High-Frequency Price Discovery in Fragmented Crypto Markets

Carol Alexander[a,b,c] Daniel Heck[a] Andreas Kaeck[a] Ryan Riordan[d]

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Abstract

We study price formation in an electronic market that operates without order-protection rules, consolidated reporting, or mandatory routing, allowing price discovery to be observed when cross-venue integration is not institutionally enforced. Using tick-by-tick limit order book data from major centralised trading venues, we estimate the immediate and permanent impacts of market orders and limit-order submissions/cancellations, and within and across venues, at millisecond horizons. We combine high-frequency model calibrations and resultant measures to identify how information is transmitted across fragmented venues and how integration emerges as sampling horizons increase. At ultra-high frequencies, cross-venue return correlations are close to zero and price impacts are strongly asymmetric. Integration emerges at lower frequencies, typically at horizons of around one second. By isolating order-level mechanisms in a setting where arbitrage is difficult and costly, the paper refines existing microstructure evidence on limit orders and cross-market price discovery in modern electronic markets.

Keywords: Bitcoin, Limit orders, Market integration, Order flow, Price impact

JEL classification: C22, C5, E42, F31, G1, G2

[a] University of Sussex Business School, UK
[b] Exponential Science Foundation
[c] Corresponding author (email: c.alexander@sussex.ac.uk)
[d] Ludwig Maximilian University Munich, Germany and Queen's University, Canada

1 Introduction

Understanding how prices form and how information is incorporated into prices is a central concern in market microstructure. In order-driven markets, prices emerge from the interaction of market orders, limit-order submissions, and cancellations, all coordinated through the limit order book. A large empirical literature documents that order flow contains information about fundamentals and liquidity conditions, and that different order types contribute unevenly to price discovery. Advances in trading technology and the rise of automated trading have shifted attention towards increasingly short horizons, where prices adjust over milliseconds and market activity is dominated by order submissions and cancellations rather than trades.

Most evidence on high-frequency price discovery comes from equity, futures, and fixed-income markets, where consolidated reporting, order protection rules, and relatively integrated trading venues allow information to be rapidly aggregated across markets. Studies using full limit order book data in these settings show that limit orders play a dominant role in price discovery, even though market orders have larger price impacts on a per-event basis. At the same time, fragmentation at very short horizons has been shown to diminish as sampling frequency decreases, leading to integrated prices at lower frequencies.

In contrast, evidence from fragmented electronic markets without order protection or consolidated reporting remains limited, particularly at high frequencies where order submissions and cancellations dominate activity. These studies document substantial cross-exchange price discrepancies, heterogeneous liquidity conditions, and rapid information transmission across venues, suggesting fragmentation at high frequencies combined with integration at longer horizons. While this work establishes many important stylised facts about crypto markets, it does not observe directly how different order types contribute to price formation, nor how information is transmitted through the limit order book at ultra-high frequencies.

Albers et al. (2021) analyse fragmentation and cross-impact using order-book data from multiple exchanges, focusing on lead–lag relationships and short-term predictability across venues. While their results highlight the importance of fragmentation, the analysis does not decompose price discovery into distinct order events, nor does it examine the relative contributions of trades, limit-order submissions, and cancellations to permanent price changes. As a result, existing evidence

based on full order-book data remains limited in its ability to resolve the mechanisms through which information is incorporated into crypto prices at very short horizons.

This paper contributes to the literature by providing a detailed order-level analysis of price formation and price discovery in cryptocurrency markets using full tick-by-tick limit order book data from two major centralized exchanges. We decompose market activity into distinct order events and study their immediate and permanent price impacts within and across venues at horizons ranging from milliseconds to seconds. Consistent with prior findings, we show that limit orders account for a large share of price discovery, that information is incorporated rapidly, and that fragmentation is most pronounced at ultra-high frequencies. The contribution lies in observing these mechanisms directly at the message level and in identifying how and when cross-venue integration emerges as horizons increase.

By combining short-horizon price impact measures, structural variance decompositions, and information leadership metrics within a single framework, the paper refines existing evidence on price discovery in fragmented markets. Although our empirical setting is cryptocurrency trading, the analysis speaks more broadly to order-driven price formation in fragmented electronic markets, where high message intensity and incomplete venue integration shape how information is incorporated into prices.

Crypto exchanges such as Binance and Coinbase operate as independent silos, lacking the order-protection rules, cross-market routing, and central clearing that underpin price integration in traditional equity markets. Each platform internalises its own order flow and applies different tick sizes, fee structures, and margin policies. Regulatory oversight is similarly uneven: Coinbase is registered in all U.S. states and major jurisdictions, while Binance has long avoided direct supervision, operating from offshore entities and often facing restrictions. These institutional asymmetries create distinct trading environments that attract different types of participants and allow persistent price discrepancies to arise even for fungible assets. This fragmentation offers an opportunity to examine how market design and regulation shape trader incentives, information flow, and liquidity provision across decentralised trading venues.

Our aim is not merely to measure price discovery or price impact, but to understand how traders adjust their submissions, cancellations, and executions in response to microstructure frictions. Binance enforces a coarser ten-cent tick, allows up to 100X leverage, and offers low, tiered maker-taker

fees. These features encourage algorithmic activity and aggressive liquidity provision, producing fast, volatile order flow and frequent price revisions. Coinbase, by contrast, applies a one-cent tick, permits no leverage on spot products, and imposes higher taker fees, creating an environment dominated by passive, retail-oriented trading. These structural differences are consistent with the asymmetric information flows documented below, and with heterogeneous price dynamics where short-horizon price discovery is shaped less by fundamentals than by institutional design. This motivates three key questions:

1. How do different market events, limit order submissions and cancellations as well as market orders, transmit information and contribute to price discovery in fragmented crypto exchanges lacking cross-venue routing and uniform regulation?

2. How do tick-size and liquidity differences across exchanges affect the magnitude and persistence of price discovery?

3. How do fee structures, leverage, and trader composition interact to determine cross-exchange price adjustment?

To answer these questions, we use tick-level order book data to classify activity into market orders, limit order submissions, and cancellations, and quantify their frequency, price impact, and contributions to price discovery. Using established methodologies from the market microstructure literature (Hasbrouck, 1991; Biais et al., 1995; Brogaard et al., 2019; Putniņš, 2013), we examine price formation and information transmission both within and across exchanges at time intervals ranging from milliseconds to seconds. Our empirical analysis uncovers how the dynamics of different order types generate persistent short-term price discrepancies and asymmetric cross-market responses – highlighting the frictions that impede arbitrage and fragment information aggregation in crypto markets. Contrary to standard intuition, we show that although market orders exert higher immediate price impact, it is the volume of limit order submissions – especially those that improve or worsen quoted prices – that dominates total price discovery. Moreover, Binance, despite having a larger tick size, consistently leads Coinbase in integrating new information into prices, thanks to its tiered fees, high leverage, and the prevalence of algorithmic traders. These findings illustrate that the apparently similar products listed on 'competing' crypto exchanges can behave quite differently

in practice, with implications for arbitrage efficiency, regulatory oversight, and market stability.

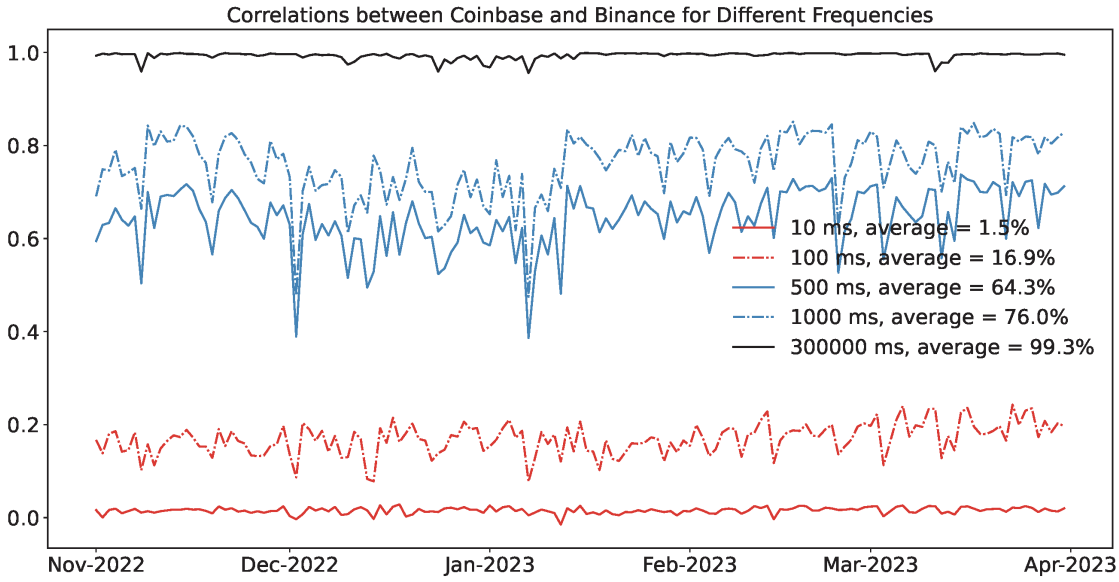
As in traditional equity markets, limit orders dominate crypto market activity, constituting roughly 98% of all order flow. Although market orders have higher individual price impacts, the sheer volume of limit orders results in their being the primary contributor to price discovery. But unlike traditional markets, price integration between Binance and Coinbase is frequency-dependent. At ultra-high frequencies (10 milliseconds), returns across exchanges exhibit near-zero correlation, indicating significant fragmentation. However, at lower frequencies (1–30 seconds), cross-exchange price integration markedly improves. Third, Binance systematically leads Coinbase in price discovery, accounting for 59% at high frequency (10 milliseconds) and 75% at lower frequencies (1 second), positioning Binance as the primary global reference point for crypto asset pricing. As shown in Figure 1, a fragmented market, coupled with frictions that hinder arbitrage activity, allows for price discrepancies to persist for extended periods of time, and much longer than in most liquid markets. These short-run price gaps across exchanges can persist and represent potential arbitrage opportunities, raising questions about the efficiency of these still-emerging markets.

We examine how traders adjust their order submission strategies in response to volatility and liquidity conditions. We employ logistic regression to analyse how market conditions predict the likelihood of each order type, and vector autoregressions to measure the short-run and long-run price impact of various actions. Our logistic regression analysis shows that traders reduce limit order submissions in periods of heightened volatility – due to adverse selection risk – while the widening spreads experienced at such times prompt increased submissions of improving limit orders. Additionally, traders frequently exploit transient informational advantages through aggressive market orders during episodes of narrow spreads and high volatility. This behaviour is consistent with the strategic liquidity management observed in traditional markets. Indeed, we document strong time-of-day effects tied to U.S. market hours, concluding that the informed, high-frequency crypto traders are not only influenced by traditional equity market signals, they also operate in U.S. time-zones.

Extending the research on price discovery in crypto markets referred to above, we incorporate order size and depth-dependent dynamics in our regressions to show that *Binance's limit order flow, not just trades, dominates cross-market price discovery*, even though it has a coarser tick size. While this dominance varies with volatility and liquidity imbalances, it persists despite fungibility,

Figure 1: Correlations

The figure reports the correlations between the log returns of BTC-USD on Coinbase and BTC-USDT on Binance. The sample period is from November 1, 2022 to March 31, 2023. Correlations are calculated daily using log returns computed from the mid quote, defined as the arithmetic average of the best bid and best ask quotes. Mid quotes are sampled at 10, 100, 500, 1000 and 300000 millisecond frequencies.



suggesting that *exchange-level microstructure features, not just asset fundamentals, shape global crypto price discovery.* These results offer a new perspective on crypto market efficiency and frictions, complementing prior studies focused on arbitrage spreads or long-run price leadership.

Our findings in this paper underscore how exchange-level microstructure choices (such as tiered fees, leverage availability, and minimum price increments) can dominate traditional determinants of price discovery and liquidity. They have significant economic and policy implications. The persistent high-frequency fragmentation suggests substantial inefficiencies remain in crypto markets, creating opportunities for arbitrage strategies but also highlighting the limitations imposed by current regulatory and technological frictions. Binance's dominant role in global price discovery further reinforces the critical need for coordinated regulatory standards to mitigate systemic risks associated with market centralization. Our results should inform policy discussions regarding market transparency, efficiency, and investor protection in crypto asset markets, offering guidance for institutional investors, market designers, and regulators seeking to understand this rapidly evolving landscape. This is particularly relevant given the shifting U.S. regulatory environment.

Following the SEC's 2023 enforcement actions against major exchanges, including Binance and Coinbase, a policy reversal under the new administration has signalled a more permissive stance, potentially allowing re-entry of previously restricted platforms. In this context, our results highlight the informational dominance of offshore venues like Binance, despite their coarser tick sizes and less stringent investor protections. This dominance, coupled with persistent short-term price discrepancies and limited arbitrage effectiveness, raises important questions about market integrity and price efficiency in crypto spot markets. Our framework for decomposing price discovery by order type and exchange context offers a useful diagnostic for assessing trading frictions in markets that lack centralized clearing, consolidated reporting, or order protection. As U.S. policymakers reconsider how to regulate centralized exchanges, our evidence supports calls for more coordinated oversight to ensure fair access, price transparency, and competitive market structure.

In the following: Section 2 reviews the literature; Section 3 sets the context; Section 4 describes the data; Section 5 describes the models and summarizes our empirical results; and Section 6 concludes.

2 Literature Review

The market microstructure literature has long examined how order flow and market design shape price formation and price discovery in order-driven markets. Seminal contributions show that prices incorporate information through a combination of trades, limit-order submissions, and cancellations, and that the informational role of each order type depends on market conditions, trader heterogeneity, and execution risk. Hasbrouck (1991) develops a framework for decomposing price variance into components attributable to different sources of order flow, establishing the foundation for empirical price discovery analysis. Early empirical studies of limit order books, such as Biais et al. (1995), document how traders strategically manage liquidity provision through submissions and cancellations, and how these actions affect prices even in the absence of trades.

A large subsequent literature confirms several stylised facts for traditional equity, futures, and fixed-income markets. In particular, studies using detailed order-level data show that limit orders play a central role in price discovery, despite market orders exhibiting larger price impacts on a per-event basis. Using NASDAQ data, Brogaard et al. (2014) decompose price changes into permanent

and transitory components and show that high-frequency traders primarily use market orders to exploit short-lived pricing errors, while limit orders contribute substantially to the incorporation of information over time. Later evidence from Canadian equity markets in Brogaard et al. (2019) demonstrates that although market orders have greater individual price impact, limit orders account for the majority of price discovery because they represent the vast majority of order-book messages. Related findings for U.S. Treasury and foreign exchange markets in Fleming et al. (2018) and Chaboud et al. (2021) confirm that informed traders use both market and limit orders, and that the importance of limit-order activity has increased with the rise of automated trading.

Theoretical models provide a unifying interpretation of these results. Models such as Kyle (1985), Parlour and Seppi (2003), and Goettler et al. (2009) emphasise the trade-off between execution certainty and price impact when choosing between market and limit orders. These models predict that order informativeness varies with volatility, depth, and execution risk, and that price discovery is distributed across order types rather than concentrated solely in trades. Empirical evidence from traditional markets broadly supports these predictions.

