# When bigger is better:
# The impact of a tiny tick size on undercutting behavior
# Online Appendix

The material in this online appendix supports the findings of the paper and provides numerous additional analyses and robustness tests.

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**Appendix A1: Institutional Detail of Cryptocurrency Exchanges**

This appendix presents institutional detail about Kraken and the tick size increases. Table A1 shows the pre and post tick sizes in number of decimal places for each currency pair in the extended sample from Kaiko. Table A2 shows the currency pairs we have excluded from the analysis and the individual reasons. Univariate statistics for each currency pair and market quality metric are shown in Table A3 for the original high frequency data collected directly from Kraken's API and in Table A4 for the extended sample from Kaiko. Table A5 shows the individual depth level cutoffs used in the calculation of the depth metric introduced by Van Kervel (2015).

**TABLE A1**
**Tick Sizes by Currency Pair Pre and Post**

The table shows the tick size of the currency pairs in the pre period, before August 30th 2017, in the intermediate period before September 6th 2017 and in the post period after September 6th 2017. The tick size is displayed as the number of decimal places. Panel A shows the currency pairs which experienced a tick size increase. Panel B shows the currency pairs which experience no tick size change.

| Currency pair | Pre 30 August | Post 30 August | Post 6 September |
|---|---|---|---|
| Panel A: Treatment group | | | |
| BCH-BTC | 6 | 6 | 5 |
| BCH-EUR | 4 | 3 | 1 |
| BCH-USD | 4 | 3 | 1 |
| BTC-CAD | 3 | 2 | 2 |
| BTC-EUR | 3 | 2 | 1 |
| BTC-USD | 3 | 2 | 1 |
| DASH-BTC | 6 | 6 | 5 |
| DASH-EUR | 5 | 3 | 3 |
| DASH-USD | 5 | 3 | 3 |
| ETC-BTC | 8 | 6 | 6 |
| ETC-ETH | 8 | 6 | 6 |
| ETC-EUR | 5 | 4 | 3 |
| ETC-USD | 5 | 4 | 3 |
| ETH-BTC | 6 | 6 | 5 |
| ETH-CAD | 5 | 3 | 2 |
| ETH-EUR | 5 | 3 | 2 |
| ETH-JPY | 3 | 1 | 0 |
| ETH-USD | 5 | 3 | 2 |
| GNO-BTC | 6 | 6 | 5 |
| LTC-EUR | 5 | 4 | 2 |
| LTC-USD | 5 | 4 | 2 |
| REP-EUR | 5 | 4 | 3 |
| XRP-EUR | 6 | 6 | 5 |
| XRP-USD | 6 | 6 | 5 |
| ZEC-BTC | 6 | 6 | 5 |
| ZEC-EUR | 5 | 3 | 3 |
| ZEC-USD | 5 | 3 | 2 |
| Panel B: Control group | | | |
| EOS-ETH | 6 | 6 | 6 |
| ICN-BTC | 6 | 6 | 6 |
| LTC-BTC | 6 | 6 | 6 |
| MLN-BTC | 6 | 6 | 6 |
| MLN-ETH | 5 | 5 | 5 |
| REP-BTC | 6 | 6 | 6 |
| REP-ETH | 5 | 5 | 5 |
| USDT-USD | 4 | 4 | 4 |
| XLM-BTC | 8 | 7 | 8 |
| XRP-BTC | 8 | 6 | 8 |

**TABLE A2**
**Currency Pairs Excluded from the Sample**

The table shows the currency pairs which are excluded from the sample and the reason for the exclusion. No Post/Pre period indicates that there were no data recorded by Kaiko in the relevant period. This often occurs due to delisted/newly listed pairs respectively. Tick size decrease indicates that during our sample period the tick size was reduced. Unbalanced indicates that whilst there are observations in both the post and pre period, the imbalance between the observations is so large as to render the DiD impractical (i.e. 2 days pre vs 30 days post).

| Currency pairs | Reason for exclusion |
|---|---|
| BTC-GBP | No post period |
| BTC-JPY | Tick size decrease |
| EOS-BTC | Tick size decrease |
| EOS-EUR | No post period |
| EOS-USD | No pre period |
| ETH-GBP | No post period |
| GNO-ETH | Unbalanced |
| GNO-EUR | No post period |
| GNO-USD | No post period |
| ICN-ETH | Tick size decrease |
| REP-USD | No post period |
| XDG-BTC | Unbalanced |
| XLM-EUR | No post period |
| XLM-USD | No post period |
| XMR-BTC | No pre period |
| XMR-EUR | No pre period |
| XMR-USD | No pre period |
| XRP-CAD | No post period |
| XRP-JPY | No post period |

**TABLE A3**
**Market Quality Metrics for all Cryptocurrency Pairs**

Metrics for market quality across our sample for all 6 currency pairs using high-frequency trade and quote data. QUOTED_SPREAD is time weighted and in bps. EFFECTIVE_SPREAD, REALIZED_SPREAD and PRICE_IMPACT are volume weighted and in bps. EFFECTIVE_SPREAD_$500 ($200K) estimate the effective spread in bps of a hypothetical trade of the respective dollar volumes. DEPTH_AT_BEST is the dollar volume available at the best bid and offer in thousands. DEPTH_AT_X_BPS sums the depth at *X* bps on either side of the midpoint where *X* takes different values per currency pair in thousands (see section IV.A). VOLUME is the average 15-minute volume. SHORT_TERM_VOLATILITY is the average 15-minute midpoint return volatility.

