The components of Bitcoin's bid-ask spread. Does the change in tick size matter?

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Abstract:
We follow McGroarty et al. (2007) and disentangle the bid-ask spread of Bitcoin traded at Bitstamp against the US dollar into the private information, buy-sell imbalances and price clustering components. Using GMM and quantile regression frameworks and transaction data from March 2022 through February 2023, we assess the impact of the August 2022 tick size update on the magnitude of these components and show how their shares in the spread vary across the centiles of Bitcoin's price change distribution.

Keywords: Bitcoin, Bitstamp, bid-ask spread decomposition, GMM, quantile regression
JEL Classifications: G15, C58, C21, C26

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Introduction

The research interest in cryptocurrencies has grown enormously over the past decade, resulting in numerous papers primarily focusing on Bitcoin, the largest capitalisation and trading volume cryptocurrency. A substantial number of studies on Bitcoin, to name few but the most recent, concentrated on (i) market informational efficiency (Urquhart, 2016; Bariviera, 2017; Kristoufek, 2018; Vidal-Tomás & Ibañez, 2018; Sensoy, 2019); (ii) price discovery (Brauneis and Mestel, 2018; Aalborg et al., 2019; Dimpfl and Peter, 2021); (iii) volatility (Dyhrberg, 2016a; Katsiampa, 2017; Katsiampa et al., 2019; Baur and Dimpfl, 2021; Dimpfl and Elshiaty, 2021); (iv) assets correlation and portfolio formation (Klein et al., 2018; Aslanidis et al., 2019; Liu, 2019; Zieba et al., 2019); (v) hedge and safe-haven properties (Dyhrberg, 2016b; Bouri et al., 2017a; 2017b; Corbet et al., 2018b; Shahzad et al., 2019; Smales, 2019; Urquhart and Zhang, 2019; Ustaoglu, 2022); (vi) speculative bubbles (Cheah and Fry, 2015; Fry and Cheah, 2016; Corbet et al. 2018a; Geuder et al. 2019; Podhorsky 2024); (vii) statistical properties of Bitcoin's prices (Dwyer, 2015; Bariviera et al., 2017); (viii) predictability of Bitcoin's returns, volume, and volatility (Balcilar et al. 2017; Demir et al., 2018; Urquhart 2018; Adcock and Gradojevic, 2019; Bleher and Dimpfl, 2019; Shen et al., 2019; Corbet et al. 2020; Cheah et al., 2022; Bianchi et al., 2023); (ix) intraday trading patterns (Eross et al., 2019; Petukhina et al., 2021; Su et al., 2022; Wang et al., 2022), and (x) price clustering and sentiment (Urquhart, 2017; Baig et al., 2019; Li et al., 2020; Kalyvas et al., 2021; Karaa et al., 2021; Ma and Tanizaki, 2022).[1]

Less attention has been paid to transaction costs and liquidity. If so, they both have been approximated by the bid-ask spread and related measures; however, being rarely computed on high-frequency data. Using such data, Dyhrberg et al. (2018) and Brauneis et al. (2022) revealed the existence of intraday patterns in Bitcoin's quoted and effective spreads, while Dimpfl (2017) and Tiniç et al. (2023), based on the models of Glosten and Harris (1988), Huang and Stoll (1997), and Madhavan et al. (1997), decomposed the spread into the adverse selection and transitory components, reflecting permanent and temporary price changes, and other processing costs. They found that the adverse

[1] The state of the art in the research on cryptocurrencies is summarized by Corbet et al. (2019), Bariviera and Merediz-Solà (2021), Kayal and Rohilla (2021), Fang et al. (2022), Halaburda et al. (2022), and Pattnaik et al. (2023).

selection component had a prominent stake in the spread, many times greater than that Huang and Stoll (1997) reported for stocks. Feng et al. (2018) confirmed the vital role of information asymmetry, showing that informed trading preceded significant Bitcoin-related and other market events. Guégan and Renault (2021), Karaa et al. (2021), and Kim and Kauffman (2024) proved that Bitcoin transactions were affected by the prevailing social sentiment, resulting in significant information asymmetry that impacted transactions within the whole ecosystem. Natashekara and Sampath (2024) detected the existence of stealth trading. Finally, Liu et al. (2023) identified five distinct types of Bitcoin traders: casual ones, fundamental and technical liquidity takers, and the same kind of liquidity providers, out of which the latter four types profited from information asymmetry.

This paper aims to identify factors underlying Bitcoin's bid-ask spread and assess their importance in addressing its market specificity. Since leading crypto exchanges charge market and limit orders under the maker-taker fee model the same way, we assume that the order processing component is no longer valid. We also consider that the size of market orders may exceed the available depth at the best bid/ask quotes, as noted by Dyhrberg et al. (2018), and, following Li et al. (2020), take into account the frequent price clustering in Bitcoin. Thus, we build on McGroarty et al. (2007), who adapted the trade indicator model of Huang and Stoll (1997) for the order-driven FX market. Then, having nested the analysis within the GMM framework, we disentangle Bitcoin's bid-ask spread into three main components: private information, temporary buy-sell imbalances, and price clustering. In so doing, we purposely use transaction data on Bitcoin traded at Bitstamp against the US dollar from 27/03/2022 through 23/02/2023, to estimate their portions in the bid-ask spread and to demonstrate how they change after the tick size update from USD 0.01 to USD 1.00, intended to improve liquidity and narrow spreads, effected 10/08/2022. To ensure the robustness of our findings, we apply quantile regression, examining how the component shares in the spread vary across the centiles of its price change distribution before and after the tick-size update.