A growing literature applies price discovery methods to cryptocurrency markets. Much of this work focuses on traded prices only, also sampled at relatively low frequencies. The extant literature documents fragmentation across exchanges, rapid information transmission, and heterogeneity in liquidity. For example, Brandvold et al. (2015), Makarov and Schoar (2019), Baur and Dimpfl (2019), Alexander et al. (2019) and Alexander and Heck (2020) show that cryptocurrency prices exhibit cross-exchange lead–lag relationships and that price discovery is unevenly distributed across venues. These studies establish that crypto markets are fragmented at short horizons but integrated at longer horizons, and that differences in liquidity and trading activity across exchanges matter for price formation.

Several studies demonstrate a growing focus on ultra–high-frequency market microstructure using order-book-adjacent data not the entire order book. Khomyn and Putniņš (2021) analyse extreme order cancellation behaviour in modern electronic markets and show that millisecond-level message traffic is central to understanding liquidity provision and short-run price dynamics. Kemme et al. (2022) exploit sub-millisecond latency changes on the Tokyo Stock Exchange to study the effects of microstructure design on market fairness and efficiency, while Aitken et al. (2023) use colocation errors as a quasi-natural experiment to identify high-frequency trading activity and its

impact on market quality. Although these studies do not examine cryptocurrency markets, they establish that order submissions, cancellations, latency, and venue-specific frictions are essential for understanding price discovery at very short horizons, motivating the use of full order-level data.

In cryptocurrency markets, most evidence on price discovery is based on prices or trades sampled at relatively low frequencies, documenting fragmentation at short horizons and integration at longer horizons. Only a small number of studies use order-book information. Galati (2024) examines changes in spreads and depth around a fee-structure shock, highlighting the role of liquidity provision and market makers, while Albers et al. (2021) study fragmentation and cross-impact across multiple exchanges using order-book data and lead–lag relationships. These papers provide important insights into market structure but do not decompose price discovery into distinct order events or quantify the relative permanent price impacts of trades, limit-order submissions, and cancellations. Our paper builds on this literature by using full tick-by-tick limit order book data to analyse order-level price discovery within and across exchanges at millisecond horizons, allowing us to observe directly the mechanisms through which information is incorporated into crypto prices.

This paper contributes to the literature by providing a unified order-level analysis of price discovery in cryptocurrency markets using full tick-by-tick limit order book data from two major centralized exchanges. Consistent with prior work, we find that limit orders play a dominant role in price discovery, that information is incorporated rapidly at high frequencies, and that markets are fragmented at ultra-short horizons. The contribution lies not in overturning these established findings, but in resolving the mechanisms and timing through which they arise. By decomposing price discovery into specific order events and analysing both short-run and permanent price effects within and across exchanges, we provide direct evidence on how different order types transmit information in a fragmented trading environment. This level of granularity allows us to refine existing results by identifying the horizons at which fragmentation matters most and the channels through which integration occurs as frequencies decrease.

3 Institutional Context and Market Design

Crypto exchanges operate within a fundamentally different institutional and regulatory landscape compared to traditional equity and futures markets. In established equity markets, robust frame-

works – such as best-execution obligations, order-protection rules, consolidated tapes, and central clearing – promote efficient price integration, ensure liquidity is shared, and maintain market integrity. By contrast, crypto exchanges function as fragmented silos, lacking these integrating mechanisms. This fragmentation creates a natural experiment for examining how diverse market structures shape trader behaviour, price discovery, and liquidity provision.

Traditional equity markets are themselves highly fragmented. U.S. equities trade across roughly a dozen lit exchanges alongside dozens of off-exchange venues, so that a large share of volume executes away from the primary listing venue (O'Hara and Ye, 2011; Menkveld, 2013). What distinguishes these markets from crypto is not the number of venues but the presence of regulation under Reg NMS, order-protection (trade-through) rules, a consolidated tape, and best-execution obligations that bind the venues together. This means that fragmentation in venue need not imply fragmentation in price. Price discovery is therefore concentrated on the lit, quote-displaying venues, while dark pools and internalisers typically execute at or within the prevailing consolidated quote and contribute little price discovery of their own, free-riding on the lit market. Crypto exchanges have the fragmentation without a consolidated tape, order-protection rule, or best-execution duty, so price discovery can concentrate on a single venue while cross-venue price gaps persist at high frequency. This is precisely the sense in which our setting lets us observe price formation when integration is not institutionally enforced: the leadership of Binance over Coinbase that we document is the analogue of lit-venue price leadership in equities, stripped of the routing and protection rules that would otherwise force the follower venue to converge on the leader's price.

A key distinction lies in tick size, which shapes liquidity and price discovery across venues. Unlike regulated equity markets where tick sizes are harmonised, crypto exchanges set their own. Binance applies a coarse ten-cent tick for BTC–USDT, concentrating liquidity and amplifying the price impact of each limit order. Coinbase uses a finer one-cent grid for BTC–USD, promoting shallow quoting and frequent but less informative revisions. This structural divergence affects the informativeness of order flow: Binance's revisions carry more weight in price discovery, while Coinbase's micro-tick regime fosters penny-jumping. Fee structures reinforce this: Binance's lower, tiered maker–taker fees encourage algorithmic liquidity provision, while Coinbase's higher taker fees discourage aggressive liquidity-taking but leave passive, quote-updating market making unaffected.

Another critical mechanism is the presence – or absence – of order-protection and routing rules.

Equity markets require that all orders are routed to the venue quoting the best price, ensuring that liquidity and information are pooled, and price discrepancies are quickly arbitraged away. Crypto exchanges lack such routing and order-protection rules, so each platform internalises its own order flow. This allows transient price discrepancies between Binance and Coinbase to persist at sub-second intervals, since there is no external mechanism to enforce integration. Without mandatory routing, order flow becomes venue-specific, and price impacts become more localised and persistent, undermining the efficiency seen in mature equity markets.

Leverage and participant access represent powerful mechanisms shaping trading behaviour across exchanges. In traditional equity markets, strict margin requirements and regulatory oversight constrain risk-taking and dampen high-frequency speculation. In contrast, Binance offers leverage up to 100× on its perpetual futures, attracting professional and algorithmic traders who exploit short-term informational advantages through automated execution. Coinbase, which provides no leverage on its spot BTC–USD product and faces much tighter U.S. supervision, appeals mainly to retail and long-horizon investors. These differences generate distinct order-flow characteristics: Binance's flows are deeper, more volatile, and more sensitive to market conditions, whereas Coinbase's are steadier and less reactive. During turbulent periods these asymmetries become especially pronounced, with leveraged venues showing faster but more erratic price adjustments and unleveraged venues providing relative stability.

Unlike traditional financial institutions, most crypto exchanges are vertically integrated platforms combining brokerage, custody, lending, staking, and even stablecoin issuance. Although crypto assets are fungible, the absence of central clearing and best-execution requirements introduces settlement risk, latency, and capital constraints that limit cross-market arbitrage. These frictions slow the transmission of information and hinder complete price integration.

Fee structures further accentuate behavioural differences. Binance's lower, volume-tiered maker-taker fees incentivise algorithmic liquidity provision and rapid quote revision. Coinbase's higher taker fees discourage high-frequency activity and promote more passive, retail-driven order flow. As a result, liquidity becomes fragmented and price discovery tends to concentrate where professional traders dominate.

Together, these institutional contrasts provide a plausible explanation for why two exchanges listing the same underlying asset can exhibit divergent price dynamics, volatility patterns, and infor-

mation leadership. Binance's lightly regulated, leveraged, low-fee environment produces swift but uneven information incorporation; Coinbase's more regulated, higher-fee, low-leverage environment generates slower yet steadier price adjustment.

4 Data

Throughout the paper, the mid quote is defined as the arithmetic average of the prevailing best bid and best ask quotes and is used as our reference price for computing returns and price impacts. Our analysis uses a tick-by-tick data set from Tardis.dev which includes all transactions and order book messages for the bitcoin contracts having the deepest markets on the two exchanges, namely the BTC-USD spot contract on Coinbase and the BTC-USDT perpetual on Binance.[1] This mixes two sources of variation: exchange (Binance vs. Coinbase) and product (spot vs. perpetual futures). This could, in principle, confound the effects of market microstructure with those of product structure, since prior work has shown that futures often lead spot in price discovery. However, previous research also shows that the Binance BTC-USDT perpetual is the dominant venue for volatility transmission and information incorporation in bitcoin markets Alexander et al. (2022b) Moreover, arbitrage and the funding mechanism of perpetual futures keep perpetual prices very closely aligned with the underlying spot market He et al. (2022). Consequently, at the ultra-high frequencies considered here, our results primarily capture differences in informational leadership across exchanges rather than being mechanically driven by product differences.

We also note that Binance's spot BTC-USD market, while available, has historically lower liquidity and higher noise than the perpetual, which is by far the dominant trading asset on Binance. For this reason, the perpetual contract offers a more representative source of price discovery on that platform. Nonetheless, a direct spot–spot comparison across exchanges is a valuable extension, and we have included this in Section 5.1.

The Binance and Coinbase contracts have different tick sizes. It is only one cent for BTC-USD spot, but very small tick sizes can deter standing limit orders from retail traders because high-frequency algorithms can so easily "penny jump" them through undercutting the best bid or

[1] USDT is a stablecoin called 'tether' whose price is pegged to the U.S. dollar. A perpetual is a type of futures contract, unique to crypto markets, that never expires and whose price is tied to the spot price via frequent periodic funding payments between the long and short parties.

offer by exactly one tick (Albers et al., 2021). Given the importance of retail trade for Binance, the exchange changed the one-cent tick size for the BTC-USDT perpetual in February 2022 and now it is ten cents. Smaller tick sizes allow more frequent and incremental price updates, and hence more rapid incorporation of new information, making the exchange more likely to lead in price discovery (Brogaard et al., 2014; Fleming et al., 2018). Exchanges with finer price increments also attract more informed traders who prefer precision in setting prices, thereby increasing the information content of trades (Hasbrouck, 1995). Excessively small tick sizes may fragment liquidity by spreading it thinly across many price levels, potentially weakening an exchange's leading status if liquidity depth is significantly impaired (Philip, 2020). However, our sample covers 151 trading days from November 1, 2022, to March 31, 2023, corresponding to 151 trading days. The BTC-USD market was very active on most days in our sample, with daily trading volumes ranging from around 50 million to around two billion USD. Traditional market microstructure theory would therefore predict Coinbase to be the more efficient, price-leading market because its tick size is one-tenth that of Binance.

Transactions records specify the price and quantity traded, and they carry a flag called the order sign (+1 for a buy-initiated trade and −1 for a sell-initiated trade) which indicates the taker side of the transaction. When a marketable order executes against multiple resting limit orders, the records contain a separate entry for each limit order but we do not interpret these as separate transactions. As Upson et al. (2018) demonstrates, this would introduce a significant bias to empirical results. Binance only records order book data that affect the best bid or best offer price, or their respective volumes, namely top of the order book (TOB) price and volume data. The order book data set contains separate files for each day in the sample, measured from 00:00:00 UTC since trading is 24/7. Each of these 151 files starts with an initial snapshot of the entire order book, containing all active price levels and the respective available volumes.[2] After the initial snapshot, all updates to any of the price levels are recorded. Specifically, for each change in the order book, we obtain a record specifying the price level that was changed, the order book side of the change (bid, offer), whether the volume at this level was increased or reduced, and the volume available at this price

[2]Due to latency issues, the initial snapshot is usually not taken exactly at midnight but a few milliseconds after. Therefore, on some days, the file contains a few order book update messages before the initial snapshot. Since we cannot accurately determine the top-of-book quotes for these updates without going back to data from the previous day, we ignore these very few messages.

level after the change.

Transaction and order book data are double timestamped with microsecond precision: by the exchange to record the exact time that the market order causing the trade actually hit the order book; and by the Tardis servers when the trade message arrives. We use the exchange-provided timestamp to match order book updates with transactions and identify which volume reductions in the order book are caused by market orders rather than cancellations of limit orders. This matching for Coinbase is almost perfect, but for Binance, some trades need to be matched with order book changes using a time and/or price priority rule, similar to Hautsch and Huang (2012). The Tardis timestamp represents the information flow investors observe in real-time, so we use this to compare order book changes across exchanges.

Tardis stores Binance data from Asia-Pacific servers (Tokyo) and Coinbase data from Europe-West 2 (London) while Coinbase's matching engine resides in the state of Virginia. This setup may induce small latency differences, potentially biasing lead–lag results. However, both exchanges and Tardis employ dedicated low-latency cloud links with typical round-trip delays below 2–3 milliseconds, which is orders of magnitude less than the time horizons of our analysis. We also note that Hasbrouck (2021) shows that "at a one-second resolution, the information share of the direct feeds is indistinguishable from that of the consolidated tape," despite known latency differences between data sources. Supporting this, Hasbrouck (2021) analyzes US equity market data timestamped to the nanosecond, and finds that latency differences between direct feeds and consolidated tapes only affect price discovery measures at extremely high (microsecond) frequencies.

Table 1 provides descriptive statistics for bitcoin spot prices on Coinbase (BTC-USD) and Binance (BTC-USDT) for the full sample period. All variables are calculated per day and the average, standard deviation, minimum, and maximum of these daily values are reported. The price and return characteristics are almost identical on these platforms. However, daily trading volume is almost fifteen times larger on Binance, on average, and on some low-volume days it can even be twenty times larger; consequently spreads are very much tighter on Binance. The Binance market for BTC-USDT has huge depth and, even though Coinbase is the most active U.S. exchange and BTC-USD its most liquid product, trading activity on Coinbase pales in comparison with Binance. The quoted spread on Binance averages at 1.22 ticks, which is close to the optimal tick size for market makers to profit from the spread (Albers et al., 2021). But on Coinbase, where the tick size

Table 1: Summary Statistics Nov. 2022 to March 2023

The table reports summary statistics for BTC-USD on Coinbase and BTC-USDT on Binance. The sample period is from November 1, 2022 to March 31, 2023. *Price* is defined as the arithmetic average of the best bid and best ask quotes, expressed in thousands of dollars. *Daily Return* is the daily return calculated from the closing mid quote, in percent. *Native Trading Volume* is the number of bitcoin traded. *Dollar Trading Volume* is the number of bitcoin traded multiplied by the transaction price, in millions of dollars. *Number of Trades* is the number of transactions, in thousands. *Dollar Trade Size* is the trade size, in dollars. *Quoted Spread* is the bid-ask spread, in ticks. *Relative Spread* is the bid-ask spread divided by the mid quote, in basis points. *Depth* is the total volume available at the best quotes, in thousands of dollars. Apart from the daily returns, all variables are calculated per day and the average, standard deviation, minimum, and maximum of these daily values are reported. All statistics are calculated based on TOB actions.