| Currency pair | Quoted Spread | Effective Spread | Realized Spread | Price impact | Effective Spread $500 | Effective Spread $200K | Depth at best | Depth at X bps | Volume ($10K) | Short-term vol |
|---|---|---|---|---|---|---|---|---|---|---|
| BTC-USD | 8.1 | 14.4 | 11.9 | 2.5 | 9.9 | 480 | 20.2 | 164.2 | 26.20 | 1.9 |
| ETC-BTC | 94.3 | 94.5 | 89.3 | 5.1 | 118.2 | 2504 | 9.8 | 134.3 | 0.67 | 4.1 |
| ETC-ETH | 120.5 | 113.7 | 107.8 | 5.9 | 159.8 | 7936 | 6.5 | 136.1 | 0.27 | 3.6 |
| ETC-USD | 74.8 | 74.7 | 66.2 | 8.5 | 118.6 | 12766 | 4.7 | 98.3 | 0.72 | 4.1 |
| ETH-BTC | 14.0 | 24.3 | 23.0 | 1.3 | 20.5 | 471 | 13.6 | 145.8 | 9.27 | 2.3 |
| LTC-USD | 33.6 | 42.2 | 37.5 | 4.7 | 51.8 | 3699 | 6.2 | 75.8 | 2.70 | 3.0 |
| Average | 57.6 | 60.6 | 56.0 | 4.7 | 79.8 | 4643 | 10.2 | 125.8 | 6.6 | 3.2 |

**TABLE A4**
**Market Quality Metrics for all Cryptocurrency Pairs**

Metrics for market quality across our sample for all 37 currency pairs from the Kaiko dataset. QUOTED_SPREAD is time weighted and in bps. EFFECTIVE_SPREAD and REALIZED_SPREAD are volume weighted and in bps. EFFECTIVE_SPREAD_$500 ($200K) estimates the effective spread in bps of a hypothetical trade of the respective dollar volumes. DEPTH_AT_BEST is the dollar volume available at the best bid and offer in thousands. DEPTH_AT_X_BPS sums the depth at *X* bps on either side of the midpoint where *X* takes different values per currency pair in thousands (see section IV.A). Volume is the average 15-minute volume. SHORT_TERM_VOLATILITY is the average 15-minute midpoint return volatility.

| Currency pair | Tick size change ratio | Quoted Spread | Effective Spread | Realized Spread | Effective Spread $500 | Effective Spread $200K | Depth at best | Depth at X bps | Volume ($10K) | Short-term vol |
|---|---|---|---|---|---|---|---|---|---|---|
| BCH-BTC | 10 (T) | 50.5 | 43.5 | 30.5 | 58.3 | 900 | 11.5 | 144.4 | 4.69 | 16.1 |
| BCH-EUR | 1000 (T) | 31.6 | 32.2 | 15.6 | 40.4 | 1186 | 7.6 | 82.6 | 5.24 | 16.8 |
| BCH-USD | 1000 (T) | 35.7 | 32.5 | 15.2 | 44.4 | 1197 | 7.3 | 106.7 | 4.26 | 17.0 |
| BTC-CAD | 10 (T) | 116.8 | 82.6 | 68.7 | 131.3 | 2909 | 10.0 | 85.3 | 0.27 | 9.5 |
| BTC-EUR | 100 (T) | 8.3 | 10.3 | 3.3 | 9.0 | 134 | 21.2 | 148.9 | 36.23 | 8.5 |
| BTC-USD | 100 (T) | 8.4 | 10.7 | 3.7 | 9.5 | 139 | 18.0 | 149.0 | 23.23 | 8.7 |
| DASH-BTC | 10 (T) | 71.6 | 59.3 | 45.6 | 91.8 | 1690 | 11.7 | 144.7 | 1.17 | 13.4 |
| DASH-EUR | 100 (T) | 81.5 | 69.0 | 53.9 | 102.5 | 3133 | 3.4 | 75.3 | 0.77 | 12.9 |
| DASH-USD | 100 (T) | 104.5 | 72.6 | 51.3 | 122.3 | 3437 | 3.4 | 88.9 | 0.53 | 11.9 |
| EOS-ETH | 1 (C) | 112.3 | 95.7 | 77.9 | 138.9 | 5725 | 7.3 | 86.8 | 0.34 | 15.1 |
| ETC-BTC | 100 (T) | 88.4 | 70.0 | 57.1 | 109.2 | 1871 | 9.4 | 119.2 | 0.52 | 13.5 |
| ETC-ETH | 100 (T) | 104.0 | 74.8 | 59.1 | 137.5 | 5044 | 6.6 | 129.9 | 0.23 | 11.4 |
| ETC-EUR | 100 (T) | 61.3 | 54.3 | 37.9 | 84.2 | 3279 | 3.8 | 62.9 | 0.67 | 14.6 |
| ETC-USD | 100 (T) | 72.5 | 52.9 | 35.2 | 113.1 | 11428 | 4.2 | 72.9 | 0.64 | 15.2 |
| ETH-BTC | 10 (T) | 13.9 | 19.0 | 12.7 | 19.7 | 431 | 10.2 | 135.2 | 7.33 | 9.6 |
| ETH-CAD | 1000 (T) | 152.4 | 98.6 | 83.2 | 175.8 | 10265 | 4.5 | 50.8 | 0.12 | 10.3 |
| ETH-EUR | 1000 (T) | 12.0 | 14.1 | 5.8 | 13.7 | 257 | 18.9 | 146.6 | 21.06 | 10.2 |
| ETH-JPY | 1000 (T) | 127.8 | 84.7 | 55.9 | 329.2 | 71709 | 1.2 | 22.9 | 0.03 | 11.1 |
| ETH-USD | 1000 (T) | 12.7 | 16.2 | 7.8 | 14.9 | 265 | 14.5 | 130.7 | 18.65 | 10.4 |
| GNO-BTC | 10 (T) | 143.3 | 108.6 | 83.8 | 236.0 | 34118 | 1.8 | 17.8 | 0.06 | 9.9 |
| ICN-BTC | 1 (C) | 84.8 | 78.2 | 55.0 | 121.4 | 4928 | 2.9 | 49.6 | 0.42 | 20.7 |
| LTC-BTC | 1 (C) | 38.3 | 32.5 | 20.7 | 51.1 | 1699 | 7.5 | 90.8 | 1.78 | 13.2 |
| LTC-EUR | 1000 (T) | 35.3 | 32.9 | 19.9 | 46.4 | 1590 | 4.8 | 72.6 | 2.84 | 14.4 |
| LTC-USD | 1000 (T) | 32.9 | 29.5 | 16.2 | 49.7 | 3194 | 4.7 | 65.4 | 2.50 | 13.2 |
| MLN-BTC | 1 (C) | 154.9 | 114.3 | 87.7 | 233.9 | 30440 | 1.0 | 13.9 | 0.05 | 8.1 |
| MLN-ETH | 1 (C) | 154.9 | 96.2 | 70.7 | 257.0 | 44774 | 0.7 | 8.4 | 0.04 | 8.5 |
| REP-BTC | 1 (C) | 106.6 | 77.3 | 59.2 | 137.6 | 9642 | 2.8 | 32.6 | 0.14 | 13.4 |
| REP-ETH | 1 (C) | 137.7 | 99.5 | 78.1 | 170.9 | 8200 | 4.9 | 63.1 | 0.06 | 11.6 |
| REP-EUR | 100 (T) | 85.9 | 72.0 | 54.9 | 116.6 | 6841 | 1.9 | 44.1 | 0.19 | 12.2 |
| USDT-USD | 1 (C) | 16.0 | 15.1 | 13.2 | 18.0 | 245 | 10.8 | 240.6 | 0.72 | 2.1 |
| XLM-BTC | 1 (C) | 96.8 | 88.6 | 68.5 | 130.8 | 7906 | 2.9 | 47.4 | 0.19 | 19.0 |
| XRP-BTC | 1 (C) | 51.6 | 45.1 | 33.1 | 65.9 | 1207 | 9.6 | 136.6 | 1.70 | 14.9 |
| XRP-EUR | 10 (T) | 32.0 | 30.1 | 18.5 | 41.2 | 1317 | 4.6 | 71.3 | 3.10 | 13.9 |
| XRP-USD | 10 (T) | 34.3 | 31.8 | 18.6 | 47.5 | 2427 | 3.3 | 60.3 | 2.30 | 15.0 |
| ZEC-BTC | 10 (T) | 93.8 | 75.7 | 59.8 | 117.4 | 3240 | 8.4 | 103.4 | 0.48 | 14.2 |
| ZEC-EUR | 100 (T) | 70.9 | 52.4 | 36.3 | 91.9 | 4200 | 2.6 | 53.0 | 0.62 | 14.4 |
| ZEC-USD | 1000 (T) | 90.5 | 61.2 | 44.1 | 122.8 | 10338 | 3.9 | 73.3 | 0.55 | 12.2 |
| Average | | 75.0 | 58.9 | 42.8 | 104.7 | 8037 | 6.6 | 84.5 | 3.61 | 12.8 |