Our research makes a threefold contribution to the existing literature on Bitcoin. First, we show that while the tick size update substantially narrowed the bid-ask spread, enhancing liquidity and reducing transaction costs, it did not notably improve market depth around the best bid/ask quotes. Second, based on GMM, we assess the share of private information, buy-sell imbalances and price clustering components in the bid-ask spread, demonstrating that each of them had a significant share in it, both before and after the tick size update; however, the update more than doubled the share of buy-sell imbalances component, cut the share of price clustering one by about one fifth, and left that of private information almost unchanged. Third, based on quantile regression, we conclude that the impact of these factors on the spread depended on the centiles of Bitcoin's price change and the period in question and was asymmetric.

The rest of the paper is organised as follows. Section 2 introduces the data used in the analysis and highlights the research method. Section 3 shows and discusses the empirical results. The last section briefly concludes.

Data and Method

Bitcoin is being traded at Bitstamp against three major currencies: the US dollar (USD), euro (EUR) and British pound (GBP). Volumes traded in USD prevail. Our data on trade, sourced from Refinitiv, exhibit transactions in USD recorded with the accuracy of one millisecond executed in two periods: before the tick size update (27/03/2022, 03:00 GMT–9/08/2022, 23:59 GMT; 2,342,590 observations) and after that (11/08/2022, 00:00 GMT–23/02/2023, 23:59 GMT; 2,855,880 observations). They comprise information on the last trade price, best bid, best ask, trade volume and turnover. We remove transactions executed on 10/08/2022 to control for temporary market adjustments following the tick size update.

The trading characteristics exhibited in Fig. 1 show significant differences within the two time periods we are considering. The trade price dropped from about 44,700 USD/BTC in the first period to 23,200 USD/BTC. In the subsequent period, it remained around 20,000 USD/BTC for an extended time. The volatility of the bid ask spread was much higher in the first period. The same applies to the trade price when the price change across the centiles of its distribution is considered (see Fig. 2). More interestingly, the tick size update resulted in many more transactions being executed at unchanged and little changing prices.

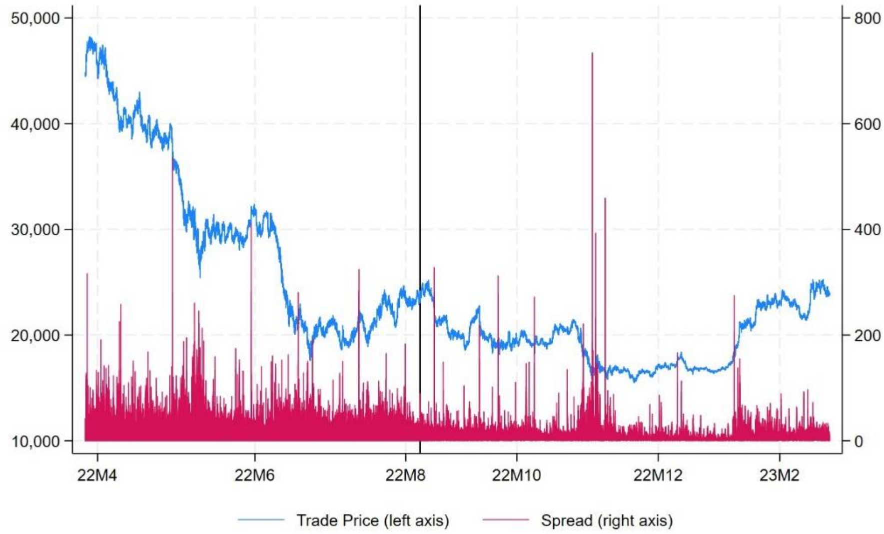

Fig. 1: Trade price (USD) and bid-ask spread (USD), 27/03/2022–23/02/2023.[2]

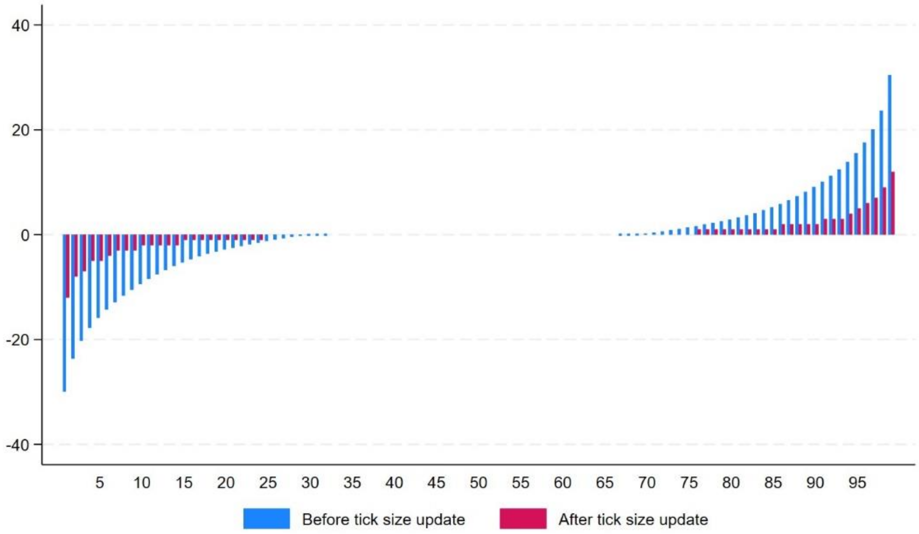

Fig. 2: Trade Price change (USD) across the centiles of its distribution before and after the tick size update.