Panel A: Coinbase BTC-USD

	Average	Std. Dev.	Minimum	Maximum
Price ($ thousand)	20.59	3.71	15.93	28.38
Daily Return (in %)	0.26	3.03	-14.32	10.45
Native Trading Volume (in thousands)	24.30	16.57	2.27	119.59
Dollar Trading Volume ($ million)	486.99	308.62	50.63	2,048.80
Number of Trades (in thousands)	278.60	109.67	82.35	831.06
Dollar Trade Size	1,623.95	491.26	545.55	2,901.51
Quoted Spread (in ticks)	178.41	86.22	39.73	452.55
Relative Spread (in bps)	0.87	0.42	0.18	2.67
Depth ($ thousand)	4.76	1.65	2.45	13.39

Panel B: Binance BTC-USDT

	Average	Std. Dev.	Minimum	Maximum
Price ($ thousand)	20.57	3.70	15.95	28.37
Daily Return (in %)	0.26	3.04	-14.18	10.58
Native Trading Volume (in thousands)	311.42	154.77	64.01	1,034.83
Dollar Trading Volume ($ million)	6,555.81	3,580.25	1,083.73	19,946.58
Number of Trades (in thousands)	1,056.62	649.13	221.33	4,087.53
Dollar Trade Size	6,285.67	874.99	3,751.01	7,744.64
Quoted Spread (in ticks)	1.22	0.35	1.00	3.62
Relative Spread (in bps)	0.06	0.02	0.04	0.19
Depth ($ thousand)	617.74	253.58	88.48	1,140.06

is only one cent, the average quoted spread of more than 178 ticks leaves multiple entry levels for HFTs to post aggressive limit orders. The relative spread, measured in basis points, is on average 14.5 times larger on Coinbase than it is on Binance. These relative spread levels are broadly consistent with prior estimates for highly liquid crypto exchanges (e.g., Brandvold et al., 2015; Dimpfl and Peter, 2021), and substantially tighter than spreads observed in traditional spot FX markets (e.g., Fleming et al., 2018; Chaboud et al., 2021).

Spreads vary considerably with Coinbase exhibiting especially pronounced fluctuations. Wider spreads generally increase the price impact of market orders, because traders must cross a larger gap to transact, thus consuming more liquidity and incurring higher transaction costs, which translate into larger price movements (Kyle, 1985; Hautsch and Huang, 2012). Limit orders respond differently to spread size: narrower spreads encourage traders to place orders closer to the best quotes, thereby boosting price discovery but raising adverse-selection risk, while wider spreads may discourage placing orders near the mid-price, potentially lowering these orders' overall informational contribution (Goettler et al., 2009; Alexander et al., 2022a).

To study the impact of different order book changes, we allocate each order book change to one of eight different actions listed below: the first three actions each change the ticker price immediately, so we call them *price-changing* actions for short; the next three actions are called *price-reinforcing* because they affect liquidity at the best price but do not lead to an immediate price change; and the last two actions are *price-neutral* because they have no immediate effect on liquidity, namely the volume quoted at the best price.

1. *Trade Change Price*: A trade that consumes all liquidity available at the best bid or offer;
2. *Improving Submission*: A limit order that improves the best bid or offer;
3. *Worsening Cancellation*: A limit order cancellation that worsens the best bid or offer;
4. *Trade Same Price*: A trade that does not consume all available liquidity at the best price;
5. *Order at Best*: A limit order submission at the best price;
6. *Cancel at Best*: Cancellation of limit order at best price that leaves that price unchanged;
7. *Order Behind Best*: A limit order submitted behind the best price;
8. *Cancel Behind Best*: Cancellation of a limit order submitted behind the best price.

Table 2 reports the frequency of messages grouped into these eight types. Since we do not have data for price-neutral actions on Binance, we report Coinbase statistics for all eight actions as well as for the six TOB actions that are also available on Binance. On average, there are more than twelve million TOB messages per day on Binance, compared to only around five million TOB

Table 2: Message Frequency

The table reports the frequency of order messages for BTC-USD and BTC-USDT on Coinbase and Binance. The sample period is from November 1, 2022 to March 31, 2023. *Trade Change Price* captures trades that consume all liquidity available at the best bid or offer. *Improving submission* captures order submissions that improve the best bid or offer. *Worsening Cancellation* captures order cancellations that worsen the best bid or offer. *Trade Same Price* captures trades that do not consume all liquidity available at the best bid or offer. *Order at Best* captures order submissions at the best bid or offer. *Cancel at Best* captures order cancellations at the best bid or offer that do not worsen the best bid or offer. *Order Behind Best* captures order submissions behind the best bid or offer. *Cancel Behind Best* captures order cancellations behind the best bid or offer. For Binance, we report the percentage of each of the TOB actions over the sample period, and the average number of messages per day. For Coinbase, we report the same TOB statistics, as well as the statistics for all eight actions (i.e., including changes to the order book behind best bid or offer, see column *All*).

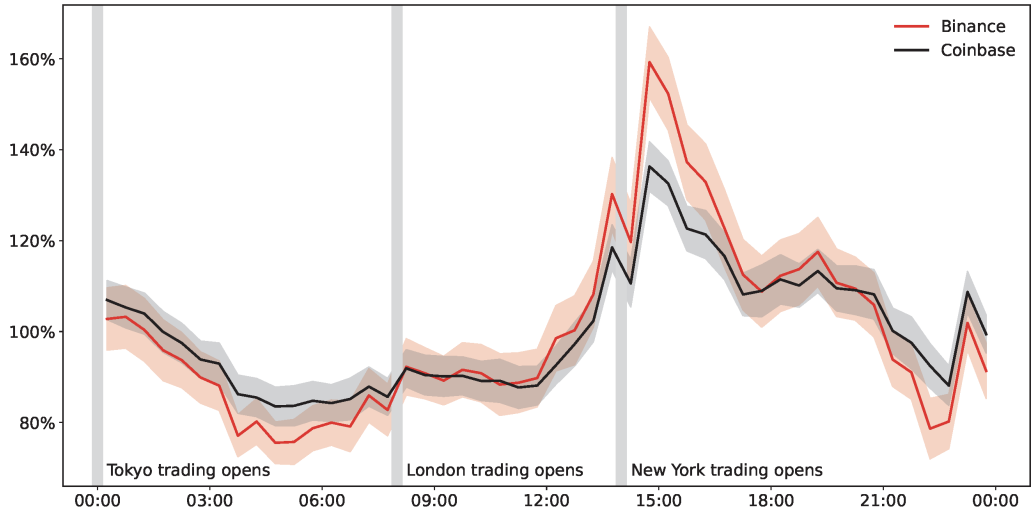
Action	Binance (TOB)	Coinbase (TOB)	Coinbase (All)
Trade Change Price	1.09%	2.20%	0.31%
Improving Submission	1.68%	39.39%	5.52%
Worsening Cancel	0.50%	11.38%	1.60%
Trade Same Price	7.66%	3.30%	0.46%
Order at Best	58.93%	30.89%	4.33%
Cancel at Best	30.14%	12.84%	1.80%
Order Behind Best	–	–	40.13%
Cancel Behind Best	–	–	45.85%
Average per Day	12,112,158	5,086,778	36,275,554

messages on Coinbase. On Coinbase, limit order submissions behind the best bid or offer are the most frequent and make up about 86% of all messages. About 50% of all limit orders on Coinbase are cancelled rather than executed. Market orders (trades) account only for less than 1% of all message activity. In terms of aggressiveness, over 85% of messages are related to limit order activity behind the best prices.

Figure 2 provides the relative frequency of TOB messages during the trading day, which we construct as follows. First, we divide our sample into thirty-minute intervals and count the number of messages on both Binance and Coinbase for each of these intervals. Secondly, we average the number of messages across the sample days. This provides us with the average number of messages for both exchanges for intervals ranging from 0:00-0:30 UTC to 23:30-24:00 UTC. Thirdly, since the message frequency on Binance is substantially higher than on Coinbase, we report the message frequency in each thirty-minute interval as a percentage of the average over all intervals on the same exchange. The shaded regions represent one-standard-error bands calculated across the 151 trading

Figure 2: Intraday Message Frequency

This figure provides a comparison of TOB message frequencies during the trading day. Our calculation of the relative frequency follows several steps: (a) we split the sample into thirty-minute intervals starting with 0:00-0:30 UTC on the first sample day to the final interval which is between 23:30-24:00 UTC on the final sample day; (b) for both Coinbase and Binance, we calculate the number of messages for each of the six different TOB actions for each thirty-minute window; (c) we average the number of messages across all sample days which provides us with the average number of messages for 48 thirty-minute intra-daily intervals; (d) as the message frequency on Binance is significantly higher than on Coinbase, we plot the message frequency in each interval as a percentage of the average of all thirty-minute intervals on each exchange. Shaded regions represent ±1 standard error bands calculated across the daily estimates.



days in our sample. Unlike the subsequent figures, these bands are not especially narrow because intraday message intensity varies substantially from day to day, reflecting differences in market activity, volatility and news arrival. Nevertheless, the broad intraday patterns are remarkably stable across the sample, with both exchanges exhibiting clear increases in activity during the overlap with U.S. trading hours.

This time-of-day trading pattern is similar to that observed in traditional markets, with peak volumes reached during the first few hours of New York trading time on both exchanges. This might be construed as evidence that U.S. traders were accessing Binance through virtual private networks or off-shore accounts during the period of our sample, because at that time it was forbidden under U.S. law to trade on Binance through normal channels.[3] It may also be that traders from outside

[3]In June 2023 the SEC brought charges against Binance precisely to this effect, but these were dropped a few weeks after President Trump took office in January 2025.

the U.S. are using signals from U.S. equity markets to trade on bitcoin. In addition, bitcoin trades could be prompted by signals from Coinbase volumes, which spillover to Binance rather than the converse, as shown by Alexander et al. (2022b).

5 Results

5.1 Simple Price Impact

Our first comparison of the price formation processes on Coinbase and Binance examines the impact of price-changing actions, within and between exchanges. We begin with the simplest possible price impact analysis by matching an action on an exchange with an immediate or subsequent price change on the same exchange, or on the other exchange. Note there are four possible combinations depending on which exchange the action originates and on which exchange the impact is recorded. We shall use the *signed price impact* defined as the log change in the mid quote in the direction of the action over a certain time horizon, measured in basis points: $\pm(\ln P_t - \ln P_0) \times 100^2$, where the sign is $+1$ for a buy-side and -1 for a sell-side action, P_0 is the mid quote recorded at the time the action hits the order book and P_t is the mid quote at some time t afterwards, with t selected to be 0, 0.1, 0.5, 1, 10, 30, 60 or 300 seconds. The simple price impact after zero seconds captures the immediate change in the mid quote caused by an action, and price impacts at longer horizons capture the change in the log mid quote in the direction of the action after it hits the order book. Note that a non-zero impact after zero seconds by definition occurs only with trades which consume all available liquidity, namely improving submissions and worsening cancellations.

Table 3, Panel A reports simple same-exchange price impacts for the three price-changing actions, namely a trade that changes the price, an improving submission, and a worsening cancellation.[4] Most of the impact is realized within the first second, indicating the regular presence of trading algorithms. Trades that consume all liquidity available at the best bid or offer have the largest price impact on both exchanges. The immediate change in the mid quote caused by the trade is 0.22 bps on both exchanges, but the long-term impact is greater on Binance (0.94 vs 0.70 bps). Both improving submissions and worsening cancellations exhibit smaller price impacts, especially on Coinbase where the immediate impact of improving submissions is only 0.03 bps, and for

[4]In this and the following tables statistical significance is derived using heteroscedasticity and autocorrelation consistent (HAC) corrected standard errors, similar to Brogaard et al. (2019).

Table 3: Signed Price Impacts of Price-Changing Actions

Signed price impacts (in basis points) for different time horizons (in seconds) for BTC-USD on Coinbase and BTC-USDT on Binance. There are four possible combinations, depending on where the action originates and where the impact is recorded: action on Binance and impact on Binance, action on Binance and impact on Coinbase, action on Coinbase and impact on Binance, action on Coinbase and impact on Coinbase. The sample period is from November 1, 2022 to March 31, 2023. Signed price impacts are averaged for each day and the average of these daily averages is reported, using * and ** next to the average to indicate significantly different from zero at the 5% and 1% level, respectively, using HAC-corrected standard errors.

Panel A: Price-Changing Actions: Same Exchange Impact

Horizon	Trade Change Price		Improving Submission		Worsening Cancellation		Average	
Action on:	Binance	Coinbase	Binance	Coinbase	Binance	Coinbase	Binance	Coinbase
Impact on:	Binance	Coinbase	Binance	Coinbase	Binance	Coinbase	Binance	Coinbase
0.0	0.22**	0.22**	0.21**	0.03**	0.18**	0.07**	0.21**	0.05**
0.1	0.49**	0.50**	0.44**	0.08**	0.46**	0.07**	0.46**	0.09**
0.5	0.69**	0.68**	0.61**	0.13**	0.65**	0.08**	0.65**	0.14**
1.0	0.76**	0.71**	0.68**	0.15**	0.72**	0.08**	0.72**	0.16**
10.0	0.95**	0.74**	0.87**	0.19**	0.88**	0.07**	0.91**	0.18**
30.0	0.96**	0.73**	0.87**	0.19**	0.87**	0.07**	0.91**	0.18**
60.0	0.96**	0.72**	0.87**	0.19**	0.86**	0.08**	0.91**	0.18**
300.0	0.94**	0.70**	0.83**	0.19**	0.81**	0.07**	0.87**	0.18**

Panel B: Price-Changing Actions: Cross Exchange Impact

Horizon	Trade Change Price		Improving Submission		Worsening Cancellation		Average	
Action on:	Binance	Coinbase	Binance	Coinbase	Binance	Coinbase	Binance	Coinbase
Impact on:	Coinbase	Binance	Coinbase	Binance	Coinbase	Binance	Coinbase	Binance
0.1	0.20**	0.10**	0.24**	0.02**	0.29**	0.01**	0.24**	0.02**
0.5	0.62**	0.24**	0.65**	0.06**	0.73**	0.02**	0.66**	0.06**
1.0	0.67**	0.30**	0.70**	0.09**	0.78**	0.03**	0.71**	0.08**
10.0	0.72**	0.44**	0.75**	0.17**	0.82**	0.03**	0.76**	0.15**
30.0	0.72**	0.45**	0.75**	0.18**	0.81**	0.03**	0.75**	0.16**
60.0	0.72**	0.44**	0.75**	0.18**	0.80**	0.03**	0.75**	0.16**
300.0	0.71**	0.41**	0.72**	0.18**	0.77**	0.02	0.73**	0.15**

worsening cancellations, it is only 0.07 bps. This is because improving submissions mostly undercut the current best bid or offer by exactly one tick, whereas the gap behind the best prices (which determines the immediate impact of a worsening cancellation) is on average more than one tick. The most obvious difference between the two exchanges is that limit orders, either improving or

worsening, have a much greater impact on Binance than they do on Coinbase, and this is not just the immediate impact (on average, 0.21 bps for Binance but only 0.05 for Coinbase) but subsequent price changes (on average, after ten seconds, 0.91 bps for Binance but just 0.18 bps for Coinbase).

