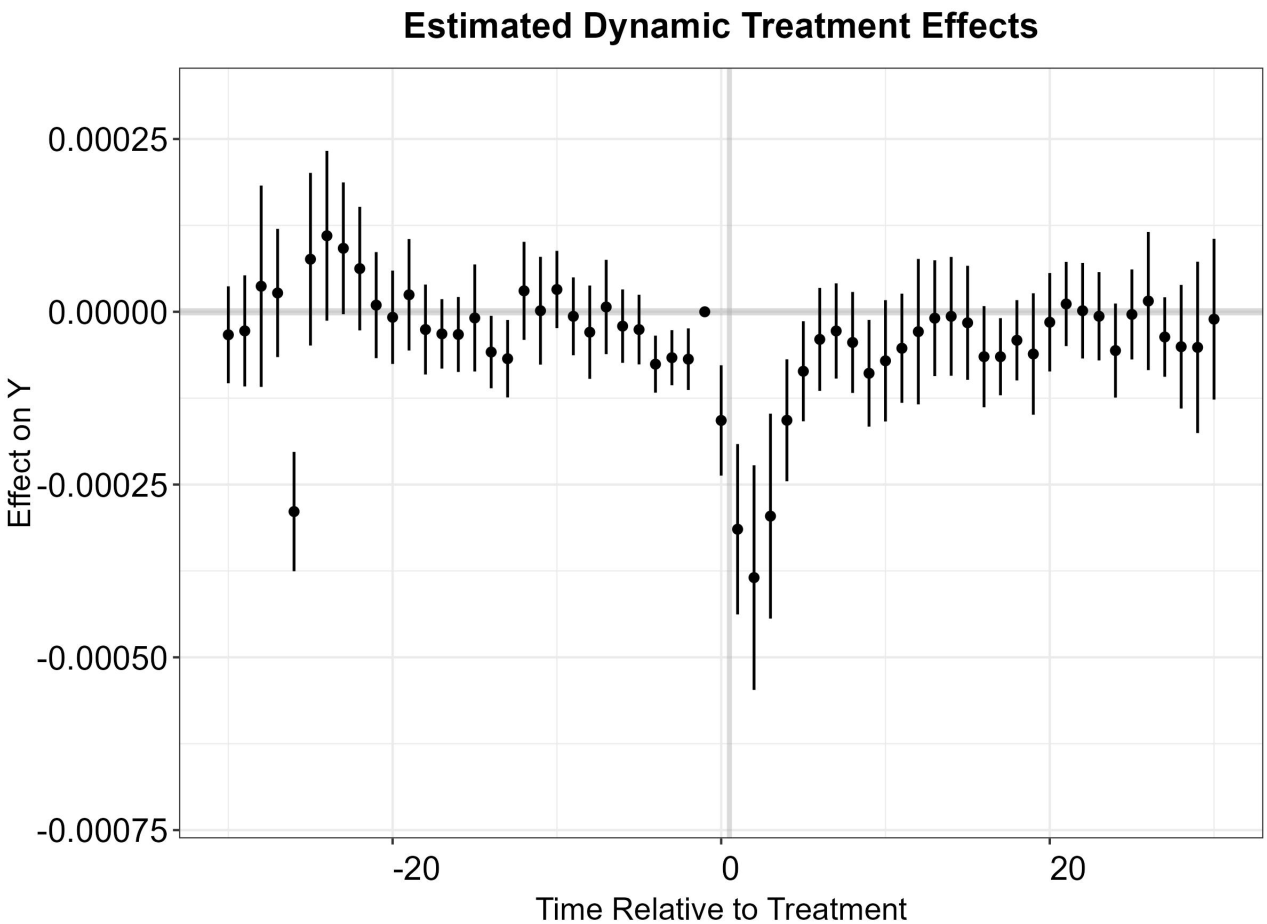


Figure A2: Dynamic Effects: Huobi and synthetic control Percentage Quoted Spread around Huobi perpetual trading termination.

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.