**TABLE A5**
**Depth at Best X Basis Points Cutoffs by Currency Pair**

This table shows the values of X for each currency pair in the dataset used for the primary analysis and for the currency pairs in the dataset from Kaiko. The values are used to compute the depth metric proposed by Van Kervel (2015) which sums the dollar volume depth available at X basis points on either side of the midpoint.

| Currency pair | X basis points |
|---|---|
| Panel A: high frequency dataset | |
| BTC-USD | 13 |
| ETC-BTC | 99 |
| ETC-ETH | 102 |
| ETC-USD | 66 |
| ETH-BTC | 22 |
| LTC-USD | 39 |
| Panel B: Kaiko dataset | |
| BCH-BTC | 62 |
| BCH-EUR | 46 |
| BCH-USD | 55 |
| BTC-CAD | 138 |
| BTC-EUR | 11 |
| BTC-USD | 13 |
| DASH-BTC | 83 |
| DASH-EUR | 75 |
| DASH-USD | 102 |
| EOS-ETH | 136 |
| ETC-BTC | 99 |
| ETC-ETH | 101 |
| ETC-EUR | 60 |
| ETC-USD | 67 |
| ETH-BTC | 22 |
| ETH-CAD | 170 |
| ETH-EUR | 16 |
| ETH-JPY | 223 |
| ETH-USD | 18 |
| GNO-BTC | 201 |
| ICN-BTC | 150 |
| LTC-BTC | 43 |
| LTC-EUR | 41 |
| LTC-USD | 39 |
| MLN-BTC | 188 |
| MLN-ETH | 233 |
| REP-BTC | 139 |
| REP-ETH | 195 |
| REP-EUR | 87 |
| USDT-USD | 21 |
| XLM-BTC | 215 |
| XRP-BTC | 86 |
| XRP-EUR | 43 |
| XRP-USD | 42 |
| ZEC-BTC | 109 |
| ZEC-EUR | 70 |
| ZEC-USD | 80 |

In order to demonstrate the ability of Level 10 data to capture all meaningful economic and orderbook activity, the following three figures present cumulative distributions across: number of price levels per market order (Figure A1), as well as the number of ticks observed between L1 and L10 (Figure A2 and A3 document for the pre-tick size increase and post-tick size increase period, respectively). These figures show that the vast majority of activity is captured within a major cryptocurrency exchange by using only L10 data.

**FIGURE A1**
**Price Levels Interaction with Market Orders**

This figure documents the cumulative distribution of the number of price levels an individual trade interacts with. Note, that if limit orders are unevenly spaced within the tick grid, there may be more 'ticks' in a market order than there are price levels.