Panel B of Table 3 reports the cross-exchange effects of price-changing actions. Limit orders on Binance are influencing price formation on Coinbase, not immediately, but after 0.1 secs the Binance to Coinbase signed impact is 0.24 bps, on average, compared with only 0.02 bps for the Coinbase to Binance signed impact. Trades on Binance have a similar impact on Coinbase trades (0.20 bps after 0.1 secs) and the reverse flow from Coinbase to Binance (0.10 bps after 0.1 secs) is greater for trades than it is for limit orders. Long-term cross-exchange price impacts are also asymmetric, with much more significant information flowing from Binance to Coinbase than in the opposite direction. After 300 seconds, the signed impact of Binance trades on Coinbase prices is 0.71 bps, and for Binance limit orders it is 0.73, on average.

Table 4 repeats this exercise using Binance's BTC-USD spot market in place of the BTC-USDT perpetual, providing a direct spot-to-spot comparison across the two exchanges. The Coinbase-side price impacts are unchanged from Table 3, as expected since the Coinbase leg of the analysis is identical. On the Binance side, however, price impacts are substantially larger than in the perpetual comparison: same-exchange effects are roughly two-and-a-half times larger (the 300-second average rises from 0.87 to 2.16 bps), while Binance's cross-exchange influence on Coinbase is around 60% larger (0.73 to 1.17 bps). This is consistent with Binance's BTC-USD spot market being a considerably thinner and noisier venue than its perpetual contract, which handles the bulk of Binance's trading volume. With less resting liquidity at the best quotes, the same trade, improving submission, or worsening cancellation represents a larger share of available depth and therefore produces a correspondingly larger price movement. Notably, this cannot be attributed to tick size, since Binance's BTC-USD spot tick (one cent) is finer than its perpetual's (ten cents) and would, if anything, be expected to dampen rather than amplify per-action impacts. The results therefore suggest that it is Binance's concentration of liquidity and informed trading in the perpetual contract, rather than spot-versus-derivative distinction per se, that drives the differences in spot-spot price impacts relative to the perpetual comparison in Table 3.

However, these averages only tell part of the story. The price impact results change considerably from day to day over our sample period. Figure 3 depicts the evolution of the impacts of the three

Table 4: Signed Price Impacts of Price-Changing Actions

Signed price impacts (in basis points) for different time horizons (in seconds) for BTC-USD on Coinbase and BTC-USD on Binance. There are four possible combinations, depending on where the action originates and where the impact is recorded: action on Binance and impact on Binance, action on Binance and impact on Coinbase, action on Coinbase and impact on Binance, action on Coinbase and impact on Coinbase. The sample period is from November 1, 2022 to March 31, 2023. Signed price impacts are averaged for each day and the average of these daily averages is reported, using * and ** next to the average to indicate significantly different from zero at the 5% and 1% level, respectively, using HAC-corrected standard errors.

Panel A: Price Changing Actions: Same Exchange Impact

Horizon	Trade		Improving Order		Worsening Order		Average	
Action on	binance	coinbase	binance	coinbase	binance	coinbase	binance	coinbase
Impact on	binance	coinbase	binance	coinbase	binance	coinbase	binance	coinbase
0.0	0.26**	0.22**	0.20**	0.03**	0.19**	0.08**	0.21**	0.05**
0.1	0.79**	0.50**	0.68**	0.08**	0.84**	0.07**	0.73**	0.09**
0.5	1.14**	0.68**	1.02**	0.13**	1.21**	0.09**	1.07**	0.14**
1.0	1.33**	0.71**	1.18**	0.16**	1.38**	0.09**	1.24**	0.16**
10.0	2.04**	0.74**	1.83**	0.19**	2.03**	0.09**	1.88**	0.18**
30.0	2.30**	0.73**	2.05**	0.19**	2.24**	0.09**	2.10**	0.18**
60.0	2.39**	0.72**	2.12**	0.19**	2.32**	0.09**	2.17**	0.18**
300.0	2.44**	0.70**	2.10**	0.19**	2.31**	0.09**	2.16**	0.18**

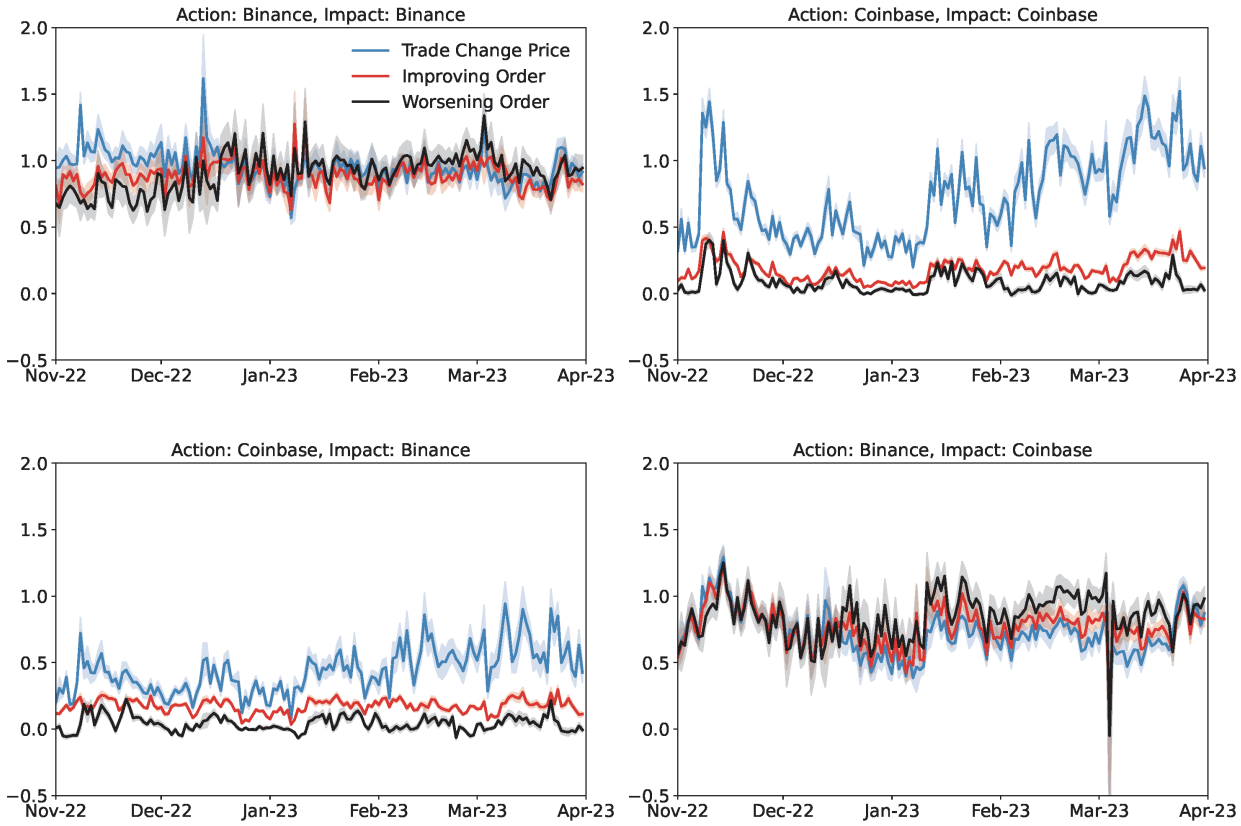
Panel B: Price Changing Actions: Cross Exchange Impact

Horizon	Trade		Improving Order		Worsening Order		Average	
Action on	binance	coinbase	binance	coinbase	binance	coinbase	binance	coinbase
Impact on	coinbase	binance	coinbase	binance	coinbase	binance	coinbase	binance
0.1	0.47**	0.08**	0.58**	0.01**	0.63**	0.01**	0.56**	0.01**
0.5	1.05**	0.20**	1.19**	0.05**	1.34**	0.03**	1.17**	0.05**
1.0	1.13**	0.26**	1.26**	0.07**	1.41**	0.04**	1.24**	0.07**
10.0	1.16**	0.49**	1.28**	0.22**	1.43**	0.06**	1.26**	0.19**
30.0	1.16**	0.56**	1.27**	0.27**	1.41**	0.07**	1.25**	0.23**
60.0	1.15**	0.57**	1.26**	0.29**	1.41**	0.07**	1.24**	0.25**
300.0	1.14**	0.57**	1.20**	0.31**	1.35**	0.06**	1.17**	0.26**

price-changing actions over the entire sample. We plot the daily average 10-second price impact of the action, both within one exchange and between the two exchanges. The upper section shows own-exchange impacts on Binance (left) and Coinbase (right). To assess whether the apparent variation over time reflects genuine changes in price impacts rather than estimation uncertainty, we also depict HAC-corrected 98% confidence bands (±2.326 standard errors). Despite this stringent

Figure 3: Evolution of Price Impacts for Price-Changing Actions

The figures depict signed price impacts (in basis points) for BTC-USD on Coinbase and BTC-USDT on Binance. The sample period is from November 1, 2022, to March 31, 2023, and on each day in the sample we report the average of same-exchange and cross-exchange 10-second price impact of the three price changing actions described in Section 4. Shaded regions represent ± 2.326 standard-error intervals.



confidence level, the bands are barely visible because each daily estimate is based on an extremely large number of order-book events. The observed movements therefore reflect genuine variation in the estimated price impacts rather than sampling variability.

The obvious difference between these time series is that improving submissions and worsening cancellations have a much greater impact on Binance, where they have about the same impact as price-changing trades. On Coinbase there is much less impact, except from price-changing trades. The lower section shows cross-exchange impacts: Coinbase to Binance (left) and Binance to Coinbase (right). A very different pattern is evident here. All three price-changing actions on Binance have a very high impact on Coinbase. Improving submissions and worsening cancellations on Binance even have a greater impact on Coinbase than they do on Binance.

It may seem puzzling that a limit-order revision on Binance moves the Coinbase mid quote by

more than an equivalent revision on Coinbase itself. Two features of the markets can partially explain this asymmetry. First, Binance is the information-leading venue, its information leadership share is roughly 75% at the one-second horizon, and on its coarse ten-cent grid, populated largely by professional and algorithmic traders, a quote revision is a large and informative event. Coinbase's own limit-order flow, by contrast, consists largely of penny changes on a one-cent grid. Coinbase's efficient price therefore tracks the informative Binance signal more closely than its own quoting, while Binance has less to learn from Coinbase. Second, a reaction within 0.1 seconds requires automated trading on Coinbase, which is consistent with our message data once the role of fees is made precise: Coinbase's higher taker fees discourage liquidity-taking high-frequency strategies, but not passive, quote-updating market making. Indeed, over 85% of Coinbase messages are limit-order submissions and cancellations. These quote-updating algorithms reprice Coinbase within milliseconds: the conditional frequencies in We further show that a price-changing action on Binance is followed by a same-signed improving submission on Coinbase about 30% of the time.

Limit orders on Binance have as much effect on *both* exchanges as large market orders, but limit orders on Coinbase have very little impact. There is no clear trend in any series, except a small increase in the impact (on both Coinbase and Binance) of price-changing trades on Coinbase, although these vary considerably from day to day. The main takeaway here is that actions on Binance play a key role in the bitcoin price formation process on both Binance and Coinbase.

Table 5 reports the sample average of n-second impacts for price-reinforcing actions (trade same price, submission at best and cancel at best) both within and between the two exchanges, for $n = 0.1, 0.5, 1, 10, 30, 60$ and 300 seconds. Price-reinforcing actions leave the mid quote *instantaneously* unchanged because a trade does not consume all available liquidity, or a submission at the best price does not cause an improvement or worsening of the best bid or offer price. Nevertheless, 0.1 seconds after the action there is a small but significant price impact. Compared with the price-changing actions, for price-reinforcing actions there is more similarity between the two exchanges in terms of both within- and between-exchange impact. Unsurprisingly, price-reinforcing actions have a much lower impact than price-changing actions, in general. Notably, actions on Binance no longer have a much greater within-exchange and cross-exchange impact than the same actions on Coinbase, contrasting the results in Table 3. Compared with price-reinforcing trades, submissions at the best price on Binance exhibit a relatively large long-term price impact on both exchanges, of 0.39 bps on

Table 5: Simple Price Impacts of Price-Reinforcing Actions

The table reports signed price impacts (in basis points) for different time horizons (in seconds) for BTC-USD on Coinbase and BTC-USDT on Binance. There are four possible combinations, depending on where the action originates and where the impact is recorded: action on Binance and impact on Binance, action on Binance and impact on Coinbase, action on Coinbase and impact on Binance, action on Coinbase and impact on Coinbase. The sample period is from November 1, 2022 to March 31, 2023. Signed price impacts capture the change in the log mid quote in the direction of the action after it hits the order book. Signed price impacts are averaged for each day and the average of these daily averages is reported. * and ** next to the coefficient indicate that the coefficient is statistically different from zero at the 5% and 1% level, respectively, using HAC-corrected standard errors.

Panel A: Price-Reinforcing Actions: Same Exchange Impact

Horizon	Trade Same Price		Submission at Best		Cancel at Best		Average	
Action on:	Binance	Coinbase	Binance	Coinbase	Binance	Coinbase	Binance	Coinbase
Impact on:	Binance	Coinbase	Binance	Coinbase	Binance	Coinbase	Binance	Coinbase
0.1	0.04**	0.10**	0.08**	0.06**	-0.00**	-0.02**	0.05**	0.04**
0.5	0.08**	0.15**	0.18**	0.13**	-0.01**	-0.05**	0.11**	0.08**
1.0	0.09**	0.16**	0.24**	0.16**	-0.02**	-0.07**	0.15**	0.10**
10.0	0.12**	0.16**	0.39**	0.21**	-0.07**	-0.11**	0.23**	0.12**
30.0	0.12**	0.17**	0.41**	0.22**	-0.07**	-0.12**	0.23**	0.13**
60.0	0.12**	0.17**	0.41**	0.22**	-0.07**	-0.12**	0.24**	0.13**
300.0	0.12**	0.20**	0.39**	0.21**	-0.06**	-0.11**	0.23**	0.13**

Panel B: Price-Reinforcing Actions: Cross Exchange Impact

Horizon	Trade Same Price		Submission at Best		Cancel at Best		Average	
Action on:	Binance	Coinbase	Binance	Coinbase	Binance	Coinbase	Binance	Coinbase
Impact on:	Coinbase	Binance	Coinbase	Binance	Coinbase	Binance	Coinbase	Binance
0.1	0.02**	0.02**	0.10**	0.02**	-0.02**	-0.01**	0.05**	0.01**
0.5	0.08**	0.05**	0.24**	0.07**	0.01	-0.03**	0.16**	0.04**
1.0	0.09**	0.06**	0.28**	0.10**	0.01	-0.05**	0.18**	0.06**
10.0	0.10**	0.09**	0.33**	0.22**	-0.00	-0.13**	0.21**	0.12**
30.0	0.09**	0.09**	0.33**	0.24**	0.00	-0.14**	0.21**	0.13**
60.0	0.10**	0.09**	0.34**	0.24**	0.00	-0.14**	0.22**	0.13**
300.0	0.10**	0.09	0.32**	0.22**	0.01	-0.13**	0.21**	0.12**