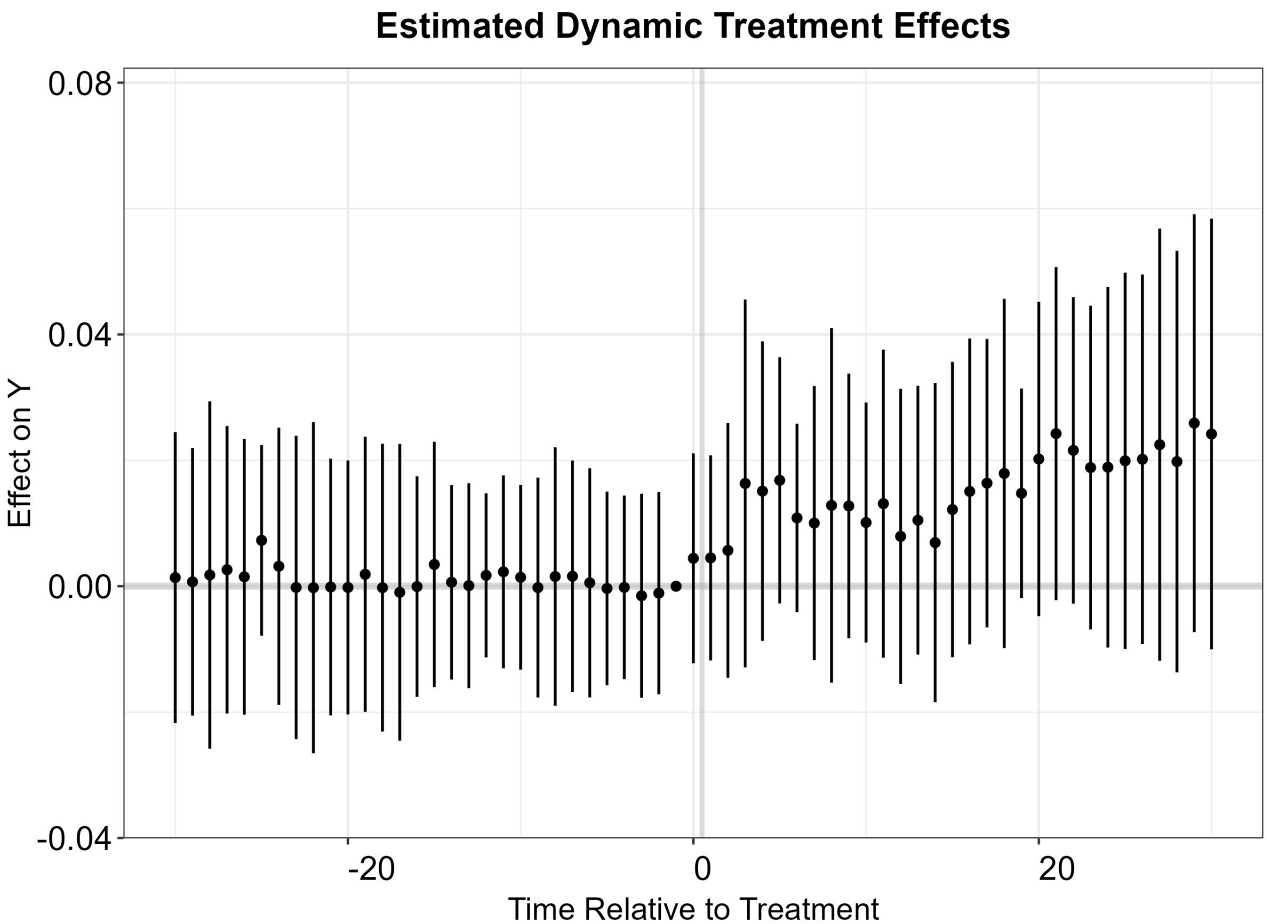


Figure A3: Dynamic Effects: Huobi and synthetic control Probability of Informed Trading (VPIN) around Huobi perpetual trading termination.

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.

