The impact of tick sizes on trader behavior: Evidence from cryptocurrency exchanges[1]

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Abstract

This paper analyses the effect of a tick size on a major cryptocurrency exchange where spreads are unconstrained, assets have limited fundamental value and tick sizes are extremely small, which facilitates undercutting. Using a unique high frequency dataset surrounding a significant increase in tick sizes on the cryptocurrency exchange Kraken, we find that undercutting decreases, leading to traders posting more and larger limit orders. Transaction costs and short-term volatility both decrease, contrary to previous findings in equity markets. We show that when spreads are unconstrained, market quality can be improved by increasing extremely small tick sizes. Our findings contribute to the optimal tick size debate, with particular implications for cryptocurrency and foreign exchange markets, where tick sizes are typically very small.

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1 Introduction

Exchanges have historically decreased tick sizes to reduce transaction costs and improve liquidity. The impact of reduced tick size on market quality has been studied extensively for exchanges in North America (Bacidore, 1997; Goldstein & A. Kavajecz, 2000; Harris, 1991, 1994; Porter & Weaver, 1997), Europe (Bourghelle & Declerck, 2004; Meling & Odegaard, 2017), and Asia (Aitken & Comerton-forde, 2006; Lau & McInish, 1995). Listed firms are able to change the relative tick size by implementing stock splits or reverse stock splits to obtain an optimal tick size and increase the stock's appeal to small investors (Conroy, Harris, & Benet, 1990; Gray, Tom, & Whaley, 2003; Schultz, 2000). What the optimal tick size is and the consequences of changing the tick size for market quality has been modelled theoretically (Cordella & Foucault, 1999; Foucault, Kadan, & Kandel, 2005; Harris, 1991; Seppi, 1997; Werner, Wen, Rindi, Consonni, & Buti, 2015) but as empirical work has exclusively focused on stock markets we do not have a complete understanding of the tick size under different market structures. For example, what happens when the relative tick size is so small that time priority has a limited effect on the likelihood of execution? What is the trading behavior and liquidity observed when tick sizes are extremely small, spreads are unconstrained and there are few market makers facilitating trading? Does the importance of the tick size change when the asset has limited fundamental value and the majority of price information is contained within order flow?

Using a unique dataset from the cryptocurrency exchange "Kraken" we investigate the impact of increasing tick sizes on trading behavior and market quality. The burgeoning cryptocurrency market with unit prices frequently exceeding thousands of dollars, and the recent staggered increase of tick sizes, provides a unique market within which to explore new aspects of the importance of tick sizes and assess the role of unconstrained spreads. Our findings have implications for cryptocurrency market design at a critical point in their development, by showing how the market structure impacts trading behavior. Our work also has wider potential implications for other markets including foreign exchange markets which, similarly to cryptocurrency markets, operate in an environment of fine tick sizes where order flow is the primary determinant of daily price fluctuations (Baillie & Bollerslev, 1990; Breedon & Ranaldo, 2013; Ranaldo, 2009).

One of the central issues in market design is creating incentives for market participants to supply liquidity by exposing their intentions to trade. When a trader decides to post a limit order she is faced with a variety of risks (Harris, 1996). First, she risks trading with market participants with better information. Second, other traders may employ front running strategies to profit from the information contained within her order flow, increasing transaction costs. Liquidity providers thus need tools to mitigate these risks. They can use different order types (such as fill-or-kill or iceberg orders) which limit order exposure time, or disguise the true size of their order. The minimum price increment on an exchange, or “tick size”, has a substantial effect on these tools as it determines the relative importance of speed and price in the precedence rules. If the tick size is large and the quoted spread is constrained (equal to one tick), speed (and hence time priority) becomes the primary competing factor as liquidity providers cannot improve the price to gain execution priority. High Frequency Traders (HFT) can take advantage of such situations by employing superior speed, meaning larger relative tick sizes are favorable to HFTs (O’Hara, Saar, & Zhong, 2015). The tick size thus influences the type of behavior traders undertake in the market.

In cryptocurrency markets both tick and lot sizes are extremely small, rendering time priority largely ineffective. Traders can price improve limit orders by an economically insignificant amount, undercutting larger orders and free riding on the information in the order for little economic cost. Consequently, we frequently observe situations where the best prices have little volume at prices marginally better than a larger order at lower levels. This undercutting or queue-jumping behavior disincentivizes traders from exposing large orders, encouraging traders to cross the spread to get executed. This limits the depth of the orderbook and creates excessive activity and variability of the best prices due to excessive price competition. Implementation shortfall increases due to this behavior as an investor may decide to trade based on the best bid and offer (BBO) but faces worse average executed prices as she has to go through multiple levels to execute a trade. The problem is especially pronounced in cryptocurrency markets by the relative lack of institutional investors and market makers to provide liquidity.