Binance and 0.32 bps on Coinbase. In fact, submissions at best on Binance impact Coinbase prices more than submissions at best on Coinbase (0.32 vs 0.21 bps). As for price-reinforcing actions, most of the price impact is already realized within the first second due to the presence of trading

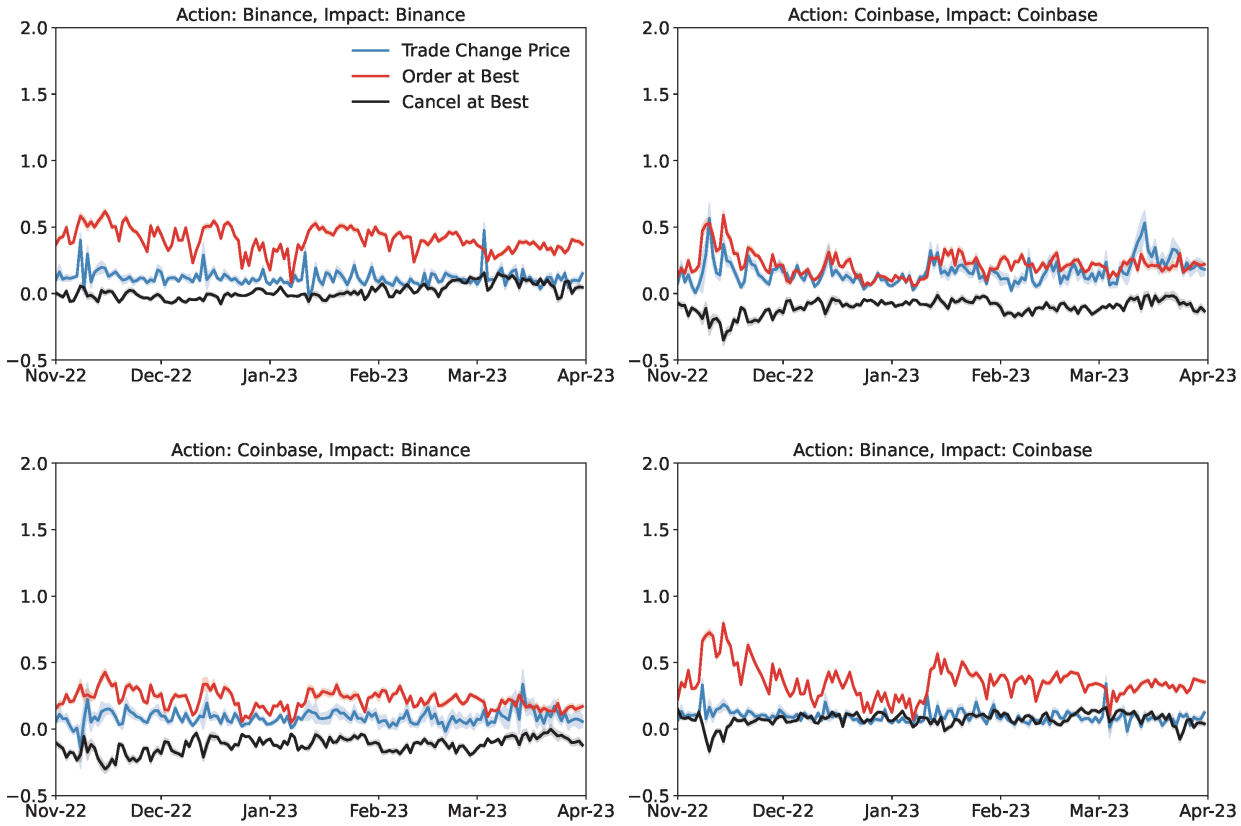
algorithms. Interestingly, on Coinbase the trades that do not consume all liquidity available at the best bid or offer have a commensurate impact to submissions at best, but on Binance these limit orders have an impact three times greater than trades, on both Binance and Coinbase. This adds further evidence on the importance of Binance order book flows for price formation on Coinbase. It is important to note that Binance's tick size is an order of magnitude larger than Coinbase's (ten cents vs. one cent). As such, any price-changing event that moves the price by a single tick on Binance will mechanically result in a larger nominal change than a similar event on Coinbase. While we report price impacts in basis points to account for differences in price levels, this does not fully neutralize the coarseness of Binance's price grid. Therefore, the observed differences in price impact should be interpreted with caution. Reinforcing cancellations at the best prices exhibit small negative price impacts, i.e. they lead to movements in the mid quote opposite to their direction. In Section 5.2 we show that these cancellations are typically followed by improving submissions in the opposite direction, which causes their price impact to be negative. Such a sequence, of a reinforcing cancellation at the best price and a subsequent improving submission, is probably the same trader cancelling their existing orders at the best prices and gaining priority over other traders by submitting a new improving limit order.

Figure 4 depicts time series of daily averages of 10-second impacts of the price-reinforcing actions averaged in Table 5. There is more uniformity in the impacts of these actions compared with the price-changing impacts displayed in Figure 3 and, as already noted, these impacts are much smaller than those for price-changing actions. As before we report HAC-corrected 98% confidence bands (± 2.326 standard errors). These are again extremely narrow throughout the sample, confirming that the observed variation in information leadership reflects genuine changes over time rather than estimation uncertainty..

These findings indicate that coarser tick sizes amplify the informational content and price impact of limit-order submissions. The slower and asymmetric transmission of price changes across exchanges illustrates how the absence of routing and order-protection rules, combined with weaker regulatory oversight on Binance, produces uneven information flow and delayed cross-venue price adjustment. Finally, the heterogeneous impact magnitudes across order types reveal how differing microstructure incentives and fee structures fragment liquidity provision and price discovery in crypto markets.

Figure 4: Evolution of Price Impacts for Price-Reinforcing Actions

The panels depict signed price impacts (in basis points) for BTC-USD on Coinbase and BTC-USDT on Binance. The sample period is from November 1, 2022 to March 31, 2023 and on each day in the sample we report the average of same-exchange and cross-exchange 10-second price impact of the three price reinforcing actions described in Section 4. Shaded regions represent ± 2.326 standard-error intervals.



5.2 Determinants of Simple Price Impact

To investigate the effect of market conditions on the strength of a price impact and to compare this for different types of actions, we use ordinary least squares (OLS) to regress the ten-second simple signed price impact of each price-changing or price-reinforcing action on the following market variables:

1. *Lagged Return* is the previous signed ten-second log mid return, in percent;

2. *Volatility* is the absolute value of the previous ten-second log mid return, in percent;

3. *Depth* is the contemporaneous depth at the best bid and offer, in bitcoin;

4. *Order Book Imbalance* is the contemporaneous signed order book imbalance calculated as

(depth at best bid − depth at best offer)/(depth at best bid + depth at best offer);

5. *Relative Spread* is the contemporaneous bid-offer spread divided by the mid quote, at the time of the action, measured in percent;

6. *Size* is bitcoin amount of the action.

Table 6: Determinants of 10-Second Price Impacts

The table reports averages of OLS regressions of the ten-second signed price impacts (in basis points) of price-changing and price-reinforcing actions for BTC-USD on Coinbase and BTC-USDT on Binance. The sample period is from November 1, 2022, to March 31, 2023. The explanatory variables are as follows: *Lagged Return*, the previous signed ten-second log mid return, in percent; *Volatility*, the absolute value of the previous ten-second log mid return, in percent; *Depth*, the contemporaneous depth at the best bid and offer, in bitcoin; *Order Book Imbalance*, the contemporaneous signed order book imbalance calculated as (depth at best bid − depth at best offer)/(depth at best bid + depth at best offer); *Relative Spread*, the contemporaneous bid-offer spread divided by the mid quote, at the time of the action, measured in percent; and *Size*, the bitcoin amount of the action. The regressions are estimated for each day and the averages of the daily coefficients are reported. * and ** next to the coefficient indicate that the coefficient is statistically different from zero at the 5% and 1 % level, using HAC-corrected standard errors.

Panel A: Price Changing Actions

Variable	Trade Change Price		Improving Order		Worsening Cancellation	
Exchange	Coinbase	Binance	Coinbase	Binance	Coinbase	Binance
Intercept	0.32**	0.44**	0.12**	0.54**	−0.11**	0.62**
Lagged Return	−4.42**	−10.77**	−2.42**	−9.66**	−2.33**	−9.42**
Volatility	2.10**	0.39	1.22**	−0.06	0.37**	−0.32
Depth	0.07**	0.00*	0.00*	0.00**	−0.01**	0.00**
Order Book Imbalance	0.11**	0.60**	0.13**	0.39**	0.18**	0.23**
Relative Spread	38.44**	3.58	−0.88	−11.81**	18.88**	25.48**
Size	0.14**	0.06**	0.24**	0.01**	0.19**	0.05**

Panel B: Price-Reinforcing Actions

Variable	Trade Same Price		Order at Best		Cancel at Best	
Exchange	Coinbase	Binance	Coinbase	Binance	Coinbase	Binance
Intercept	0.06**	0.07**	0.13**	0.07**	−0.07**	0.12**
Lagged Return	−2.90**	−8.24**	−1.75**	−0.89*	−1.10**	−2.32**
Volatility	2.66**	0.71**	1.85**	1.36**	−1.00**	0.26*
Depth	0.01*	0.00*	0.03**	0.00**	−0.03**	0.00**
Order Book Imbalance	0.19**	0.60**	0.13**	0.57**	0.18**	0.57**
Relative Spread	4.22**	−10.51*	−0.09	37.48**	10.30**	5.63
Size	1.06**	0.10**	0.35**	0.04**	−0.14**	0.03**

On each day in the sample and for each exchange, we perform six separate linear regressions,

each of these with the same explanatory variables but different dependent variables corresponding to the six price-changing and price-reinforcing actions enumerated in Section 4. Then we report the average of each coefficient estimate over the 151 days in Table 6. Consistent with the simple descriptive statistics, the price impact is higher for price-changing than price-reinforcing actions and orders have a generally positive impact on prices after control for market conditions. The notable exception is cancellations on Coinbase, which have a negative average price impact. Price impact increases with volatility, order book imbalance, order size and with the depth available at the best bid and offer – and it generally declines when the last 10-second return is positive and increases when it is negative. Consistent with most models of private information (Kyle, 1985; Collin-Dufresne and Fos, 2015) larger orders are associated with higher price impacts. But for cancellations the influence of depth on price impact is very small. As the spread widens, the price impact of trades is greater on Coinbase than on Binance, indeed a wide spread on Binance can create a negative impact on trades that do not consume all available liquidity.

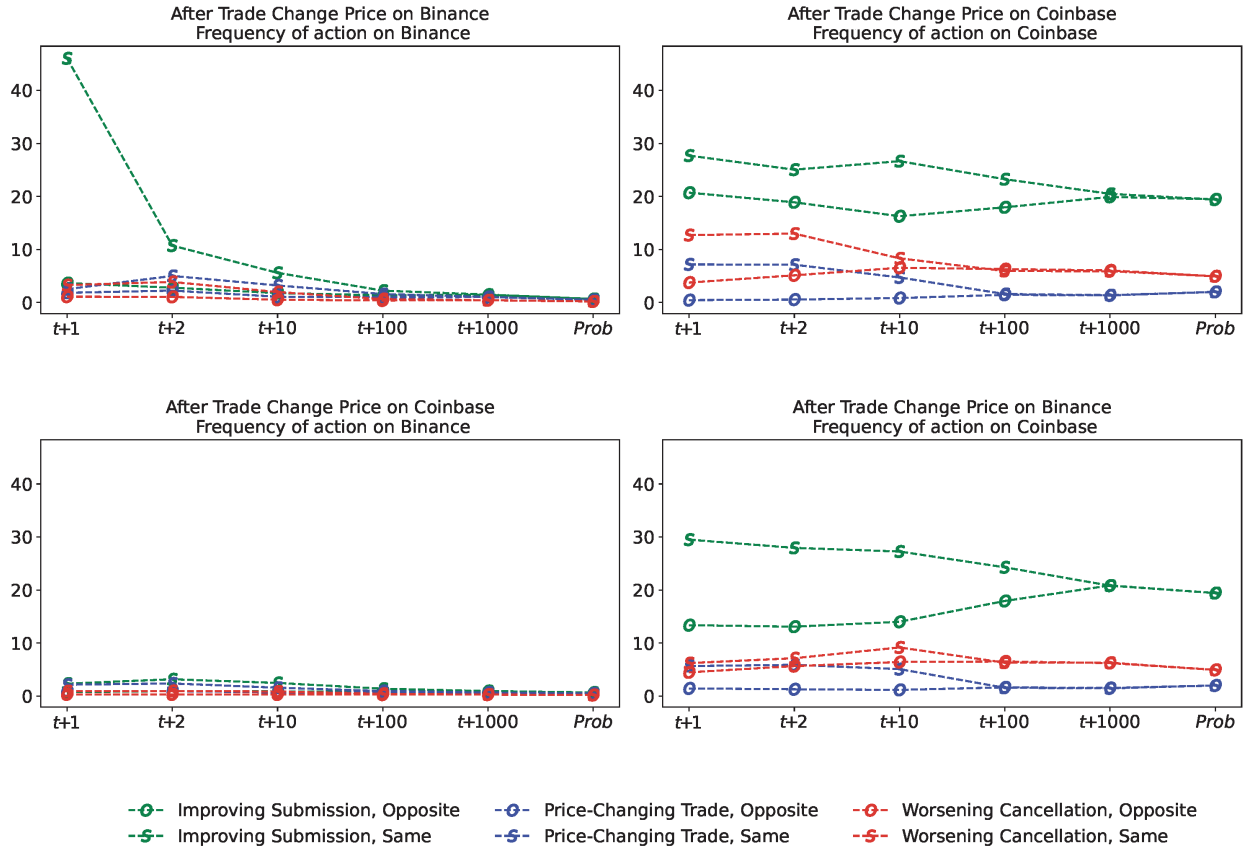
The determinants of impact presented above illustrate the positive relation between impact magnitude and both relative spread and book depth confirms that liquidity concentration – amplified by larger tick sizes – increases the price impact of each limit-order event. The higher sensitivity of Binance price impacts to market conditions reflects its trader composition and leverage: professional and algorithmic traders are more sensitive to changes in depth and volatility, producing larger, faster price adjustments than the predominantly retail order flow on Coinbase.

5.3 Market Response to Different Actions

Next we analyse how the market reacts to the three different price-changing actions by estimating the frequency of observing a price-changing action conditional on the current action, be it price-changing, price-reinforcing or price-neutral. These *conditional frequencies* are estimated by simply counting the frequency with which they occur, every day, and then averaging these empirical frequencies over each day in the sample. More specifically, we estimate the frequency with which an order of a certain type on Coinbase (or Binance) occurs after the same (or another) type of order occurs on Coinbase (or Binance). All frequencies are calculated per day and then averaged. Figures 5, 6 and 7, depict the results. *Prob* reports the frequency of each action were they to occur randomly; this represents the baseline frequency to which our conditional frequencies should be

Figure 5: Conditional Frequencies: Price-Changing Trade

The figure reports the relative frequencies of price-changing actions following trades that change the price. The frequencies are calculated taking into account only actions on one exchange. The figure reports the frequencies (in percent) of observing price-changing actions conditional on the current action. The sample period is from November 1, 2022 to March 31, 2023. *Prob* reports the frequency if actions occurred randomly. All variables are calculated per day and then averaged.