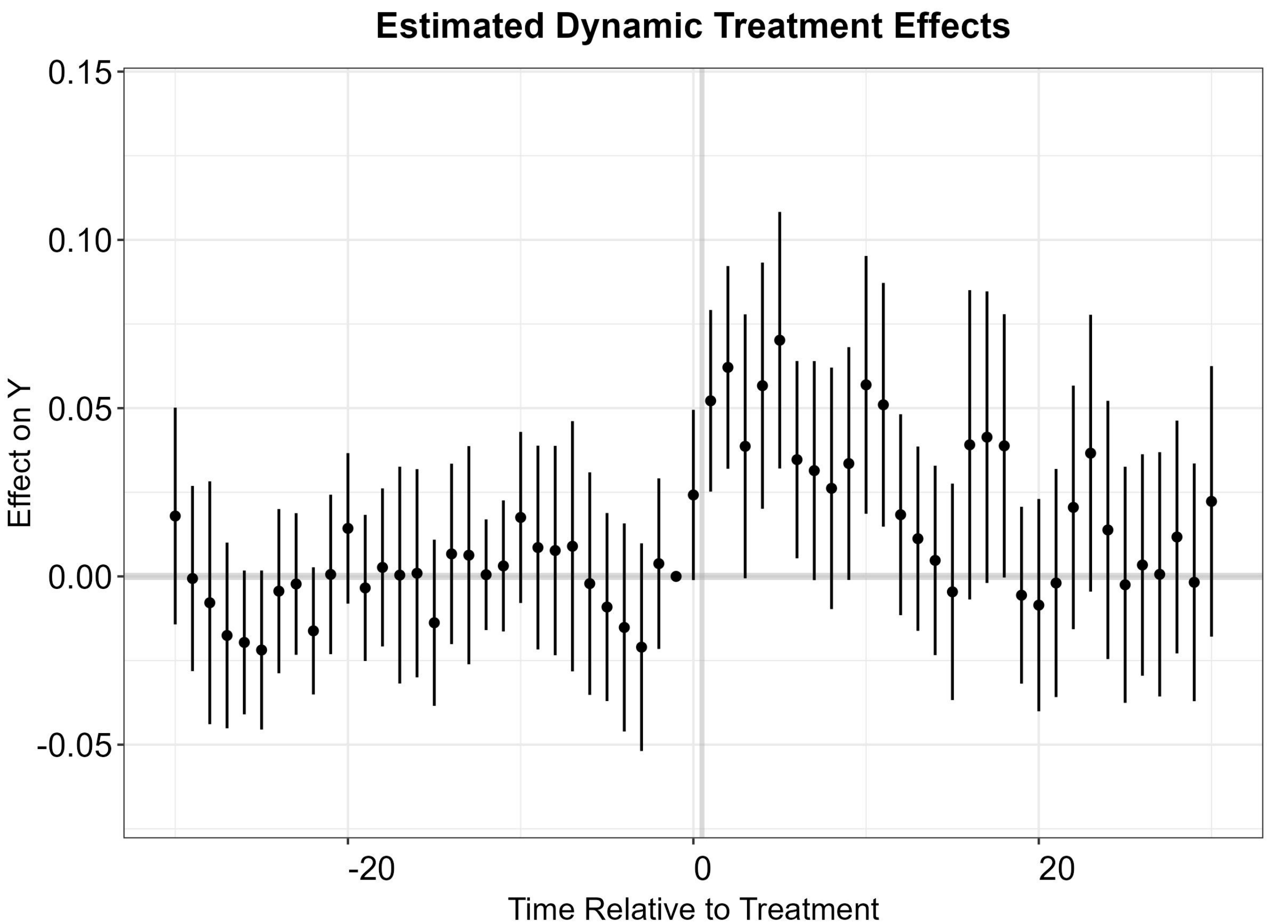


Figure A4: Dynamic Effects: Huobi and synthetic control Order Imbalance (12) around Huobi perpetual trading termination.