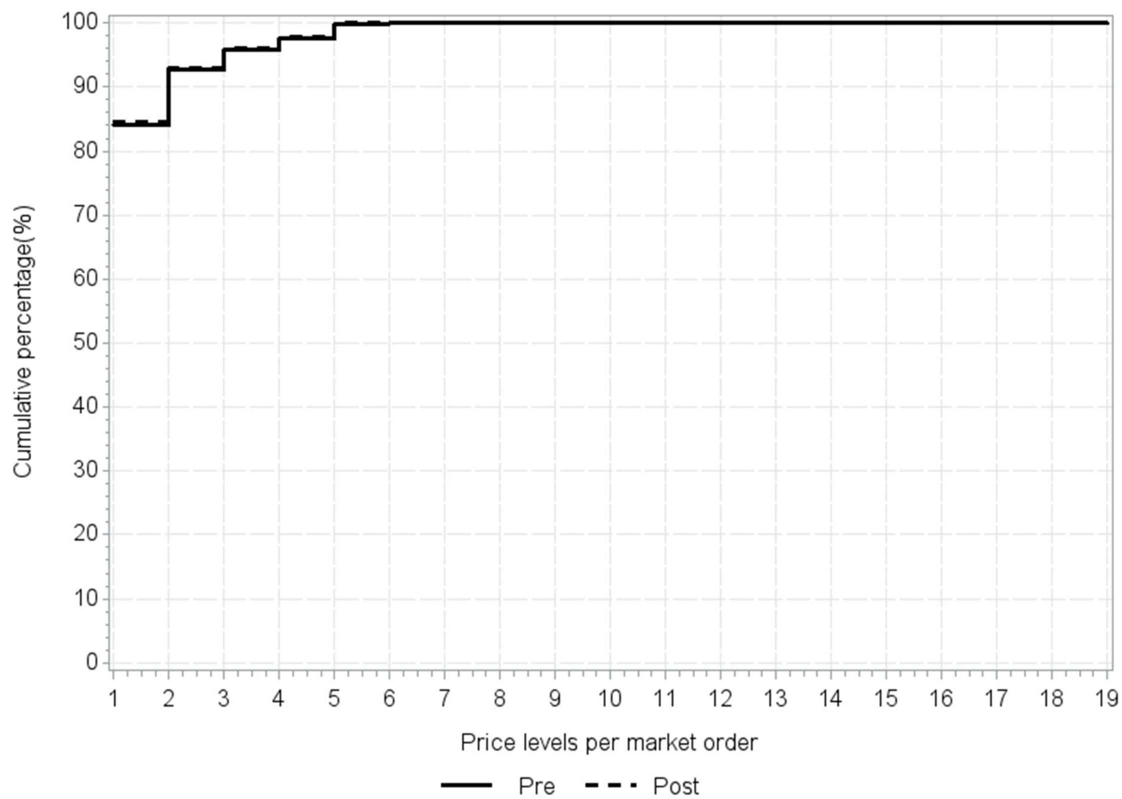


**FIGURE A2**
**Number of Ticks Between L1 and L10 – Before Tick Size Increase**

This figure documents the number of natural ticks between the first and tenth level of orderbook data. This data is time-weighted at each quote update, and is averaged across the bid and ask side for all six currency pair-days prior to the increase in the Kraken tick size.

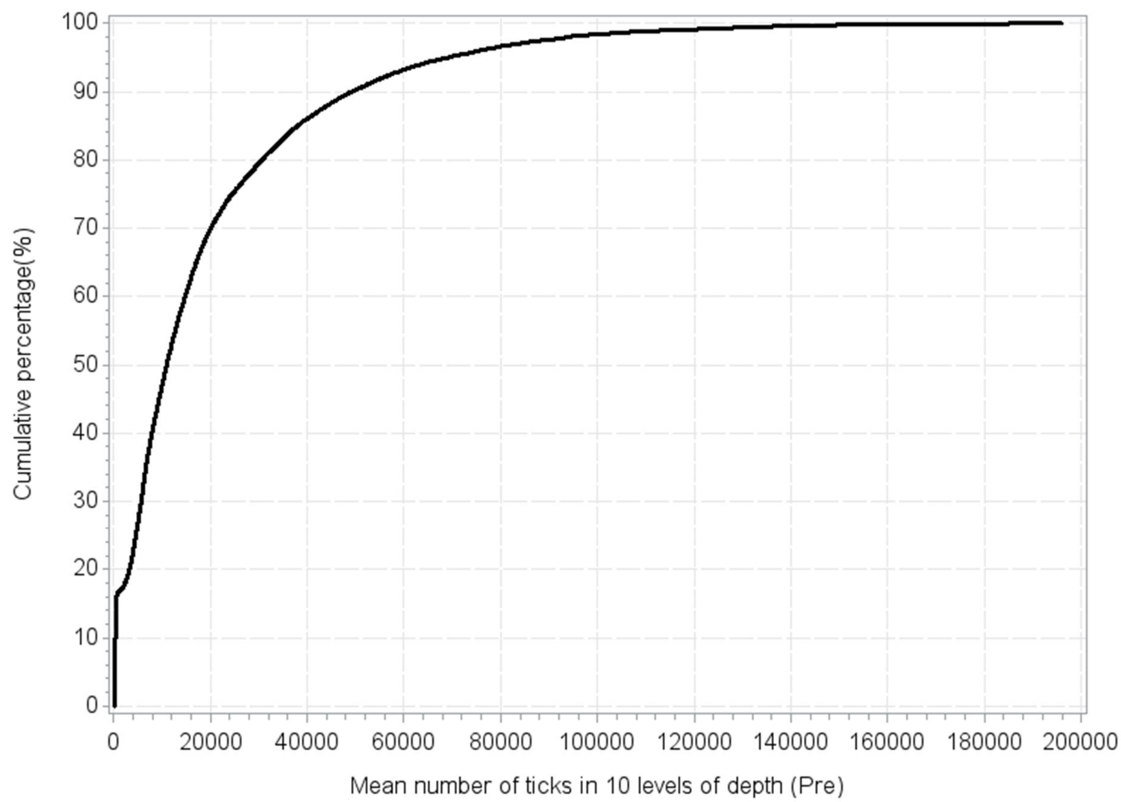
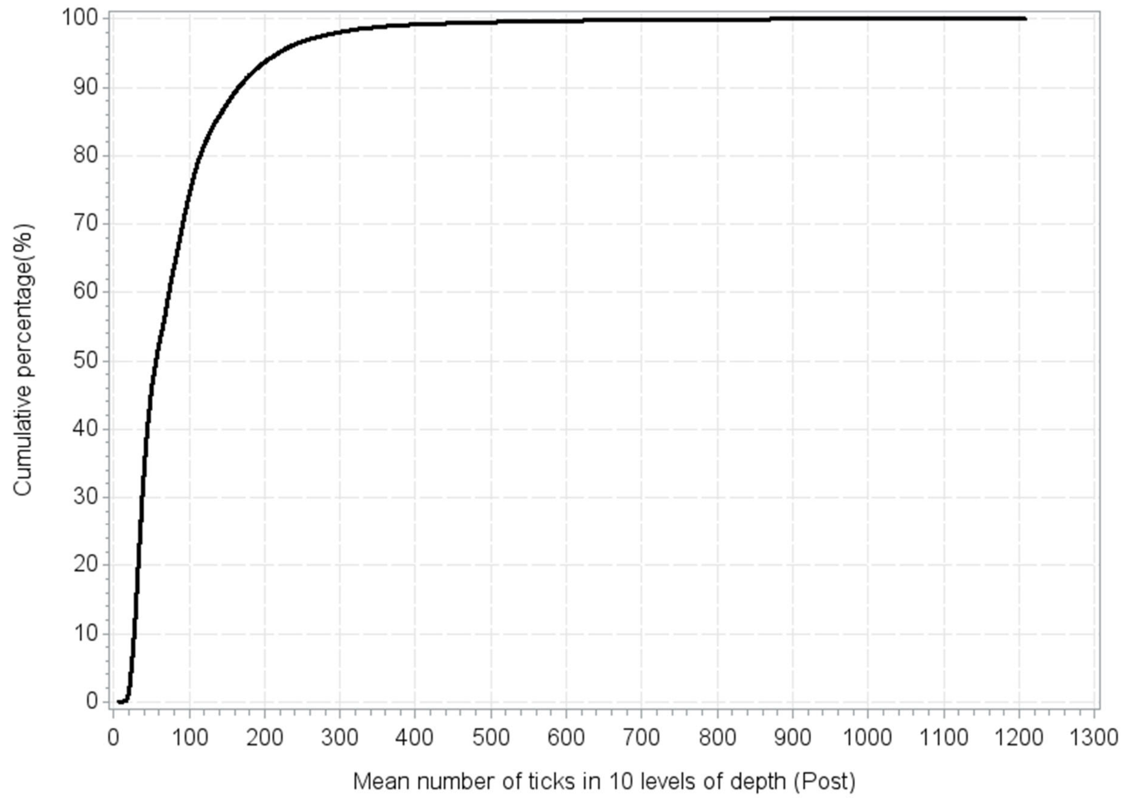