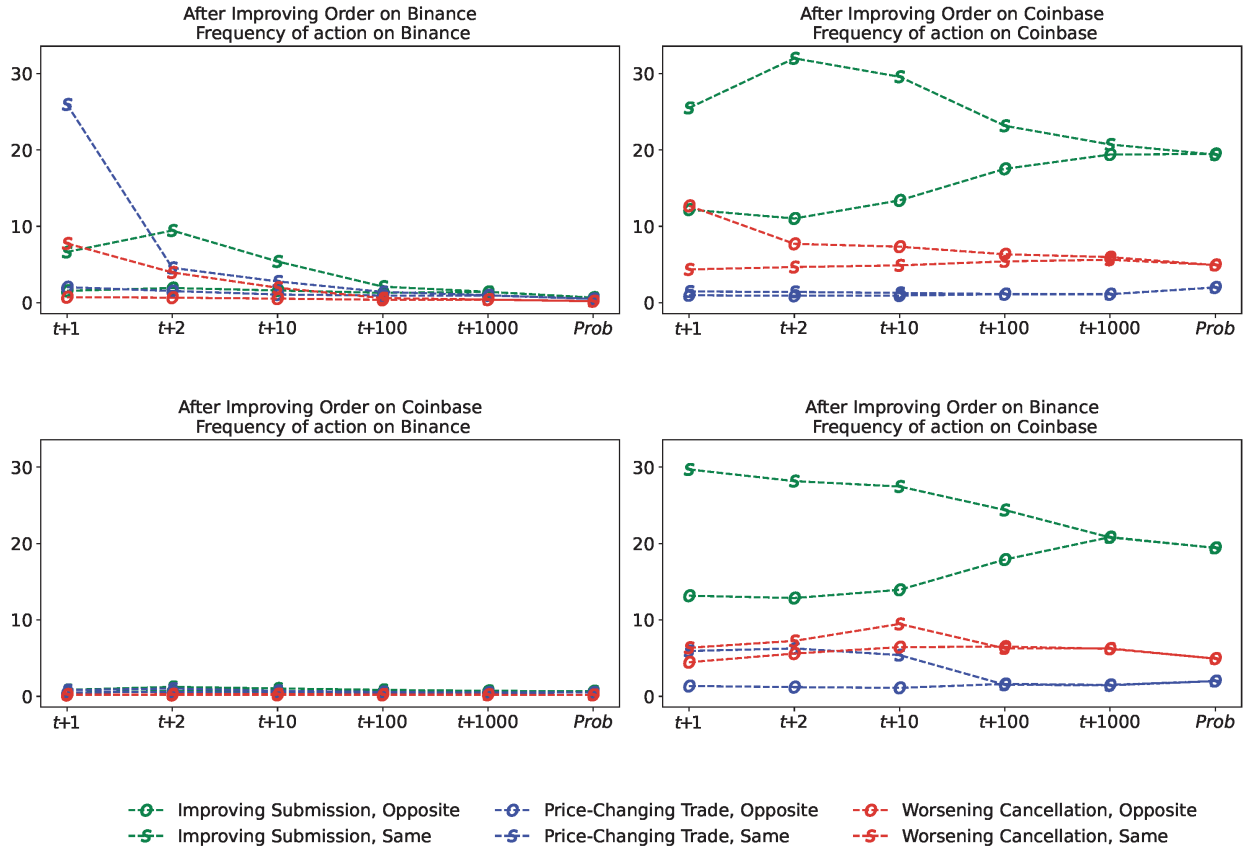


compared. Each figure has four graphs depicting the frequency with which an order of a certain type on Coinbase (or Binance) occurs one, two, ten, 100, or 1000 events after the same (or another) type of order occurs on Coinbase (or Binance). For example, the top left graph of Figure 5 shows the frequency of each price-changing action occurring on Binance between one and 1000 actions after a price-changing trade happens on Binance. The other three graphs depict the same for Coinbase, and the equivalent cross-exchange frequencies. By classifying each price-changing action into those on the same side of the book as the current action, and those on the opposite side, we provide a complete picture of the different market reactions to different orders.

The three figures have many features in common. First, regarding the graphs in the bottom

Figure 6: Conditional Frequencies: Improving Submission

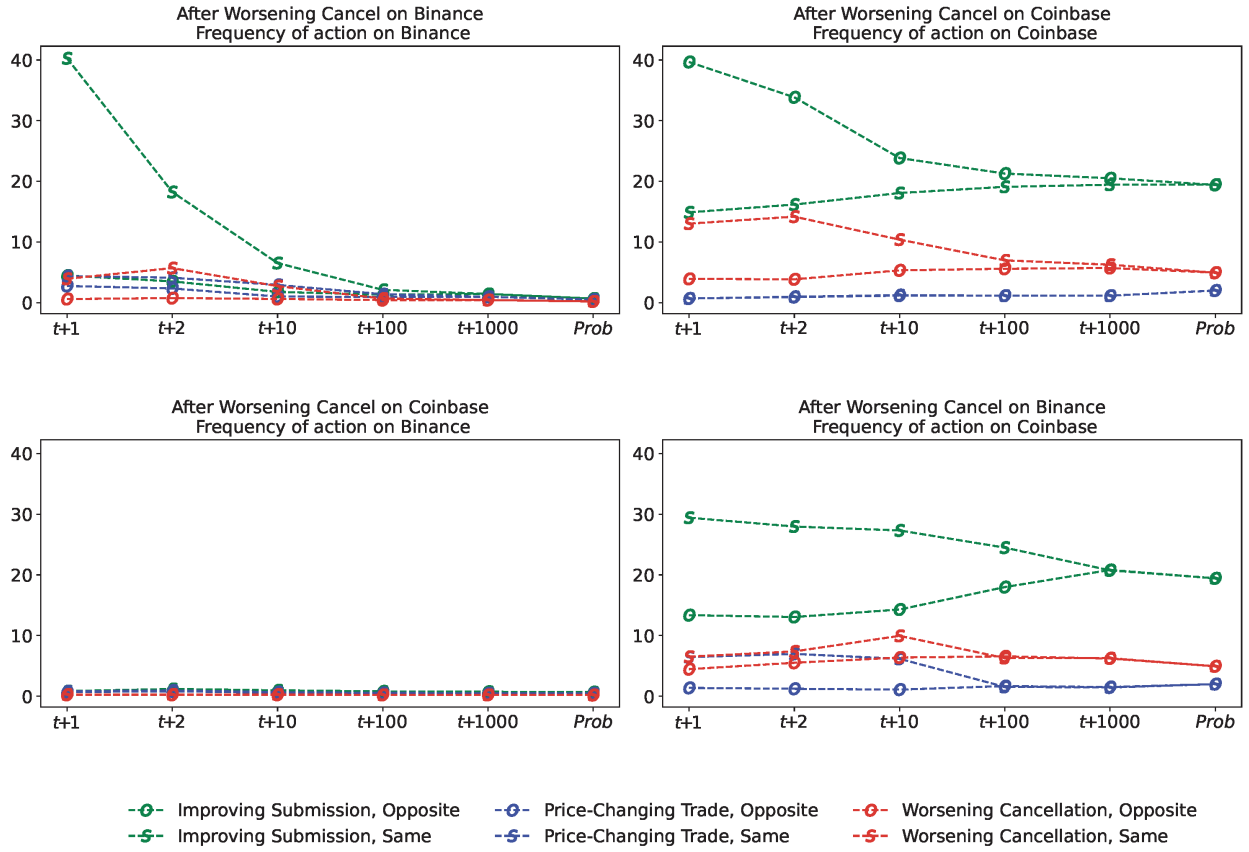
The figure reports the relative frequencies of price-changing actions following an improving submission. The frequencies are calculated taking into account only actions on one exchange. The figure reports the frequencies (in percent) of observing price-changing actions conditional on the current action. The sample period is from November 1, 2022 to March 31, 2023. *Prob* reports the frequency if actions occurred randomly. All variables are calculated per day and then averaged.



left of each figure, actions on Coinbase have no effect on price-changing actions on Binance. In contrast, on examining the bottom right graphs of each figure we see that almost all the actions on Binance have a significant influence on subsequent actions on Coinbase. Any price-changing action on Binance is immediately followed by an improving submission of the *same* sign on Coinbase about 30% of the time. The conditional frequencies of improving submissions in the *opposite* direction are also elevated compared to the baseline frequency of random occurrence. Such orders are unlikely to be placed due to traders' informational advantages, but rather to be at the head of the queue and gain priority over other traders. An improving submission on the opposite side of the book to the price-changing action on Binance happens less than 20% of the time, but the conditional frequency of such mean-reverting behaviour is still elevated by more than 1000 messages after the

Figure 7: Conditional Frequencies: Worsening Cancellation

The figure reports the relative frequencies of price-changing actions following a cancelled order that worsens the price. The frequencies are calculated taking into account only actions on one exchange. The figure reports the frequencies (in percent) of observing price-changing actions conditional on the current action. The sample period is from November 1, 2022 to March 31, 2023. *Prob* reports the frequency if actions occurred randomly. All variables are calculated per day and then averaged.



action occurred. This suggests that the strong price leadership provided by Binance, which will be more formally documented in Section 5.6, is mostly underpinned by new submissions in the limit order book rather than trades.[5] Indeed, price-changing trades on Binance hardly influence the actions of Coinbase traders at all. Secondly, comparing the two right-hand graphs within each figures, it seems that price-changing actions on both Coinbase and Binance have a similar influence on Coinbase traders,[6] suggesting that they take price-changing actions on *either* exchange as a

[5] Worsening cancellations on Binance also have an effect on Coinbase traders, but it is much less than for improving submissions.

[6] With with one exception: the greatest influence from worsening cancellations on Coinbase is on improving submissions on the *opposite* side of the book. Such a sequence probably originates from the same trader modifying or improving a previous order, because Coinbase does not allow orders to be modified. Instead, an order has to be cancelled and re-submitted.

strong information signal and will typically react in the same direction as the action, which gives rise to a temporal clustering of actions on the same side of the book.

Finally, note that there is less uniformity between the top left graphs of each figure, which depict the same-exchange conditional frequencies of an action on Binance following an action on Binance. Improving submissions on the same side of the book are highly likely after a price-changing trade (Figure 5) or a worsening cancellation (Figure 7). But after an improving submission (Figure 6) the most likely action is a trade on the same side of the book. Also, note that there is much less persistence in these effects; they are initially strong, but their influence has almost disappeared ten actions later. This is probably because the Binance platform executes actions extremely quickly, with high-frequency algorithms dominating the trading patterns that we observe.

The asymmetric transmission of price changes, where Binance actions are reflected to a greater degree on Coinbase than the reverse, shows how the absence of routing and order-protection rules, together with weaker regulatory oversight, allow price leadership to emerge from the less-regulated exchange. Moreover, the persistence of these asymmetries across order types and time horizons indicates that heterogeneous incentives and fee structures produce dislocated price formation between venues.

5.4 Determinants of Action Frequencies

The daily-average conditional frequencies change over time so we can investigate their determinants. Specifically, for each action we estimate a binary logistic regression, with the same explanatory variables as the OLS regression of Table 6, except that $Size_{t-1}$ is the size of the *preceding* action measured in bitcoin. The dependent variable is derived using a 'one-vs-rest' scheme. That is, when estimating the logistic regression for a certain action, the dependent variable is one when the action occurs and zero otherwise. This way we analyse how the probabilities of different actions change with market conditions. The regressions are estimated day by day, and the averages of the daily coefficients are reported in Table 7. Results are reported with HAC-corrected standard errors.

First, on Coinbase, a large negative return increases the likelihood of a trade or cancellation occurring during the next ten seconds but reduces the probability of a new order arriving in the book. However, on Binance, a negative return is associated with an enhanced probability of an improving submission, a worsening cancellation, or an order at best but a reduced probability of

Table 7: Logistic Regression of Action Frequencies

The table reports averages of logistic regressions of price-changing and price-reinforcing actions for BTC-USD on Coinbase and BTC-USDT on Binance. The sample period is from November 1, 2022 to March 31, 2023. The dependent and explanatory variables are defined in the main text. The regressions are estimated for each day and the averages of the daily coefficients are reported. * and ** next to the coefficient indicate that the coefficient is statistically different from zero at the 5% and 1 % level, using HAC-corrected standard errors.

Panel A: Price Changing Actions

Variable	Trade Change Price		Improving Submission		Worsening Cancellation	
Exchange	Coinbase	Binance	Coinbase	Binance	Coinbase	Binance
Intercept	−3.11**	−5.86**	−0.59**	−5.16**	−1.62**	−5.80**
Lagged Return	−2.14**	−0.31	1.92**	−0.43*	−1.86**	−0.52**
Volatility	11.05**	8.90**	−4.38**	4.65**	5.31**	6.49**
Depth	−0.37**	−0.02**	−0.09**	−0.03**	−0.15**	−0.06**
Order Book Imbalance	0.70**	1.85**	0.56**	1.56**	−0.54**	1.38**
Relative Spread	−101.46**	63.80**	64.27**	564.81**	−35.38**	43.47**
Size_{t-1}	0.15**	0.22**	−0.36**	0.05**	0.51**	0.06**

Panel B: Price-Reinforcing Actions

Variable	Trade Same Price		Order at Best		Cancel at Best	
Exchange	Coinbase	Binance	Coinbase	Binance	Coinbase	Binance
Intercept	−2.67**	−2.62**	−1.24**	0.46**	−2.18**	−0.30**
Lagged Return	−1.66**	1.99**	1.28**	−1.35**	−3.44**	0.52*
Volatility	2.36**	6.79**	−1.80**	0.79**	−1.86**	−6.55**
Depth	0.10**	0.00**	−0.04**	0.00**	0.17*	0.00**
Order Book Imbalance	−0.39**	−0.23**	0.31**	1.31**	−1.52**	−1.45**
Relative Spread	−91.49**	49.40**	−1.70	−527.10**	−50.76**	−493.32**
Size_{t-1}	−0.24**	−0.02**	−0.05	−0.01*	0.05	−0.10**

another trade, most likely a small one that doesn't consume all available liquidity, or a cancellation which doesn't affect the current price.

Second, when volatility becomes high, market participants change their behaviour and tend to prefer the immediacy of market orders over the lower execution costs of limit orders. Volatility affects both exchanges in a similar manner, except that new Coinbase orders decrease when volatility increases, whereas new Binance orders increase. Also, cancellations at best decrease when volatility is high because limit orders are likely to be picked off by market orders rather than cancelled before they can be executed.