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

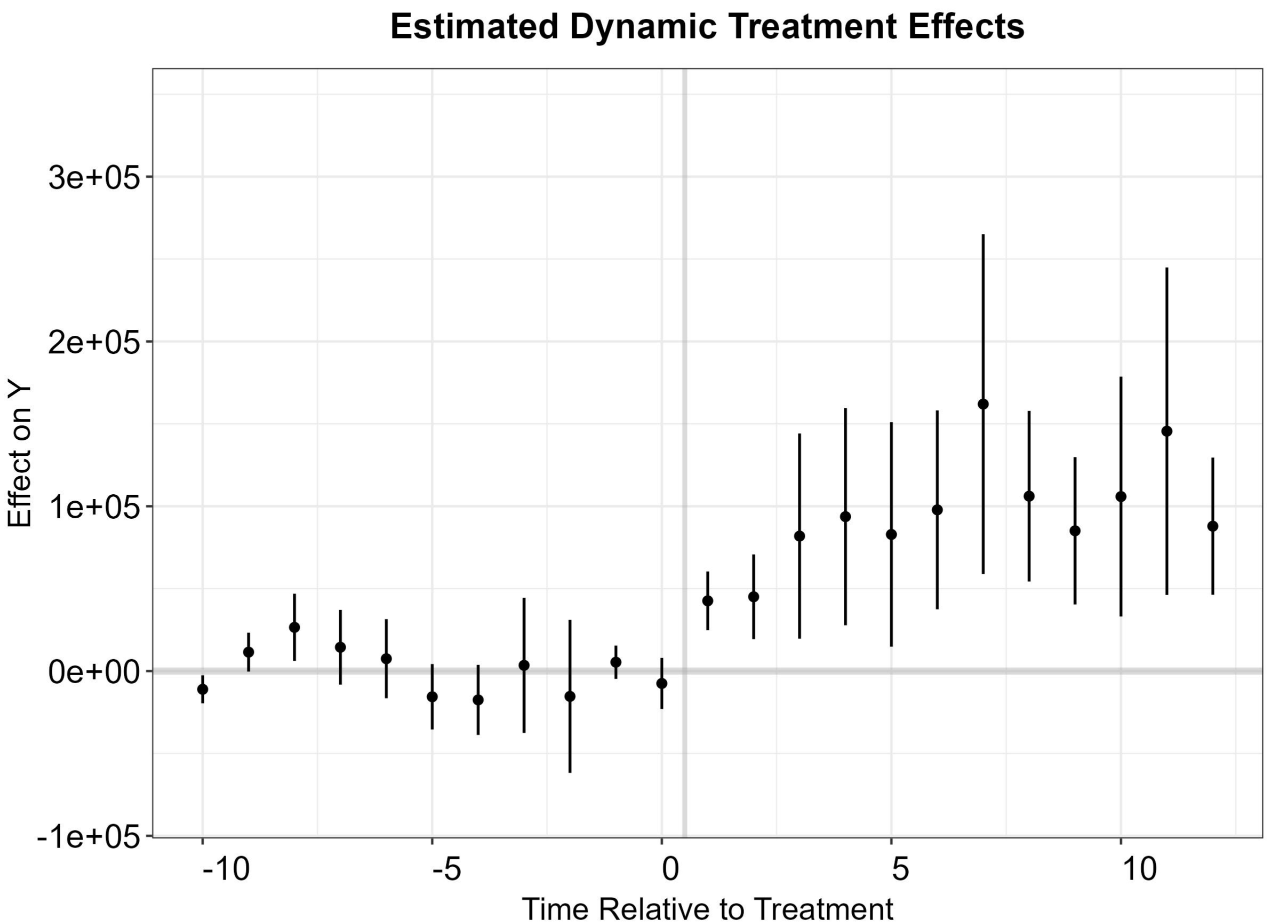


Figure A5: Perpetual introduction dollar volume Callaway and Sant'Anna (2021) dynamic effects.

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.