The summary of trade is stacked in Table 1. The figures show that the trading activity after the tick size update was, on average, less intensive. The mean daily number of transactions fell from 17,224.93 to 14,496.16, while the mean daily volume dropped from BTC 2,541.351 to BTC 2,034.254. So behaved, the mean (median) single transaction volume, which declined from BTC 0.148 (0.019) to BTC 0.140 (0.018). The mean quoted and effective spreads lowered significantly from USD 15.04 (5.30 Bps) and USD 15.61 (5.49 Bps) to USD 3.97 (2.03 Bps) and USD 4.33 (2.22 Bps), respectively, indicating transaction costs decreased and liquidity improved, in particular for small orders which

[2] The vertical black line on 10/08/2022 splits the period in question into two—before and after the tick size update.

dominate the trade. Since, in both periods, the mean effective spread was larger than its quoted counterpart, we conclude that the size of market orders exceeded the depth available at the best bid/ask quotes. Those effects are to very much extent consistent with ones reported by Cox et al. (2019) and Barardehi et al. (2022), who, using the data on pilot firms in the SEC's Tick Size Pilot Programme, documented that after the tick size implementation the trade and order volume declined on the maker-taker fee models and a larger tick size generally improved the liquidity for stocks with wide and tick unconstrained spreads.

Table 1: Summary of data

Statistics	Daily no of trans.	Daily volume	Transaction volume	Trade price	Quoted spread	Effective spread	Quoted spread	Effective spread
		BTC		USD			Bps	
	Before the tick size update							
Min	5,391.00	363.44	1.00×10^{-8}	17,592.78	0.00	0.00	0.00	0.00
Max	52,024.00	16,406.09	86.79	48,232.25	535.38	1,567.78	146.95	421.39
Mean	17,224.93	2,541.35	0.15	29,687.80	15.04	15.61	5.30	5.49
Median	16,065.00	1,928.94	0.02	29,320.82	13.55	13.57	4.79	4.79
St. dev.	8,467.36	2,422.47	0.49	8,464.94	11.10	13.95	4.01	4.87
Skew	1.81	3.22	32.00	0.52	4.24	15.11	4.27	9.58
Kurt	7.26	15.31	2,339.52	2.05	53.79	926.02	54.51	359.51
	After the tick size update							
Min	4,865.00	331.43	1.00×10^{-8}	15,479.00	0.00	0.00	0.00	0.00
Max	55,718.00	10,840.21	125.59	25,270.00	734.00	1,445.00	452.97	911.59
Mean	14,496.16	2,034.25	0.14	19,566.12	3.97	4.33	2.03	2.22
Median	13,241.00	1,724.72	0.02	19,412.00	2.00	2.00	1.01	1.04
St. dev.	6,906.29	1,425.84	0.42	2,555.60	7.31	9.41	3.96	5.22
Skew	2.62	2.51	62.59	0.35	18.56	31.54	22.52	39.85
Kurt	13.43	12.49	10,826.61	1.98	917.10	2,622.13	1,340.56	3,971.05

Our model to disentangle Bitcoin's bid-ask spread is a modification of Eq. (12) in McGroarty et al. (2007). We assume that Bitcoin's fundamental value evolution follows a semi-martingale, which results in a constant term being included.[3] We treat the price clustering component as a residual one so that the model can be written as

$$\Delta P_t = const + (1-\alpha)\Delta\left(\frac{S_t}{2}Q_t\right) + \beta\frac{S_{t-1}}{2}Q_{t-1} + \epsilon_t, \tag{1}$$

where: P_t is Bitcoin's price at time t; S_t—bid-ask spread; $Q_t = 1\ (-1,\ 0)$ if the transaction is initiated by a buyer (seller, not identified); α—a private information component; β—a temporary buy-sell imbalances component; $1-\alpha-\beta$—a price clustering component; ϵ_t—public information shock. We identify the party initiating

[3] Although it is argued that Bitcoin has no intrinsic value (Cheah and Fry, 2015), there has recently been a growing body of literature on its valuation with the opposite conclusion (Hayes, 2017; Li and Wang, 2017; García-Monleón et al., 2021; Podhorsky, 2024).

transaction using the EMO, Lee-Ready and Quote rules (Ellis et al., 2000; Lee & Ready, 1991). The results of identification, indicating the rules similarly classify the direction of trade, are shown in Tables A1 and A2 in Appendix A. Then, after variables $(S_t/2)Q_t$ and $(S_{t-1}/2)Q_{t-1}$ are properly instrumented, we estimate three versions of Eq. (1), each based on a different identification rule, using two-step heteroskedasticity robust and efficient GMM estimator. The choice of instruments is ascertained by performing the Kleibergen-Paap under identification and weak identification tests and the endogeneity test for endogenous regressors (Kleibergen nd Paap, 2006; Baum et al., 2007). Next, we set appropriate restrictions on structural parameters $1 - \alpha, \beta$ and perform the Wald-type tests to test whether the share of each component in the spread is zero. Finally, as a robustness check, we reestimate Eq. (1) using smoothed IVQR estimator of Kaplan and Sun (2017) to show how the component shares in the spread vary across the centiles of Bitcoin's price change distribution in both periods.