Third, the depth of the order book is more important for Coinbase than for Binance, possibly

because liquidity is almost a given on Binance but is more variable on Coinbase. Notably, both price-changing trades and worsening cancellations reduce as the depth improves, whereas small trades and cancellations tend to increase. All else being equal, a greater depth decreases the probability of a price-changing trade and increases the likelihood of trades that do not consume all available liquidity. Limit order submissions also become less frequent, possibly because traders prefer to execute market orders when there is a large queue. For a similar reason, cancellations at the best prices increase with depth, when the queue at best price increases traders are more likely to cancel their existing orders. In contrast, the imbalance of the two sides of the book is more important for Binance traders than it is for those on Coinbase (except for small trades that don't change the price). When liquidity on the bid side is better than sell-side liquidity, any price-changing action becomes more likely on Binance. Orders at best also increase very significantly but cancellations of small orders that don't affect the price are less likely. Similar effects are seen on Coinbase. For market trades, the impact of the order book imbalance is, to some extent, mechanical. A trade is more likely to consume all liquidity on the order book side when the depth is lower so trades are more likely to occur in the direction of the order book imbalance. However, trades that do not consume all available liquidity are less likely to occur in the direction of the order book imbalance.

Fourth, the bid-offer spread has a different effect on each exchange. On Coinbase, a wide spread decreases the frequency of cancellations, increases the probability of an improving submission, and decreases the likelihood of a trade (because trades become more expensive). This is consistent with traders rushing to establish a new best bid or best offer by submitting better-priced orders. On Binance, wider spreads *in*crease the likelihood of a trade, or a worsening cancellation. And the most obvious effect of a wider spread is to decrease the number of orders at best (as well as increasing the number of improving submissions, obviously). The differences observed here are likely to because caused by the predominance of professional traders using informed trading strategies on Binance, but not on Coinbase. Next, considering the effect of the spread on improving submissions, these orders become more attractive (and thus more likely) when the spread is wide since there is more potential to improve on the best prices. Consequently, orders at the best prices also occur less frequently when the spread is wide. Price-reinforcing cancellations at the best prices also become less likely when the spread is wide. However, this is, to some extent, just a mechanical artifact related to the higher frequency of improving submissions when the spread is wide. If an improving

submission occurs, the current best price becomes the second best price and a cancellation at this price is then a cancellation *behind* the best price, rather than at the best prices.

Finally, the probability of a price-changing action increases with the size of the previous action, except for an improving submission on Coinbase. This is consistent with traders re-pricing their orders when past activity is large suggesting the presence of informed traders and/or large liquidity traders on Binance. While Coinbase does not allow traders to use margins on any spot product, Binance BTC-USDT perpetual traders can theoretically select up to 100X leverage, although 1% margins are rarely seen.

The stronger response of Binance order submissions to volatility and order-book imbalance indicates that exchanges with higher leverage and broader direct access attract professional traders whose strategies amplify order-flow dynamics during turbulent periods. At the same time, the contrasting behaviour on Coinbase, where new orders decline when volatility rises, illustrates how different incentives and fee structures influence trader responsiveness and contribute to persistent cross-exchange asymmetries in liquidity provision.

5.5 Permanent Price Impact Analysis

Next, we analyse the permanent price impact of the different actions using a structural vector autoregression (SVAR). This model is very similar to a standard vector autoregression, but it allows for additional contemporaneous dependence between variables. It is given by

$$\mathbf{A}_0 \, \mathbf{X}_t = \boldsymbol{\alpha} + \sum_{i=1}^{5} \mathbf{A}_i \, \mathbf{X}_{t-i} + \boldsymbol{\varepsilon}_t \tag{1}$$

where $\mathbf{X}_t$ is a vector containing the *mid return*, namely the change in the log mid quote, between the log price recorded at time $t-1$ and time t, plus an element for possible actions as described below. For each choice of $\mathbf{X}_t$ (and there are three) we calibrate two SVAR models, one for each exchange. The matrices $\mathbf{A}_i$ are coefficients on the lagged dependent variables, for lags of $i = 1, \ldots, 5$, $\mathbf{A}_0$ is a matrix capturing the contemporaneous (or immediate) impacts of actions on the mid return, and $\boldsymbol{\varepsilon}_t$ is a vector of zero-mean innovations. Only price-changing actions (trades that consume all available liquidity at the best bid or offer, improving submissions, and worsening cancellations) have a contemporaneous impact on the mid quote. All other actions leave the mid

quote contemporaneously unchanged. Thus, $\mathbf{A}_0$ only allows contemporaneous impacts of the three price-changing actions on the mid return. To study the impact of different trading actions, the first SVAR model adds the following trading variables as elements of $\mathbf{X}_t$ below the mid return:

1. *Trade Change Price* is +1 for buy-initiated trades (−1 for sell-initiated trades) that consume all liquidity available at the best offer (bid), and 0 otherwise;

2. *Improving submission* is +1 for buy order submissions (−1 for sell order submissions) that improve the best bid (offer), and 0 otherwise;

3. *Worsening Cancel* is +1 for sell order cancellations (−1 for buy order cancellations) that worsen the best offer (bid), and 0 otherwise;

4. *Trade Same Price* is +1 for buy-initiated trades (−1 for sell-initiated trades) that do not consume all liquidity available at the best offer (bid), and 0 otherwise. *Order at Best* is +1 for buy order submissions (−1 for sell order submissions) at the best bid (offer), and 0 otherwise;

5. *Cancel at Best* is +1 for sell order cancellations (−1 for buy order submissions) at the best offer (bid) that do not worsen the best offer (bid), and 0 otherwise. *Order Behind Best* is +1 for buy order submissions (−1 for sell order submissions) behind the best bid (offer), and 0 otherwise;

6. *Cancel Behind Best* is +1 for sell order cancellations (−1 for buy order submissions) behind the best offer (bid), and 0 otherwise.

Each SVAR is calibrated to event-time data, where each message is an observation. The impulse response function is cumulative over twenty events and reports the expected mid return (in basis points) after an action with positive sign (buy actions for trades and order submissions, sell actions for limit order cancellations). The response of the mid return to an impulse from one of the actions is commonly interpreted as the permanent price impact of the action. In contrast to the model-free simple price impact studied above, the SVAR is able to differentiate between actions incorporating new information and actions simply being responses to other actions. In particular, the SVAR explicitly models the sequence of actions and the return impulse response function, and

then attributes to an action the immediate change due to the action plus the change caused by all predictable (re)actions to the initial action. The variance decomposition is calculated following Hasbrouck (1991) and assigns to each of the actions included in the model the fraction of variance in the mid return that the variable is responsible for. We re-scale the variance decomposition so that the contributions of the action variables sum to one.[7]

Table 8 displays our first SVAR model calibrations. We calibrate each model for every day in our sample, and estimate permanent price impacts as the size (in basis points) of the impulse response to twenty events for each of the eight actions, also reporting their corresponding variance decomposition. Table 8 reports the averages of these daily results, as well as standard errors which are calculated as before using the time series of daily coefficients as in Brogaard et al. (2019). Panel A shows that permanent price impacts are generally very small and consistently less than a quarter of a basis point. Price-changing actions on Binance clearly have the largest permanent price impacts. Price-reinforcing actions (trades that do not consume all available liquidity, submissions at best, cancellations at best) generally exhibit small price impacts of at most 0.02 basis points. Activity behind the best prices is even less significant and moves the mid quote by less than 0.01 basis points.

The reasons for finding such small price impacts are probably trading frequency and tick size. Hautsch and Huang (2012) show that the strength of market responses is negatively correlated with trading frequency and positively influenced by relative tick size. Compared with the Canadian and Australian equities studied in Brogaard et al. (2019) and Philip (2020), there are many more transactions on Coinbase and Binance. The most traded stock in Philip (2020) exhibits about 280,000 trades during a two-month period, while the average daily number of transactions for Canadian stocks included in Brogaard et al. (2019) is less than 5,000. In contrast, Table 2 shows that there are, on average, more than 690,000 BTC-USD trades per day on Coinbase and more than a million BTC-USDT trades per day, on average, on Binance. Moreover, Coinbase has a tick size of one cent which in relative terms corresponds to only about 0.002 to 0.005 bps of the bitcoin price. The tick size on Binance is ten times larger but still, both are much smaller than for

[7]Similar to Hasbrouck (1991), we impose identifying restrictions on the contemporaneous covariance structure in the model based on economic relationships between our variables. For example, a trade that changes the current best price has a contemporaneous impact on the mid return, whereas a limit order submitted at the current best price level leaves the mid quote unchanged. These economic restrictions fully identify our model and we do not need to use a Cholesky decomposition.

Table 8: Results from Own Exchange SVAR Calibrations

The table reports average permanent price impacts and variance decomposition from the structural vector-autoregression (1) for BTC-USD on Coinbase, and for BTC-USDT on Binance, where $\boldsymbol{X}_t$ is a vector containing the mid return and one entry for each action on the same exchange. The sample period is from November 1, 2022 to March 31, 2023. Panel A reports the cumulative impulse response over twenty events and Panel B presents the variance decomposition calculated following Hasbrouck (1991). The SVAR is estimated for each day and the daily estimates for impulse responses and variance decompositions are then averaged. * and ** next to the coefficient indicate that the coefficient is statistically different from zero at the 5% and 1% level, respectively, using HAC-corrected standard errors.

Panel A: Permanent Price Impact (in bps)

	Coinbase	Binance
Mid Return	0.87**	1.47**
Improving Submission	0.04**	0.23**
Worsening Cancellation	0.07**	0.25**
Trade Change Price	0.23**	0.25**
Order at Best	0.01**	0.01**
Cancel at Best	0.00**	0.00**
Trade Same Price	0.02**	0.01**
Order Behind	0.00	
Cancel Behind	0.00	

Panel B: Variance Decomposition (in %)

	Coinbase	Binance
Mid Return	73.59**	69.64**
Improving Submission	6.06**	12.47**
Worsening Cancellation	6.22**	5.45**
Trade Change Price	13.86**	11.29**
Order at Best	0.15**	0.98**
Cancel at Best	0.01**	0.06**
Trade Same Price	0.10**	0.12**
Order Behind	0.01**	
Cancel Behind	0.01**	

the Australian and Canadian equities included in Brogaard et al. (2019) and Philip (2020), which typically exhibit a relative tick size of more than one basis point. The high number of transactions and the negligible relative tick size contribute to the small magnitude of permanent price impacts on Coinbase and Binance, as previously documented by Hautsch and Huang (2012).

The variance decompositions shown in Panel B reveal that price-changing trades on both exchanges and improving submissions on Binance contribute most to price discovery. On Coinbase it is interesting that trades that change the price are more important than limit order submissions

and cancellations, whereas limit orders dominate price discovery on Binance. The large impact of improving submissions on Binance is consistent with the larger tick-size and the resulting large change in the mid-point. Coinbase has smaller ticks and wider spreads perhaps leading to small price changes. The fact that trades contribute more to price discovery on Coinbase is related to the large spread that a market order crosses, leading to a greater price impact and hence also a more significant contribution to price discovery.

A second pair of SVAR calibrations examines the impact of order size. Because activities behind the best prices have a very small price impact we now exclude these from further analysis. Retaining the mid return on the relevant exchange we add three further variables to $\mathbf{X}_t$ for each TOB action on the same exchange, broken down by action size based on time-series quantiles. If the size of an action is less than or equal to the 33.3%-quantile the action is classified as small; If it is greater than the 33.3%-quantile but less than or equal to the 66.6%-quantile, the action is classified as medium; and if the size of an action is greater than the 66.6%-quantile the order is classified as large. Such a quantization has the advantage that the resulting permanent price impact as a function of action size is a step function which is able to capture the typical concave shape of permanent price impact (Philip, 2020). With this classification, the SVAR becomes nineteen-dimensional.

Panel A of Table 9 reports the permanent price impacts, which increase with action size, and on Coinbase more so for trades than limit orders. But price-reinforcing trades have little price impact on Binance, hardly greater than price-reinforcing limit orders. As in Table 8 price-changing actions on Binance have greatest impact. but this is still modest: at most 0.30 bps for worsening cancellations and 0.31 bps for large trades. Panel B of Table 9 shows that large improving submissions and large price-changing trades contribute most to the mid-return variance on both exchanges. The large trades contribute most on Coinbase (15.44% vs 11.27% for large improving submissions), whereas large improving submissions contribute almost twice as much as price changing trades (10.27% vs 5.97%) on Binance.

Finally, we estimate a third pair of SVAR models to study the impact that price changes on one exchange have on the other exchange. The mid return on one exchange is still the first element of $\mathbf{X}_t$ but now we add twelve variables, these being the signed TOB actions from *both* exchanges, resulting in a pair of thirteen-dimensional SVAR calibrations. Both models include the same TOB actions on *both* exchanges. The results are presented in Table 10. The small but significant cross-exchange

Table 9: Results from Second (Order Size) SVAR Calibrations

Panel A reports the cumulative impulse response over twenty events and Panel B presents the variance decomposition calculated following Hasbrouck (1991). The SVAR is estimated for each day and the daily estimates for impulse responses and variance decompositions are then averaged. In (1) $\boldsymbol{X}_t$ contains the mid return and three entries for each TOB action broken down by size.

Panel A: Permanent Price Impact (in bps)

	Coinbase	Binance
Mid Return	0.60**	1.47**
Improving Submission - Small	0.04**	0.17**
Improving Submission - Medium	0.06**	0.22**
Improving Submission - Large	0.08**	0.24**
Worsening Cancellation - Small	0.06**	0.23**
Worsening Cancellation - Medium	0.05**	0.23**
Worsening Cancellation - Large	0.05**	0.30**
Trade Change Price - Small	0.25**	0.21**
Trade Change Price - Medium	0.25**	0.24**
Trade Change Price - Large	0.34**	0.31**
Order at Best - Small	0.02**	0.01**
Order at Best - Medium	0.03**	0.01**
Order at Best - Large	0.05**	0.01**
Cancel at Best - Small	0.00	0.00**
Cancel at Best - Medium	0.00	0.00**
Cancel at Best - Large	−0.01**	0.00**
Trade Same Price - Small	0.03**	0.00**
Trade Same Price - Medium	0.13**	0.01**
Trade Same Price - Large	0.17**	0.03**

Panel B: Variance Decomposition (in %)

	Coinbase	Binance
Mid Return	41.48**	67.58**
Improving Submission - Small	2.60**	0.77**
Improving Submission - Medium	5.35**	2.24**
Improving Submission - Large	11.27**	10.27**
Worsening Cancellation - Small	2.35**	1.77**
Worsening Cancellation - Medium	1.13**	1.14**
Worsening Cancellation - Large	1.14**	2.62**
Trade Change Price - Small	7.84**	3.47**
Trade Change Price - Medium	3.22**	2.60**
Trade Change Price - Large	15.44**	5.97**
Order at Best - Small	0.70**	0.20**
Order at Best - Medium	2.06**	0.38**
Order at Best - Large	2.56**	0.66**
Cancel at Best - Small	0.03**	0.03**
Cancel at Best - Medium	0.03**	0.02**
Cancel at Best - Large	0.19**	0.01**
Trade Same Price - Small	0.46**	0.02**
Trade Same Price - Medium	0.83**	0.03**
Trade Same Price - Large	1.31**	0.20**

Table 10: Results from Cross-Market SVAR Calibrations

The table reports average permanent price impacts and variance decomposition from the structural vector-autoregression (1) for BTC-USD on Coinbase, and for BTC-USDT on Binance, where $\boldsymbol{X}_t$ is a vector containing the mid return and one entry for each action on the *other* exchange. The sample period is from 1 November 2022 to 31 March 2023. Panel A reports the cumulative impulse response over twenty events and Panel B presents the variance decomposition calculated following Hasbrouck (1991). The SVAR is estimated for each day and the daily estimates for impulse responses and variance decompositions are then averaged. * and ** next to the coefficient indicate that the coefficient is statistically different from zero at the 5% and 1% level, respectively, using HAC-corrected standard errors.