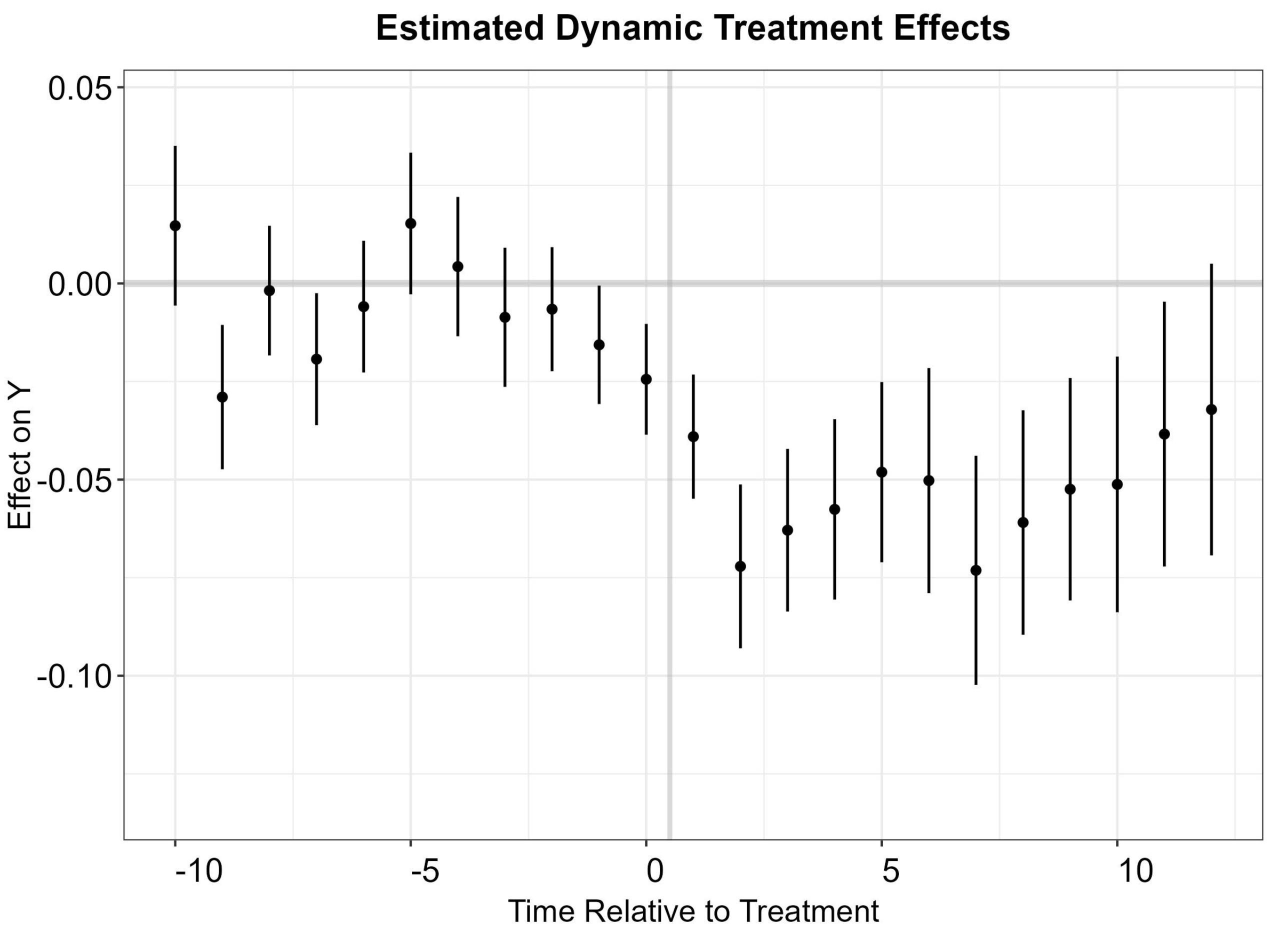


Figure A6: Perpetual introduction order imbalance volume Callaway and Sant'Anna (2021) dynamic effects.

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.