Results

The GMM estimation results of Eq. (1) for both periods using the EMO, LR and Quote rules are given in Table 2. They confirm decisions regarding the model specification. The estimates of the Kleibergen-Paap under and weak identification test statistics and that of the regressors endogeneity support the instrumentalisation of explanatory variables by Q_t and Q_{t-1}. The hypotheses stating that individual component shares in the bid-ask spread are equal zero are all rejected at the 5% significance level. Their estimates for each period, albeit different in size in cases based on a particular rule, imply that about half of the spread can be attributed to the price clustering component. In the remaining part of the spread, the buy-sell imbalances component has a greater stake than private information. Having the estimates of individual component shares averaged across the rules, one can conclude that the tick size update resulted in an increase of the buy-sell imbalances component share in the spread from 0.1872 to 0.2912, i.e. by 55.56%, and a decrease of its price clustering counterpart from 0.6014 to 0.5037—by 16.25%; the share of the private information component slightly decreased from 0.2114 to 0.2051—that is by 2.98%. A significant rise of the buy-sell imbalances component share in the spread following the tick size update supports our previous finding that the tick update has not sufficiently improved the depth around the best bid/ask quotes. However, it caused the liquidity to improve and the transaction costs to be reduced. Similar in size yet moderate share of the private information component in both periods illustrates the critical role of adverse selection and the existence of informed trading in the Bitcoin market.

More precise conclusions about the decomposition of Bitcoin's bid-ask spread can be drawn from the quantile regression outcome. The estimation results of Eq. (1) for the centiles of its price change (0.05, 0.10, …, 0.90, 0.95) in both periods, specified using the EMO, LR and Quote rules, are gathered in Tables B1–B3 (see Appendix B). They indicate that in each case, the hypothesis stating that the share of an individual component in the spread is equal to zero is rejected at the 5% significance level. The estimates of such component share based on three different identification rules are close to one another for each centile. Their distributions across the centiles of the price change have much in common: (i) the estimates of the buy-sell imbalances component for the centiles around the median are close to zero; (ii) in the same circumstance, the estimates of the price clustering component are the largest. Those and other results are visualised in Figures 3-4 after the estimates of component shares were aggregated, i.e. across the rules for each centile. That enables us to draw further conclusions about the impact of the tick size update on the components of Bitcoin's bid-ask spread.

Table 2: GMM estimation results of Eq. (1) based on the EMO, LR and Quote rules

Period	Parameter estimate			Hypothesis			Test			R^2
	α	β	γ	$\alpha = 0$	$\beta = 0$	$\gamma = 0$	ENDOG	KPU	KPW	
	EMO rule									
Before update	0.2419	0.2127	0.5454	51,484.71	89,295.97	266,534.34	3,092.13	980,479.59	1,390,034.90	0.354
After update	0.1740	0.3495	0.4766	7,731.24	71,549.61	59,371.86	891.04	42,9621.04	286,238.13	0.205
	LR rule									
Before update	0.2061	0.1623	0.6316	32,434.87	59,999.74	307,962.83	5,501.71	1,007,269.40	1,474,507.20	0.374
After update	0.2188	0.2651	0.5161	11,839.94	47,849.76	66,580.66	2,459.90	379,085.52	244,024.04	0.232
	Quote rule									
Before update	0.1861	0.1866	0.6273	23,692.14	56,843.43	269,818.96	5,369.58	1,034,149.60	1,754,322.90	0.337
After update	0.2226	0.2589	0.5185	11,974.81	45,742.77	65,642.51	2,348.27	376,813.10	242,478.47	0.232
	Rule average									
Before update	0.2114	0.1872	0.6014	×	×	×	×	×	×	×
After update	0.2051	0.2912	0.5037	×	×	×	×	×	×	×

Notes: Wald test statistic for testing individual parameter significance under H_0 of no significance distributed as $\chi^2(1)$; ENDOG – endogeneity test of endogenous regressors test statistic under H_0 stating that the specified endogenous regressors are exogenous distributed as $\chi^2(2)$; KPU – Kleibergen-Paap LM under identification test statistic under H_0 stating that the excluded instruments are correlated with the endogenous regressors distributed as $\chi^2(1)$; KPW – Kleibergen-Paap Wald weak identification test statistic under H_0 stating that the excluded instruments are correlated with the endogenous regressors but only weakly – Stock and Yogo (2005) 5% critical value 7.03; 5% critical values for $\chi^2(1)$ and $\chi^2(2)$ are 3.84 and 5.99, respectively.