One of the reasons cryptocurrencies exhibit such undercutting behavior is that they have limited or no fundamental value (Cheah and Fry, 2015), largely constraining price-moving information to that contained in order flow. A large order provides information about what direction the trader believes prices will move. Traders can then undercut the order and free ride on this information. This hypothesis is supported by Buti, Consonni, Rindi, Wen, and Werner (2015) who argue that traders who undercut prices do not have strong opinions about the fundamental value, but rather trade opportunistically to profit from small deviations in the price from the average valuation.

The American cryptocurrency exchange Kraken increased the tick size for 68 currency pairs in August and September 2017 arguing that:

> "Reducing the price precision will help reduce extraneous activity in the order books as traders continually jump in front of each other by a very small fraction, resulting in a higher volume of canceled (unfilled) orders. We have received many requests from clients for this reduction" (Kraken, 2017a, p. 2).

We use these two events as natural experiments to analyze the relation between the tick size and liquidity provision for six currency pairs between Bitcoin, Ethereum, Ethereum classic, Litecoin and the US dollar. While the quoted spread of the Bitcoin-US dollar exchange rate is 8.4 basis points on average over the sample period which is relatively low, less liquid currency pairs such as Ethereum classic-US dollar has an average quoted spread of 78.3 basis points. If traders wish to execute large orders the transaction costs can become substantial. The average effective spread for Bitcoin-US Dollar is 16.67 basis points but much higher costs are observed as trade size increases (see Figure 2). Even with the new tick size regime, spreads are rarely constrained, reflecting either that tick sizes could be even wider or the uncertainty generated by the lack of fundamental information.

We find that Kraken successfully reduced undercutting, with the tick size increase leading to fewer price changes at the best. In addition, market participants post more and larger limit orders. Limit orders posted at the same price point increase, suggesting that liquidity providers are clustering limit orders at the same price levels, restoring the relevance of time priority. The improved liquidity environment also increases the size of liquidity demanding orders.

Transaction costs improve as quoted, effective and realized spread decreases by 8.4, 6.3 and 7.5 basis points on average. This result is contrary to previous literature on stock splits which find that spreads increase (Conroy et al., 1990; Gray et al., 2003; Schultz, 2000). However, our results confirm the theoretical predictions of Foucault et al. (2005) that when spreads are wide, unconstrained and the tick size is very small, increasing the tick size reduces spreads, as it forces traders to improve the price by a larger amount than absent a tick size. Additionally, midpoint return volatility decreases, in contrast to the stock split literature which finds increased volatility when tick sizes are increased (Angel, 1997; Koski, 1998). This result shows that a larger tick size, which reduces undercutting, helps to stabilize prices. Depth at the best increases by $1,544 dollars, but cumulative depth remains unchanged, indicating that dollar volume consolidates at the best price levels.

Our findings suggest that when tick sizes are small, spreads are unconstrained, and undercutting is prevalent, a larger tick size can improve liquidity provision and market quality. Thus, in markets structurally dissimilar from traditional equity exchanges, such as forex markets and the growing number of cryptocurrency exchanges, it is important to understand how market design can impact participant behaviors.

The remainder of this paper is structured as follows. Section 2 reviews the current literature on the effects of changing the tick size and presents our hypotheses. Section 3 describes the institutional detail of cryptocurrency markets in general and Kraken in particular and describes the data collection and research design. The results of the tick size increase are presented in section 4 whilst section 5 concludes.

2 Effects of tick size changes

Optimal market design is continuously debated by policy makers, academics and exchanges as markets develop and the composition of their participants changes. The minimum tick size is one aspect of the design that has been discussed extensively in both the theoretical and empirical literature. Harris' (1991) model suggests that a nonzero tick size simplifies the trader's information set, reducing the negotiation costs and the cost of errors. Angel (1997) argues that discrete tick sizes enforce price-time priority and incentivizes liquidity provision by establishing a minimum bid-ask spread, securing liquidity providers a minimum profit. Time priority acts as a protection from quote-matching strategies and front running if the tick size is wide enough to prohibit undercutting. However, the minimum spread creates a minimum cost for liquidity demanders, counteracting some of the gains liquidity provision generates for market quality. Angel (1997) thus argues that the optimal tick size represents a trade-off between the liquidity benefits from a nonzero tick and the cost it imposes. This idea is supported by Seppi (1997) who shows that the optimal tick size for both small, medium and large traders is discrete and strictly greater than zero. The model shows that the optimal tick size for liquidity demanders and suppliers depends on the possibility of undercutting orders and costs.