**FIGURE A3**
**Number of Ticks Between L1 and L10 – After Tick Size Increase**

This figure documents the number of natural ticks between the first and tenth level of orderbook data. This data is time-weighted at each quote update, and is averaged across the bid and ask side for all six currency pair-days after the increase in the Kraken tick size.



### Appendix A2: Trade Aggregation Across Slow Matching Engines

Cryptocurrency exchange matching engines are heterogenous in their architecture. Many are self-created, and due to their 24/7 opening hours, tend not to have 'downtime' for systematic updates. These exchanges were typically built and launched with few users, and in recent years have become far busier than, perhaps, their software was designed to handle. This can lead to difficulties in dealing with slow matching engines.

In traditional equities exchanges, a large market order which executes against multiple resting limit orders would typically print multiple limit order 'parts' with identical timestamps. This allows researchers to re-aggregate market orders from the uniquely timestamped executions.

In many cryptocurrency exchanges, the precision with which timestamps are provided on trades (i.e., milliseconds) is faster than the time it takes the engine to deal with the individual parts of a single market order. When dealt with in sequence, a 'buy' market order which hits several resting limit orders may result in successive sequence of trade reports, for example trades at 10,11 and 12, as the order 'walks the book'. In the instance of the Kraken exchange, such trades carried timestamps between 4-15 milliseconds apart, as shown in Figure A4.

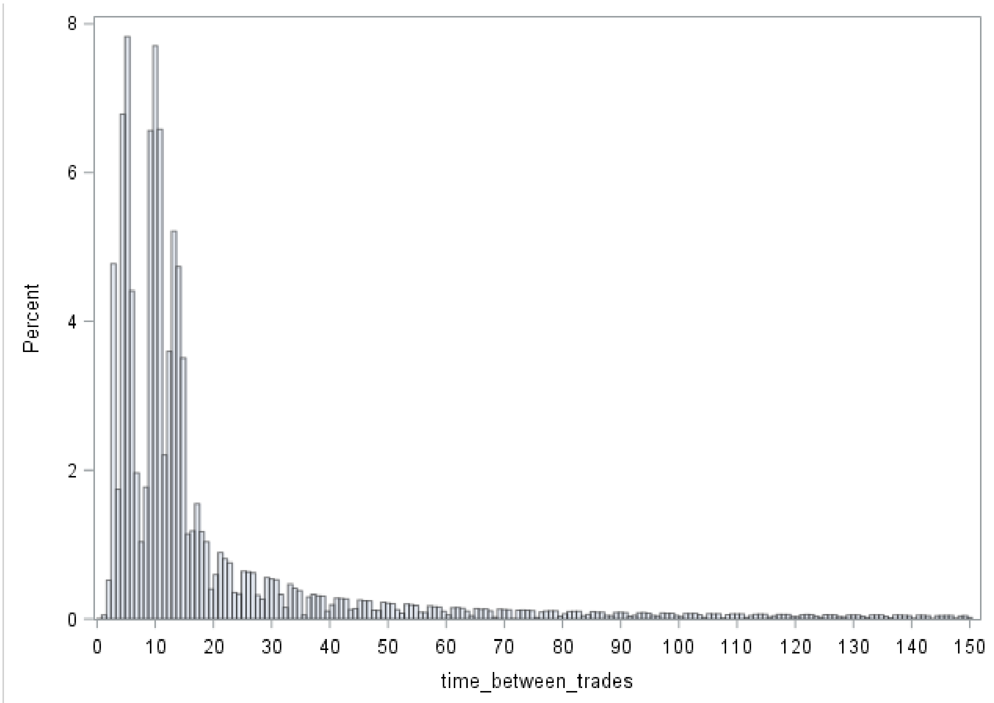
This delay in the internal workings of the matching engine requires a modified method for identifying executions as a result of the same incoming market order. As seen in Figure A4, there are NO recorded executions with identical timestamps. This either means that the matching engine is slow, or all market orders interacted with a single limit order (incredibly unlikely). In order to correctly link successive executions as a result of the same market order, sequential trades at increasing (decreasing) prices represent market buy (sell) orders respectively. In order to choose an appropriate time horizon with which to 'join' sequential orders, we examine two features: the average time between trades, and the resulting number of limit orders per market order. In such an analysis, there is a trade-off between false positives generated by overly long aggregation periods (combining unrelated executions) and false negatives generated by overly short horizons (splitting related executions). Our empirical analysis methods are designed to optimize between these two tensions.