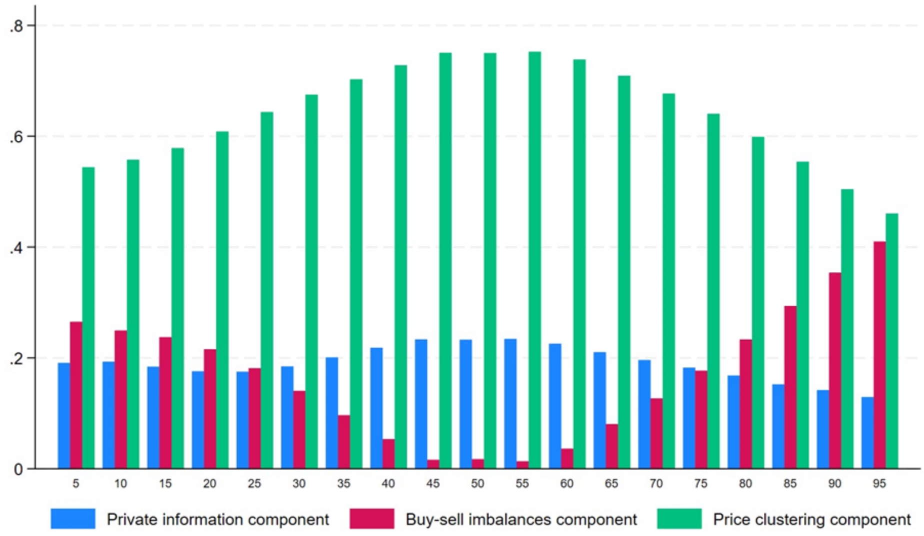

Fig. 3: Estimates of the component shares in the spread averaged across the EMO, LR and Quote rules—Period before the tick size update.

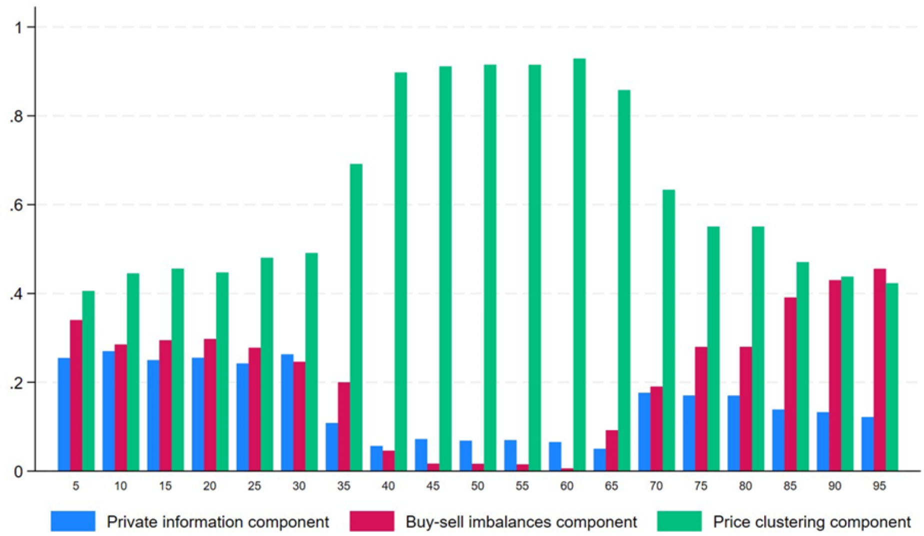

Fig. 4: Estimates of the component shares in the spread averaged across the EMO, LR and quote rules—Period after the tick size update.

First, the revealed decrease in the price clustering component share in the spread within the GMM framework in the period after the tick size update is due to its sharp decline at the marginal centiles, i.e. those from the 5th through the 30th centile and from the 70th through the 95th one, exhibiting the significant and extreme price changes. Second, in the same period, price clustering contributes about 90% to the spread at the middle centiles, leaving the contribution of the other two components very small or meaningless. Third, an increased contribution of the buy-sell imbalances to the spread is a consequence of their rise at the marginal centiles, so the significant and extreme price changes strengthen the importance of this factor much more than the moderate price changes do. Fourth, in both periods, however, their contribution to the spread is much more substantial at the right tail of the price change distribution than at the left tail. Fifth, the opposite of the last finding applies to the contribution of private information.

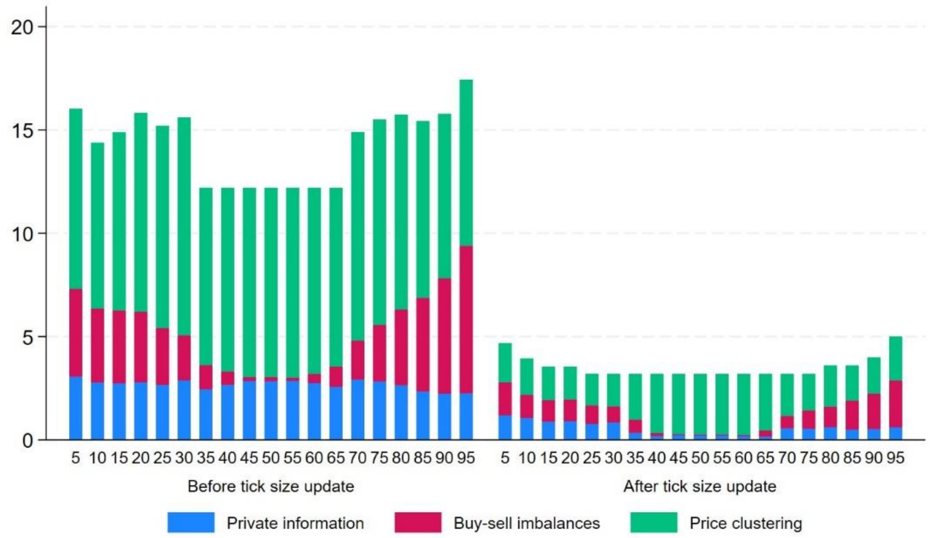

Fig. 5: Distribution of the bid-ask spread and its components across Bitcoin's price change centiles.