Panel A: Permanent Price Impact (in bps)

	Binance	Coinbase
Mid Return	1.49**	0.72**
Coinbase - Improving Submission	0.00**	0.04**
Coinbase - Worsening Cancellation	0.00**	0.06**
Coinbase - Trade Change Price	0.01**	0.25**
Coinbase - Order at Best	0.00**	0.02**
Coinbase - Cancel at Best	-0.00**	-0.00**
Coinbase - Trade Same Price	0.00**	0.03**
Binance - Improving Submission	0.22**	0.02**
Binance - Worsening Cancellation	0.23**	0.02**
Binance - Trade Change Price	0.23**	0.01**
Binance - Order at Best	0.01**	0.01**
Binance - Cancel at Best	-0.00**	-0.00**
Binance - Trade Same Price	0.01**	0.00**

Panel A: Variance Decomposition (in %)

	Binance	Coinbase
Mid Return	73.06**	61.88**
Coinbase - Improving Submission	0.07**	9.68**
Coinbase - Worsening Cancellation	0.00**	5.41**
Coinbase - Trade Change Price	0.03**	20.50**
Coinbase - Order at Best	0.06**	1.14**
Coinbase - Cancel at Best	0.00**	0.06**
Coinbase - Trade Same Price	0.00**	0.60**
Binance - Improving Submission	11.33**	0.11**
Binance - Worsening Cancellation	4.69**	0.05**
Binance - Trade Change Price	10.10**	0.07**
Binance - Order at Best	0.56**	0.43**
Binance - Cancel at Best	0.02**	0.05**
Binance - Trade Same Price	0.07**	0.01**

effects suggest that high-frequency activity on one exchange does have some permanent price effect on the other, albeit rather limited. The cross-exchange effects in the variance decomposition are also significant. Notably, orders at best on Binance influence Coinbase nearly as much as Binance.

The much larger and more persistent impact of improving limit orders on Binance relative to Coinbase shows that coarser tick sizes magnify both the magnitude and horizon of limit-order impacts. The dominant role of Binance in variance-decomposition shares reflects how lighter regulatory oversight and higher leverage permit faster incorporation of information into prices.

5.6 Price Discovery Analysis

Next we estimate a cointegration relationship between the mid quotes on Binance and Coinbase using a two-dimensional vector error correction model (VECM) of the form

$$\Delta \mathbf{p}_t = \boldsymbol{\alpha} + \sum_{i=1}^{10} \boldsymbol{\Gamma}_i \Delta \mathbf{p}_{t-i} + \boldsymbol{\delta} z_{t-1} + \mathbf{e}_t, \tag{2}$$

where $\mathbf{p}_t$ is the 2×1 vector representing the two log mid quotes at time t, the 2×1 vector $\boldsymbol{\alpha}$ is a constant, $\boldsymbol{\delta}$ is a 2×1 error correction vector which captures the prices' reactions to transitory deviations from the long-run equilibrium, $\boldsymbol{\Gamma}_i$ are 2×2 coefficient matrices and $\mathbf{e}_t$ is a 2×1 vector of serially uncorrelated innovations with zero mean and covariance matrix $\boldsymbol{\Omega}$. The number of lags in the VECM is fixed at ten.

On each day in the sample we perform four different calibrations of the structural model to mid quotes for BTC-USD on Coinbase and BTC-USDT on Binance, sampled at three different frequencies (100ms, 500ms and 1 second).[8] Given each calibration, we estimate the relative price discovery contributions of Binance and Coinbase from the reduced-form vector moving average version of the model. Recall from Table 1 that the two markets have very different microstructure characteristics. On average, the relative spread (in basis points) is fourteen times larger on Coinbase, and the quoted spread (in ticks) is almost 150 times larger on Coinbase than on Binance. Binance is also a far deeper market with much higher trading volumes, and where up to 100X leverage is allowed. When two markets have different microstructure frictions, associated with different tick

[8]The error correction adjustments coefficients show a pattern of variation that is similar to the pattern of the information ladershp share over time. As we aggregate the data to lower frequencies they increase in absolute size. For example, the average adjustment for Binance is 0.0005 at the 100ms frequency and increases to 0.0033 as we aggregate to the 1-second frequency.

sizes and/or the extent of bid–ask bounce, Putniņš (2013) shows that neither the Hasbrouck (1995) information share (IS) nor the Gonzalo and Granger (1995) component share (CS) measure price discovery accurately with large differences in noise levels.

We therefore report the information leadership share (ILS) of Putniņš (2013) which uses the IS and the CS together to identify the market that is the first to impound new information.[9] Following Hasbrouck (2021) the VECM coefficients are constrained to be identical across autoregressive blocks. We leave the coefficient at lag 1 unrestricted; coefficients for lags 2–10 have the same value and coefficients for lags 11–100 have the same value. The number of lags is chosen so that the maximum lag is 10 seconds in natural time. The sample average of the daily ILS estimates for (Binance, Coinbase) are: (68.60%, 31.40%) at 1 second; (62.16%, 37.84%) at 500ms; and (54.22%, 45.78%) at 100ms.[10] Hence, Binance is clearly the first to incorporate new information into prices at 1 second and at 500 ms, but as the sampling frequency increases, this leadership becomes less apparent. This is consistent with the price impact results that show a large impact of Binance activity on Coinbase prices and a smaller impact from Coinbase to Binance. The sample average ILS results are misleading, because the Binance ILS share jumps up significantly on days of considerable market turmoil. To see this, Figure 8 displays weekly rolling averages of the daily time series of ILS, at 100ms and 1 second frequencies, that underpin the sample averages just quoted.

That Binance leadership increases during high-volume, volatile periods is shown by examining, for each exchange separately, the pair-wise correlations between the 100ms ILS and several variables related to trading volume and volatility.[11] Table 11 reports daily correlations between the 100ms ILS and the following variables: the log mid return; the five-minute realised volatility (RV); the TOB the cancel-to-trade ratio (CT); and the TOB trade-to-order volume ratio (TV), all calculated as described in the caption to the table. The entries above the diagonal, which are for Binance, reveal a highly significant positive correlation between its 100ms ILS and both RV and TV, which themselves have a correlation of 0.79; and a highly significant negative correlation between its 100ms ILS and CT, which has a correlation of -0.77 with TV. In contrast, the entries below the

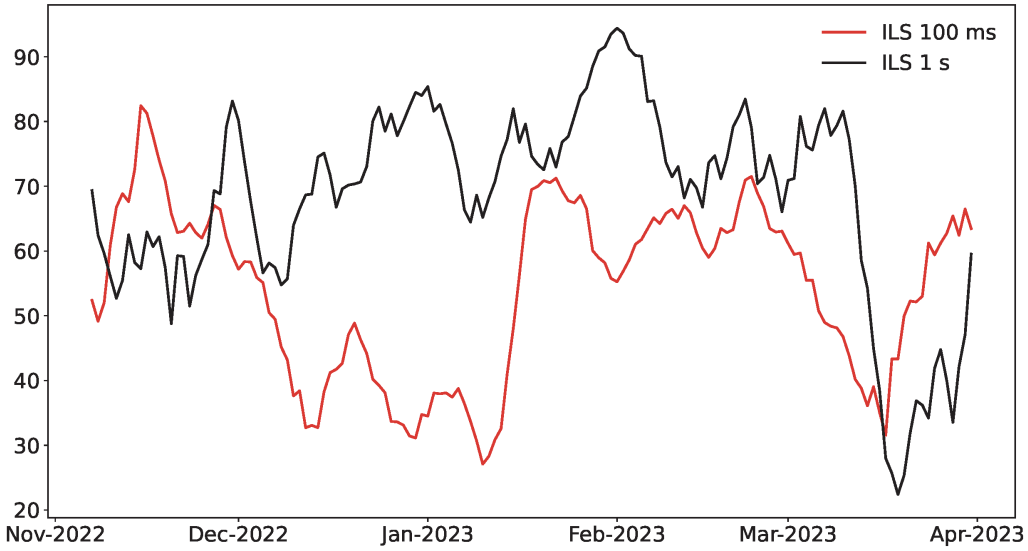
[9] To identify the IS we rely on the standard approach in the literature. That is, we use the Cholesky decomposition to get a lower and upper bound for the IS of each market. We then average these bounds to get the mid IS.

[10] Based on HAC-corrected standard errors of daily averages from November 1, 2022 to March 31, 2023, the one-second and 500ms measures are significantly different from 50% at the 1% level.

[11] Multivariate regressions are not reported because their standard errors are biased by the extreme collinearity between potential explanatory variables, which is evident from their high pair-wise correlations in Table 11.

Figure 8: Daily Results for Binance ILS Shares

This figure depicts the weekly rolling window average of daily ILS price discovery measures derived from the VECM model in Equation (2) based on mid quotes for BTC-USD on Coinbase and BTC-USDT on Binance, calibrated to data at the 100ms frequency (red) and the one-second frequency (black). The sample period is from November 1, 2022 to March 31, 2023.



diagonal, for Coinbase, show that its 100ms ILS is not related to either CT or TV and has a negative rather than positive relationship with RV. This shows that the 45.78% price leadership share that Coinbase normally has at the 100ms frequency switches more towards Binance on volatile days. These are the days where TV is high, and the CT ratio is low, on both exchanges. However, the trading patterns captured by CT and TV only affect the leadership share of Binance, they have no effect on the leadership share of Coinbase.

Our sample encompasses the period when news spread about the FTX exchange closure, on 8 and 9 November 2022. At this time Binance's 100ms ILS surged to 100%, while its one-second ILS fell below the sample average of 68.60%. A similar pattern occurred amid a major bitcoin price bull run between 11 and 13 January 2023, with the 100ms ILS reaching nearly 100% on 12 January. This discrepancy suggests HFTs may have been engaging in arbitrage between exchanges, or manipulating prices on Binance. Unlike the transparent Coinbase exchange, Binance's less regulated environment hides certain orders and cancellations, as well as trades made by its liquidation engine

Table 11: Correlations

This table reports the correlations between daily time series of different variables, constructed from BTC-USD on Coinbase and from BTC-USDT on Binance. The sample period is from November 1, 2022, to March 31, 2023. ILS 100 is the 100ms information leadership share of Putniņš (2013). The upper triangular part of the matrix reports correlations with four different variables, which are all constructed from BTC-USDT on Binance, whereas the lower triangular part of the matrix contains correlations with the same variables constructed from BTC-USD on Coinbase. The four variables are: LR is the daily log return, calculated using the mid quotes at the start and end of the day; RV is the daily realised volatility calculated from the log returns, sampled at the five-minute frequency; CT is the cancel-to-trade ratio calculated every day as the ratio of cancellations at the top of the order book divided by the number of trades; and TV is the trade-to-order volume ratio calculated as the volume of the trades divided by the volume of TOB orders not leading to a trade.

Variable	ILS 100	LR	RV	CT	TV
ILS 100		−0.19*	0.38***	−0.54***	0.42***
LR	0.19*		0.00	0.03	−0.03
RV	−0.34***	−0.02		−0.64***	0.79***
CT	0.04	−0.05	0.03		−0.77***
TV	−0.09	0.02	0.36***	−0.56***	

and insurance fund, facilitating such activities.

In June 2023 the SEC accused Binance of allowing U.S. traders to use VPNs and offshore companies to trade. Analysis of just these volatile periods reveals that Binance's 100ms ILS is even more positively correlated with realized volatility (RV) and the trade-to-order volume ratio (TV) but negatively correlated with the cancel-to-trade ratio (CT). Conversely, Coinbase's 100ms ILS remains negatively related to RV and unaffected by CT and TV. Thus, during volatile, high-volume periods, price leadership shifts from Coinbase to Binance, underscoring the integration issues and volatility-driven leadership on Binance.

These price discovery results confirm two of our previous observations, one about the level of integration between the two markets deteriorating at high frequency,[12] and the other about the price leadership of Binance being most apparent on highly volatile days when professional traders, especially in the U.S, increase their trading volumes on Binance.

The predominance of Binance in information-leadership shares, despite its coarser tick size, shows that without cross-market routing or order-protection rules, price discovery becomes concentrated on the venue with the most aggressive and liquid order flow. The direction of information flow, consistently from Binance to Coinbase, highlights how weaker regulatory constraints allow

[12] As illustrated by Figure 1, they are highly integrated at the thirty-minute frequency, having a daily average returns correlation of 99.3%, but at a frequency of 10ms the two market's returns have an average correlation of only 1.5%.

faster and larger trader responses to new information. Finally, the dependence of Binance's leadership on volatility and trading intensity reflects how professional, leveraged participants dominate short-horizon information transmission on exchanges with greater access and flexibility.

6 Conclusion

This paper studies price formation and price discovery in cryptocurrency markets using full tick-by-tick limit order book data from two major centralized exchanges. By decomposing market activity into distinct order events, we analyse how trades, limit-order submissions, and cancellations contribute to price dynamics within and across venues at horizons ranging from milliseconds to seconds.

Our findings are broadly consistent with existing evidence from both traditional financial markets and cryptocurrency markets. In particular, we confirm that limit orders play a central role in price discovery, that information is incorporated rapidly at high frequencies, and that markets are fragmented at ultra-short horizons but increasingly integrated as the sampling frequency decreases. These outcomes have been documented previously using trade- or price-based data, and our results do not overturn these established stylised facts.

The contribution of the paper lies in resolving the mechanisms and timing underlying these findings using full order-book data. By observing order flow directly at the message level, we are able to distinguish the informational roles of different order events and to quantify their short-run and permanent price impacts. This allows us to identify how price discovery is distributed across order types and how cross-venue information transmission emerges as horizons increase. In contrast to existing studies based on lower-frequency data, our approach provides direct evidence on the channels through which information enters prices in fragmented crypto markets.

The analysis also highlights important differences across trading venues in terms of order flow composition and price response at very short horizons, while showing that these differences diminish as information is aggregated over time. Importantly, our results are descriptive and pertain to bilateral dynamics between the exchanges studied; they do not imply market-wide price leadership or causal effects of specific institutional features.

Overall, the paper contributes to the market microstructure literature by extending order-level

price discovery analysis to a setting characterised by extreme message intensity and incomplete venue integration. While cryptocurrency markets provide the empirical context, the findings are relevant more generally for understanding price formation in modern electronic markets. Future research could build on this framework by incorporating a broader set of venues or exploiting exogenous changes in market design to further identify the drivers of cross-market information transmission.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used ChatGPT to assist but only in the very final revisions. The authors thoroughly reviewed and edited the content as needed and we take full responsibility for the content of the published article.

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