Figure A4 shows that there is a large spike in successive trades between 2-20 milliseconds, which is expected when the matching engine is processing sequential orders. This activity naturally dissipates in a smooth form from 20ms onwards. This represents the expected random (poisson) arrival rates of (uncorrelated) market orders, and indicates 20ms (or slightly before) captures the vast majority of correlated orders.

Figure A5 provides an empirical 'test' of the chosen horizon (which could be applied to any generic market). For any given horizon (i.e. 1ms, 5ms, 20ms, etc) all market orders are reconstructed. We then evaluate the average number of limit orders per market order (a feature which we expect to be relatively stable). If the aggregation window is too short, as in 0ms for Kraken, we would expect to observe a ratio of 1 limit order per 1 market order. Small increases in this horizon (to 1ms, 2ms, etc) will primarily capture other parts of the same market order (reducing our false negative rate) and only incidentally increase the false positive rate (by chance, if two orders were extremely close together). This results in the sharp increase in limit orders per market order from 1 at 0ms to around 1.7 at 20ms. Horizons longer than 20ms increase the false positive rate much faster than they reduce the false negative rate, resulting in the 'flattening' of the curve. As such, for Kraken, we use 20ms as our cutoff.

Note for Bitmex, the precision of the matching engine exceeds that of the timestamps. This results in a more familiar shape – there are approximately 1.85 limit orders per market order at both 0ms, increasing imperceptibly until around 35ms, when 'new' orders begin to creep in, resulting in the familiar Poisson increase in arrival rates. In the case of Bitmex, a 0ms horizon is thus appropriate.

**FIGURE A4**
**Histogram and Cumulative Distribution Function of Time Between Trades**
The figure shows the histogram and cumulative distribution function of the time between trades across six currency pairs listed on Kraken. The figures consider all trades from August 1st 2017 until October 5th 2017.



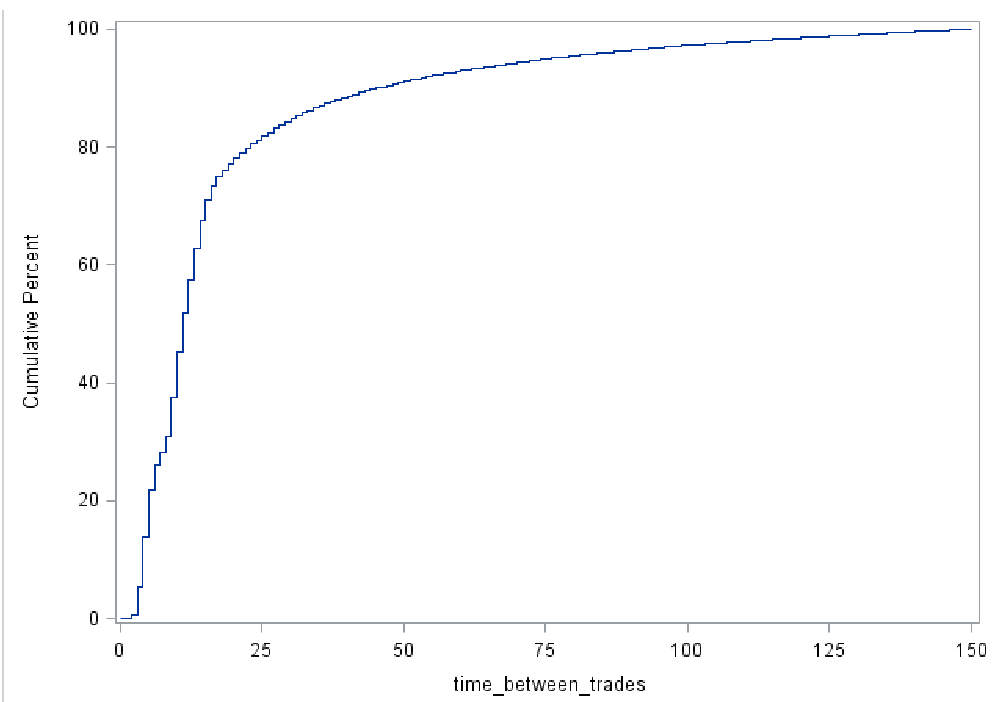
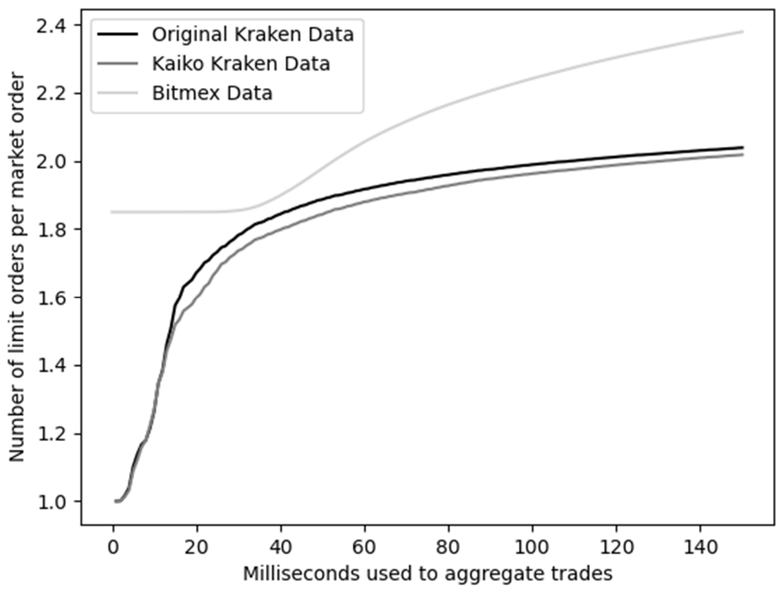