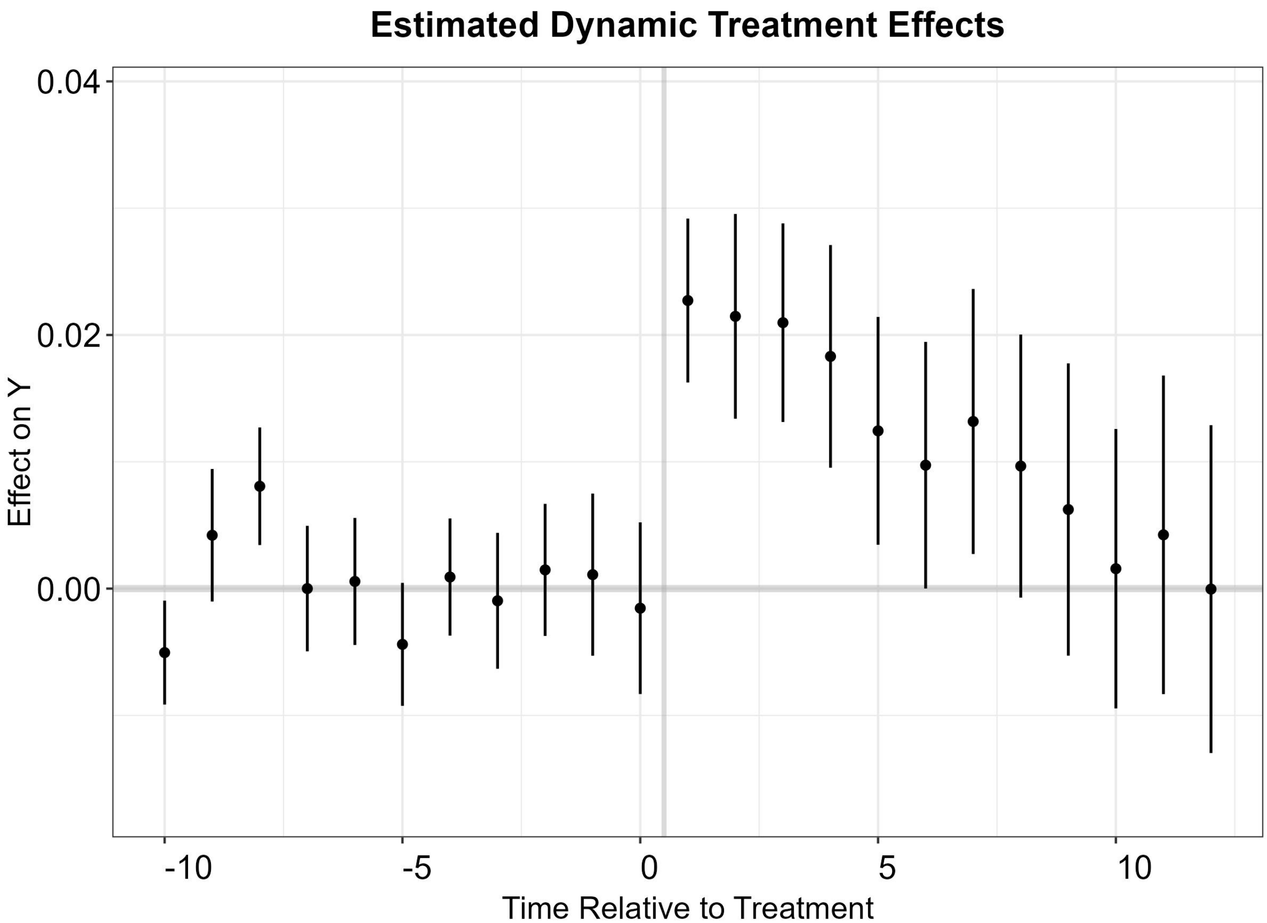


Figure A7: Perpetual introduction probability of informed trading (VPIN 5) Callaway and Sant'Anna (2021) dynamic effects.

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.