All the above discoveries relate to the relative component contribution to the bid-ask spread. Nevertheless, as the spread in the period after the tick size update many times decreased, their absolute contributions diminished accordingly (see Fig. 5). For example, the contribution of those of private information and buy-sell imbalances at the middle centiles are only about several US cents.

Conclusion

We use the transaction data on Bitcoin traded at Bitstamp against the US dollar and disentangle its bid-ask spread into the private information, buy-sell imbalances and price clustering components. We find that the tick size update introduced in August 2022 has caused significant consequences for Bitcoin. It cut its average bid-ask spread by almost four, thus improving the liquidity and reducing the transaction costs. Since the mean effective spread remained larger than its quoted counterpart, the size of market orders still exceeded the depth available at the best bid/ask quotes. The tick size update also changed the shares of particular components in the spread—it raised the share of the buy-sell imbalances component and lowered that of price clustering. The share of the private information component remained stable in both periods, confirming previous findings about the established position of informed trading in the Bitcoin market (Feng et al., 2018; Natashekara & Sampath, 2024). More importantly, the magnitude of specific components differed across the centiles of Bitcoin's price change distribution. At the middle centiles, the price clustering component dominated other components. However, the dominance was more notable in the period after the tick size update. The contribution of buy-sell imbalances to the spread was more significant at the right tail of Bitcoin's price change distribution than at the left tail. The opposite applied to private information. All these indicate that the intensity of factors underlying liquidity and transaction cost in Bitcoin's market closely tightens to large and extreme ups and downs in its price. Nevertheless, their intra-week and intra-day dynamics and the dynamics of the bid-ask spread itself, the knowledge of which is vital for all types of traders, were beyond the scope of this study and are left for future research.

Appendix A

The percentage of identified transactions using the EMO, LR, and Quote rules in the period before (after) the tick size update is equal to 97.17% (97.41%), 99.98% (99.50%), and 88.85% (98.85%), respectively (see Table A1). The number of transactions initiated by sellers prevails over those initiated by buyers, whichever rule is applied and period considered, which is reflected in the falling price of Bitcoin for most periods. The estimates of Pearson's χ^2 statistic for independence show that the direction of trade depends on the day of the week and hour of the day; however, the estimates of Cramer's V coefficient, which do not exceed 0.05, imply that the dependence is very weak. The rules, to an extent, as exhibited by the estimates of Cramer's V coefficient from Table A2, similarly classify the direction of trade. Nevertheless, since any estimate exceeds 0.85, the association of classifications is far from perfect. Each rule, therefore, is further used for the estimation purpose of Eq. (1).

Table A1: Identification of the party initiating transaction based on the EMO, LR and Quote rules

Rule	Market						Statistics			
	Buy	Sell	Not Id	Buy	Sell	Not Id	Pearson's χ^2		Cramer's V	
	Number of trades			Percentage of trades			Day	Hour	Day	Hour
	Before the tick size update, N = 2,342,590 obs.									
EMO	1,385,263	890,923	66,404	59.13	38.03	2.83	2,930.47	3,012.12	0.0250	0.0254
LR	1,440,906	901,310	374	61.51	38.47	0.02	2,629.80	2,789.89	0.0237	0.0244
Quote	1,286,390	795,072	261,128	54.91	33.94	11.15	4,688.87	4,110.23	0.0316	0.0296
	After the tick size update, N = 2,855,880 obs.									
EMO	1,762,640	1,019,364	73,878	61.72	35.69	2.59	6,531.16	11,590.31	0.0338	0.0450
LR	1,800,270	1,041,362	14,250	63.04	36.46	0.50	6,215.85	11,136.17	0.0330	0.0442
Quote	1,792,303	1,030,851	32,728	62.76	36.10	1.15	6,501.07	11,276.02	0.0337	0.0444

Note: Person's χ^2 test statistic under H_0 of independence distributed as $\chi^2(6)$ (day) and $\chi^2(23)$ (hour); 5% critical values are 12.59 and 35.17, respectively.

Table A2: Party initiating transaction rules association

Rules	Statistics	
	Pearson's χ^2	Cramer's V
	Before the tick size update	
EMO vs. LR	2,032,976.10	0.6587
EMO vs. Quote	2,665,211.30	0.7542
LR vs. Quote	2,072,901.30	0.6652
	After the tick size update	
EMO vs. LR	3,056,957.50	0.7316
EMO vs. Quote	2,775,643.50	0.6971
LR vs. Quote	4,070,223.00	0.8442

Note: Pearson's χ^2 test statistic under H_0 of independence distributed as $\chi^2(4)$; 5% critical value is 9.49.