**Figure A5**
**Trade Aggregation Method**

The figure shows the average number of limit orders which are aggregated into one market order depending on the number of milliseconds delay permitted between limit orders. The figure shows the relationship for the original Kraken data used throughout the entire paper, the Kraken data provided by Kaiko and the data from the cryptocurrency exchange Bitmex.



**Appendix A3: Realized Spread Lead Time Estimation**

When measuring the realized spread it is important to use a representative time horizon. If the time horizon used is too short, transitory inventory effects will be included, and the price impact of the trade will be overstated. If the time horizon is too long, other contemporaneous trades may have occurred in the intervening period, and the price impact of the trade will include responses to these other trades. In either case, the estimated profits to the market maker will be biased. The appropriate time horizon is therefore immediately after the inventory effect has resolved and before other trades (on average) occur. To determine when the inventory effect wears off, we estimate a vector auto regression (VAR) following the structural form shown in Eq. (a) and (b) and the reduced form in Eq. (c) and (d).

$$x_t = \mu^x + \sum_{i=1}^{180} \phi_i^r r_{t-i} + \sum_{i=1}^{180} \phi_i^x x_{t-i} + \varepsilon_t^x \quad \text{(a)}$$

$$r_t = \mu^r + \sum_{i=1}^{180} \phi_i^r r_{t-i} + \sum_{i=0}^{180} \phi_i^x x_{t-i} + \varepsilon_t^r \quad \text{(b)}$$

$$x_t = \mu^x + \sum_{i=1}^{180} \alpha_i^r r_{t-i} + \sum_{i=1}^{180} \alpha_i^x x_{t-i} + e_t^x \quad \text{(c)}$$

$$r_t = \mu^r + \sum_{i=1}^{180} \beta_i^r r_{t-i} + \sum_{i=1}^{180} \beta_i^x x_{t-i} + e_t^r \quad \text{(d)}$$

where $t$ represents one second intervals, $x_t$ is the signed dollar volume of trades in each second interval $t$, $r_t$ is midpoint return in the $t^{th}$ interval, $\varepsilon_t^x$ is unanticipated signed dollar volume, $\varepsilon_t^r$ is a midpoint innovation that is not caused by order flow, $e_t^x = \varepsilon_t^x$ and $e_t^r = b_1 e_t^x + \varepsilon_t^r$. The VAR is estimated on our high-frequency data from Kraken. All prices are converted to USD.

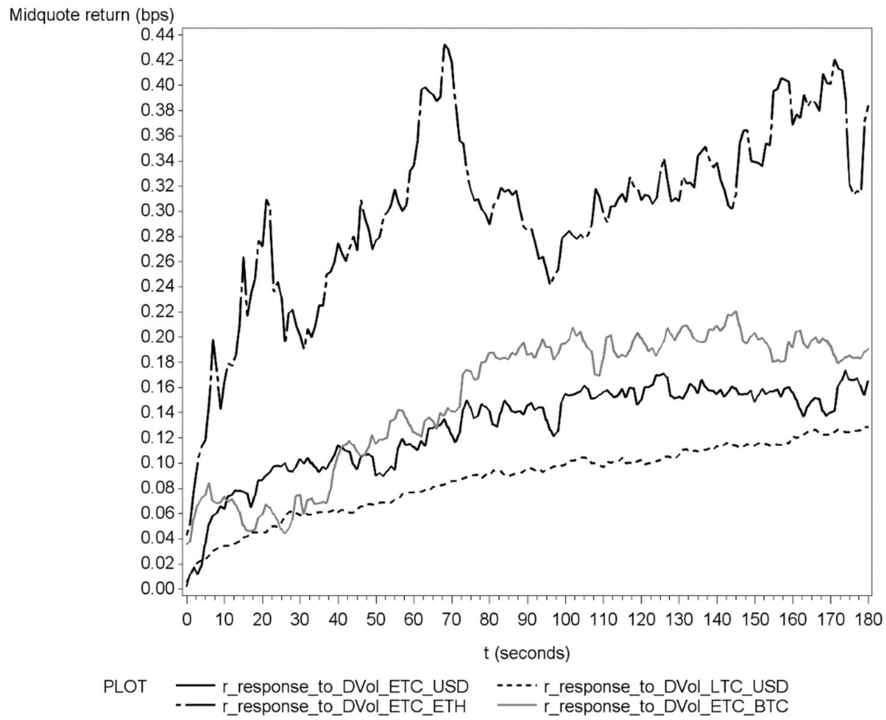
When estimating this VAR we can determine how the midpoint return reacts to an unanticipated \$200 buyer-initiated trade. A \$200 trade is used as it is a representative trade size in 2017. We present this reaction graphically by plotting the impulse response function of Eq. (d) in Figure A6. Ideally the impulse response function should show an initial upward reaction to the buyer-initiated trade (the transitory inventory effect), which then wanes and subsequently converges to the long run price impact of the trade.