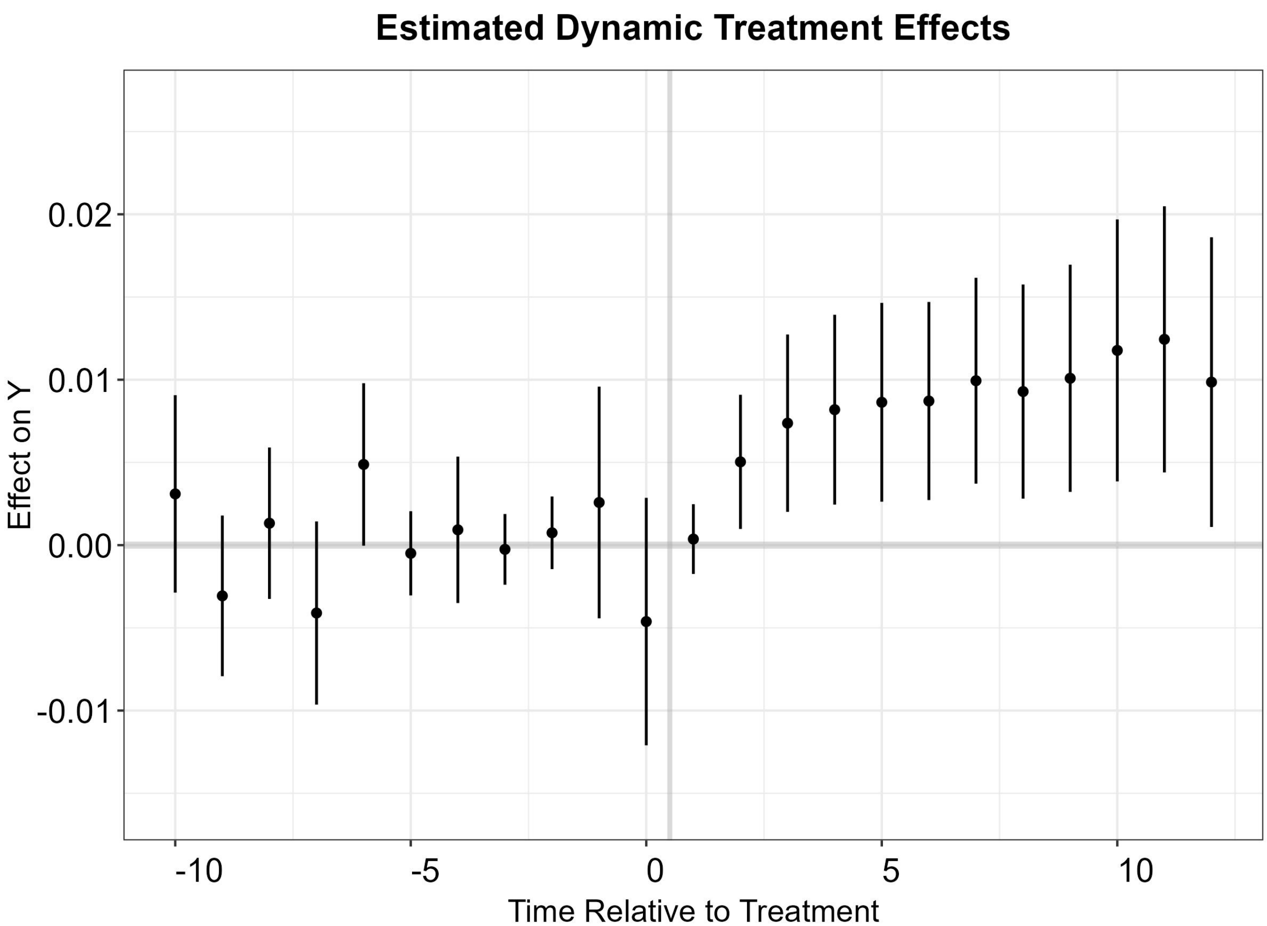


Figure A8: Perpetual introduction percentage quoted spread Callaway and Sant'Anna (2021) dynamic effects.

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

A.4 Theoretical Framework

In this section, we develop a framework of information-based market microstructure theories 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.