Appendix B

Table B1: Quantile regression estimation results of Eq. (1) based on the EMO rule

Centile	Parameter estimate			Hypothesis		
	α	β	γ	$\alpha = 0$	$\beta = 0$	$\gamma = 0$
	Before the tick size update					
5	0.1986	0.3387	0.4627	12,775.21	14,176.64	59,163.95
10	0.2008	0.3114	0.4878	13,625.50	17,571.14	94,165.79
15	0.1975	0.2869	0.5156	30,448.66	38,252.97	156,363.03
20	0.2007	0.2534	0.5459	32,929.06	48,647.29	189,454.91
25	0.2161	0.2068	0.5771	46,509.67	57,237.90	249,566.16
30	0.2370	0.1585	0.6045	27,314.80	60,257.06	173,361.40
35	0.2591	0.1115	0.6294	25,311.78	30,079.16	155,624.49
40	0.2798	0.0665	0.6537	30,963.58	18,342.14	183,896.58
45	0.2986	0.0259	0.6755	38,322.60	41,72.22	207,579.48
50	0.3005	0.0210	0.6785	35,798.31	64,680.57	183,188.94
55	0.3022	0.0168	0.6810	40,264.41	26,390.90	203,195.57
60	0.2904	0.0471	0.6625	45,147.29	24,603.72	231,472.45
65	0.2750	0.0913	0.6337	28,420.04	39120.09	148,299.65
70	0.2598	0.1381	0.6021	28,749.65	85,975.50	147,822.21
75	0.2421	0.1889	0.5690	27,888.83	105,414.93	140,763.14
80	0.2199	0.2470	0.5331	23,076.95	110,624.32	120,065.23
85	0.1915	0.3088	0.4997	16,990.59	128,623.39	109,597.04
90	0.1739	0.3713	0.4548	14,043.88	84,081.89	107,651.46
95	0.1556	0.4353	0.4091	7,612.97	45,129.37	49,302.51
	After the tick size update					
5	0.1958	0.4433	0.3609	3,659.92	23,444.86	14,857.04
10	0.2130	0.3784	0.4086	14,872.70	20,846.65	75,787.82
15	0.2239	0.3386	0.4375	6,928.67	135,569.07	25,801.34
20	0.2324	0.3561	0.4115	41,594.86	164,287.35	85,403.29
25	0.2277	0.3224	0.4499	15,067.28	227,311.68	54,373.73
30	0.2583	0.3049	0.4368	7,054.43	85,146.44	16,882.70
35	0.1222	0.2360	0.6418	10,163.09	8,004.91	27,816.60
40	0.0647	0.1100	0.8253	982.60	4,419.43	113,230.94
45	0.1090	0.0200	0.8710	736.99	48,026.28	46,824.58
50	0.1084	0.0204	0.8712	680.94	60,768.66	43,782.55
55	0.1094	0.0171	0.8735	698.42	74,436.97	44,438.84
60	0.1116	0.0064	0.8820	434.46	62,430.76	27,129.93
65	0.0682	0.1328	0.7990	87,188.32	151,886.49	2,282,188.50
70	0.1864	0.2199	0.5937	8,959.93	6,434.07	409,031.83
75	0.1549	0.3268	0.5183	16,081.63	344,520.95	150,687.43
80	0.1527	0.3206	0.5267	40,542.30	180,832.73	324,301.17
85	0.0990	0.4491	0.4519	191.95	12,372.03	11,249.04
90	0.0791	0.4962	0.4247	929.80	1,161,317.80	26,763.72
95	0.0590	0.5333	0.4077	353.63	72,389.42	33,185.88

Note: Wald test statistic for testing individual parameter significance under H_0 of no significance distributed as $\chi^2(1)$; 5% critical value is 3.84.

Table B2: Quantile regression estimation results of Eq. (1) based on the LR rule

Centile	Parameter estimate			Hypothesis		
	α	β	γ	$\alpha = 0$	$\beta = 0$	$\gamma = 0$
	Before the tick size update					
5	0.2162	0.1998	0.5840	12,017.13	5,167.28	78,050.48
10	0.2055	0.1991	0.5954	20,924.71	9,466.06	120,131.99
15	0.1855	0.1939	0.6206	30,765.57	14,601.05	198,045.32
20	0.1646	0.1764	0.6590	23,561.29	28,292.61	288,877.80
25	0.1476	0.1527	0.6997	21,524.25	61,624.63	385,175.38
30	0.1450	0.1208	0.7342	11,854.54	50,324.02	297,639.90
35	0.1535	0.0835	0.7630	10,337.14	24,077.39	261,157.78
40	0.1649	0.0464	0.7887	13,996.60	11,061.02	327,644.06
45	0.1768	0.0112	0.8120	11,973.31	1,097.36	256,218.67
50	0.1751	0.0142	0.8107	13,473.30	61,027.85	290,804.64
55	0.1763	0.0100	0.8137	16,461.60	49,762.58	352,875.91
60	0.1689	0.0300	0.8011	13,092.50	7,686.39	298,962.20
65	0.1556	0.0700	0.7744	12,137.29	37,411.90	298,027.55
70	0.1448	0.1117	0.7435	12,664.15	63,328.22	332,314.74
75	0.1381	0.1550	0.7069	12,856.21	110,805.60	314,082.98
80	0.1366	0.2036	0.6598	9,031.20	101,777.31	182,855.04
85	0.1404	0.2594	0.6002	8,702.64	145,479.60	169,178.02
90	0.1431	0.3187	0.5382	11,223.14	70,494.54	160,095.58
95	0.1447	0.3740	0.4813	4,171.02	38,662.39	42,963.28
	After the tick size update					
5	0.2806	0.2934	0.4260	4,118.99	4,285.66	9,685.45
10	0.2955	0.2430	0.4615	25,926.68	12,616.89	119,041.96
15	0.2578	0.2749	0.4673	9,675.66	29,318.72	25,003.28
20	0.2662	0.2697	0.4641	49,026.65	63,258.12	68,868.69
25	0.2509	0.2611	0.4880	5,127.53	16,616.42	16,474.07
30	0.2760	0.2205	0.5035	6,215.01	21,481.77	17,395.17
35	0.1075	0.1849	0.7076	33,47.88	17,934.64	64,259.42
40	0.0633	0.0142	0.9225	256.64	20,757.86	53,864.34
45	0.0624	0.0158	0.9218	258.23	34,597.14	55,626.06
50	0.0631	0.0148	0.9221	298.59	28,753.04	63,115.82
55	0.0629	0.0148	0.9223	367.57	37,617.41	78,066.00
60	0.0662	0.0058	0.9280	153.56	32,166.08	30,104.36
65	0.0471	0.0833	0.8696	1,429.36	947.10	48,619.00
70	0.1777	0.1818	0.6405	61,018.78	197,757.50	34,3382.6
75	0.1773	0.2576	0.5651	15,506.76	157,870.34	115,444.28
80	0.1781	0.2616	0.5603	22,822.78	49,053.42	70,778.22
85	0.1543	0.3670	0.4787	5,687.16	57,520.97	102,127.34
90	0.1554	0.3976	0.4470	4,970.35	477,968.51	38,395.41
95	0.1491	0.4190	0.4319	1,435.95	8,474.61	11,959.72