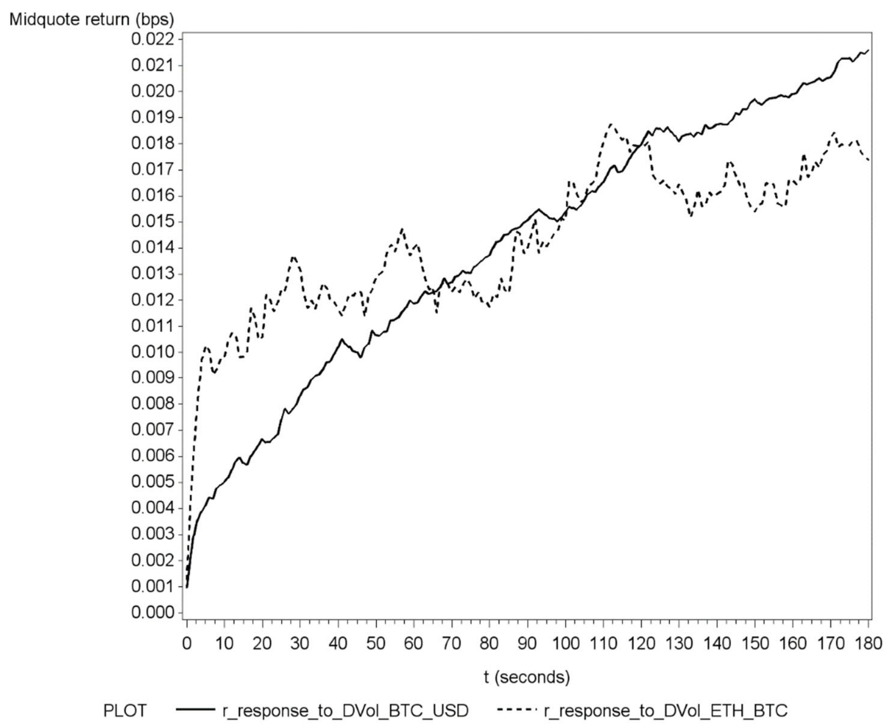
Figure A6 shows that the currency pairs ETC-BTC, ETC-ETH and ETH-BTC have quick responses which wear off within 10 seconds. The currency pairs LTC-USD, ETC-USD and BTC-USD take about 20 seconds for the initial reaction to wear off. When introducing a 200-dollar seller-initiated trade as a shock the same results are produced.

For the primary analysis we therefore use a 10 second time horizon when calculating the realized spread for the currency pairs ETC-BTC, ETC-ETH and ETH-BTC and a 20 second time horizon for the currency pairs LTC-USD, ETC-USD and BTC-USD.

**FIGURE A6**
**Response Functions of a $200 Buyer-initiated Trade on the Midpoint Return**

The figure shows the response functions of all currency pairs in the sample for the period 23rd August to 13th September 2017. Midpoints and dollar volumes are converted to USD.



However, the responses for LTC-USD, ETC-USD and BTC-USD are less clear. For robustness we therefore calculate the realized spread using a time horizon of 10 seconds, 20 seconds, 30 seconds and 60 seconds across all currency pairs to see how sensitive the results are to the time horizon definition. Table A6 reports the results of the multivariate regression $Realized\ spread_{it} = \alpha_i + \beta_1 Post_t + \beta_2 Trades_{it} + \beta_3 Volatility_{it} + \varepsilon_t$. The model has currency pair fixed effects. $Post_t$ is a dummy variable equal to one after the tick size increase and zero otherwise, $Trades_{it}$ is the number of trades in thousands. $Volatility_{it}$ is the currency-time high-low price range scaled by the high-low midpoint in percent. The dependent variables are realized spread using the time horizons determined in the above section as well as a time horizon of 10, 20, 30 and 60 seconds across all currency pairs.

The results shows that the estimated effect of a tick size increase on the realized spread does not change dramatically when using uniform time horizons across all currency pairs. Further, the choice of 10, 20, 30 or 60 seconds has little effect on either the estimated magnitude or significance of the results.

**TABLE A6**
**The Term Structure of Realized Spread**

This table depicts the robustness of the results reported in Table 4 across the term structure of realized spread between 10 and 60 seconds.

| Variable | Realized spread$_{it}$ | Realized spread$_{it}$ 10s | Realized spread$_{it}$ 20s | Realized spread$_{it}$ 30s | Realized spread$_{it}$ 60s |
|---|---|---|---|---|---|
| POST$_t$ | -17.90** | -14.71** | -14.99** | -15.00** | -15.48** |
| | (6.047) | (5.570) | (5.552) | (5.509) | (5.554) |
| TRADES$_{it}$ | -278.1* | -240.6* | -245.3* | -250.1* | -264.4* |
| | (115.5) | (105.8) | (107.1) | (110.5) | (115.2) |
| VOLATILITY$_{it}$ | 29.21*** | 21.32*** | 21.33*** | 21.19*** | 20.69*** |
| | (4.544) | (2.763) | (2.880) | (3.102) | (3.708) |
| Constant | 49.14*** | 39.01*** | 39.40*** | 39.66*** | 39.85*** |
| | (6.278) | (5.948) | (5.899) | (5.931) | (5.991) |
| | | | | | |
| Observations | 30,013 | 30,447 | 30,447 | 30,447 | 30,447 |
| R-squared | 0.428 | 0.265 | 0.263 | 0.260 | 0.252 |
| Currency pair FE | Yes | Yes | Yes | Yes | Yes |