Note: Wald test statistic for testing individual parameter significance under H_0 of no significance distributed as $\chi^2(1)$; 5% critical value is 3.84.

Table B3: Quantile regression estimation results of Eq. (1) based on the Quote rule

Centile	Parameter estimate			Hypothesis		
	α	β	γ	$\alpha = 0$	$\beta = 0$	$\gamma = 0$
	Before the tick size update					
5	0.1583	0.2564	0.5853	4,829.29	7,298.78	50,868.27
10	0.1730	0.2376	0.5894	11,559.86	8,949.65	90,368.34
15	0.1694	0.2313	0.5993	25,467.24	26,648.09	256,431.03
20	0.1622	0.2173	0.6205	22,933.90	39,783.10	264,134.66
25	0.1612	0.1850	0.6538	20,223.38	78,370.26	275,093.65
30	0.1714	0.1420	0.6866	14,338.84	53,841.79	197,469.95
35	0.1897	0.0946	0.7157	13,559.07	33,080.32	181,799.68
40	0.2103	0.0474	0.7423	21,491.54	10,548.90	255,574.69
45	0.2251	0.0110	0.7639	16,923.41	12,223.50	193,099.91
50	0.2228	0.0165	0.7607	16,028.69	86,723.21	18,6482.14
55	0.2239	0.0137	0.7624	12,690.97	51,333.66	147,127.87
60	0.2174	0.0313	0.7513	12,815.31	6,550.49	147,839.09
65	0.2002	0.0803	0.7195	11,077.98	32,079.17	140,777.13
70	0.1836	0.1314	0.6850	11,933.83	61,017.91	157,945.84
75	0.1672	0.1868	0.6460	9,250.39	87,364.46	130,644.30
80	0.1479	0.2490	0.6031	8,962.08	91,586.29	129,949.54
85	0.1248	0.3131	0.5621	7,541.63	116,218.57	155,878.42
90	0.1083	0.3714	0.5203	5,933.91	61,678.49	145,138.33
95	0.0881	0.4209	0.4910	1,243.02	38,012.77	32,699.28
	After the tick size update					
5	0.2874	0.2830	0.4296	5,038.78	3,676.37	14,566.95
10	0.3015	0.2336	0.4649	30,678.49	9,356.58	89,336.14
15	0.2673	0.2704	0.4623	4,680.55	45,006.89	13,031.63
20	0.2670	0.2665	0.4665	91,803.36	94,873.95	98,076.42
25	0.2479	0.2493	0.5028	18,694.51	279,828.95	77,080.13
30	0.2543	0.2133	0.5324	5,248.54	50,530.16	36,290.06
35	0.0958	0.1790	0.7252	1,277.71	5,847.50	1,514,631.20
40	0.0421	0.0132	0.9447	11,150.51	30,152.04	4,796,132.00
45	0.0446	0.0148	0.9406	9,711.54	49,585.05	3,905,527.40
50	0.0344	0.0138	0.9518	6,167.40	54,137.39	4,312,223.50
55	0.0372	0.0139	0.9489	3,933.30	76,323.19	2,545,113.30
60	0.0186	0.0054	0.9760	4,841.07	78,002.12	13,039,673.00
65	0.0350	0.0602	0.9048	542.33	394.74	39,868.62
70	0.1655	0.1689	0.6656	627,781.18	1,197,799.30	3,374,642.80
75	0.1782	0.2539	0.5679	18,149.12	358,274.36	152,729.25
80	0.1787	0.2569	0.5644	23,571.10	77,774.73	88,479.75
85	0.1623	0.3572	0.4805	6,657.09	19,310.46	58,200.37
90	0.1631	0.3957	0.4412	3,352.43	360,746.63	23,610.76
95	0.1573	0.4137	0.4290	1,757.76	87,143.21	11,284.13

Note: Wald test statistic for testing individual parameter significance under H_0 of no significance distributed as $\chi^2(1)$; 5% critical value is 3.84.

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