As defining a universally optimal tick size is a non-trivial task, previous literature has focused on implications of tick size changes. Harris (1994) suggests that smaller tick sizes can improve liquidity. When stocks have a tick constrained spread where the spread is equal to one tick, the quoted depth at the best prices is high as traders find liquidity provision profitable. In this situation time priority is central to execution. Harris (1994) suggests that reducing the tick size should see spreads narrow and depth disperse across more price steps as the marginal profitability of supplying liquidity reduces. In addition, as the spreads are narrower, market order volume increases. If the spreads are not constrained, Harris (1994) argues that liquidity will be likewise affected as the narrower spread and lower possible profits will reduce liquidity provision.

Focusing on dealer markets, Cordella & Foucault, (1999) show that a larger tick size can improve liquidity as a larger tick size can increase the speed at which the dealers adjust their quotes, reducing transaction costs. However, Kandan (2006) argues that smaller tick sizes are beneficial for market quality as they prevent dealers exploiting their market power. In addition, when competition is intense among many dealers, small tick sizes allow dealers to post quotes as close as possible to their reservation value, benefitting liquidity demanders.

In an order driven market, Foucault, Kadan, and Kandel (2005) show that spread improvements (the number of ticks the best price is improved by) increases with the number of impatient traders and the cost of waiting and when the order arrival rate is small. Thus, if the tick size is extremely small, spread improvements decrease and traders bid less aggressively as market orders arrive more frequently. In such a case limit orders will move towards the largest possible ask price and the lowest possible bid price. A larger tick size can therefore have a spread improvement effect as it forces traders to improve the prices by a larger amount than they would if no tick size was imposed which increases the speed at which the spread narrows and improves market resiliency. The authors conclude that small friction costs, such as small tick sizes, short waiting times between order arrivals, and large spread improvements contribute to a small average spread. However, this effect depends on the ratio of patient to impatient traders. This point is highlighted as well by Goettler, Parlour, and Rajan (2005) who show that smaller tick sizes reduce transaction costs, inducing some traders to switch from limit orders to market orders. Werner, Wen, Rindi, Consonni, and Buti, (2015) also document a switch towards market orders when tick sizes are reduced, finding that this switch benefits the market quality of liquid books. For illiquid books however, the spread widens and total and inside depth decreases as the probability of executing a limit order falls due to undercutting. So, traders move to market orders, incurring higher trading costs but increasing overall trading volume.

While the theoretical literature agrees that tick sizes should be nonzero, disagreement remains around the optimal tick size, as it depends on the size of the average trade, the patience of the trader, the liquidity of the book, level of constraint and specific market structure.

The effect of changing the tick size is thus dynamic and theory suggests that empirical findings will vary depending on specific market conditions. These dynamics have been investigated in a large body of empirical literature analyzing tick size reduction on various stock exchanges. On stock exchanges tick size reductions has been found to lead to lower transaction costs, as spreads narrow, but reduced depth at the best prices (Bacidore, 1997; Porter & Weaver, 1997; Van Ness, Van Ness, & Pruitt, 2000). However, the effect on liquidity depends on the size of the trade and the liquidity of the stock. Goldstein and Kavajecz (2000) find that cumulative depth reduces, and Jones and Lipson (2001) find that even though the average quoted and effective spread decreases, trading costs increase for large orders, indicating that smaller tick sizes improves liquidity for small trades but declines for larger trades of infrequently traded stocks. These findings are supported by Aitken and Comerton-forde (2006) who find that trading costs increase, depth decreases, and overall liquidity deteriorates for low volume stocks where liquidity improved for high volume stocks after a tick size reduction.

A tick size increase should have the opposite effect of a tick size reduction. Stock splits, which increase relative tick size, have been found to increase transaction costs, depth (Conroy et al., 1990; Gray et al., 2003; Schultz, 2000) and volatility (Angel, Brooks, & Mathew, 2004; Koski, 1998). Larger relative tick sizes are thus favorable for market makers as the minimum cost of trading is larger, increasing their profits, however Koski (1998) finds that the increase in spread does not compensate the market maker for the increased volatility. Harris (1997) hypothesize that larger tick sizes will improve liquidity provision by reducing trading and quoting errors, negotiation costs and increasing quote sizes as undercutting becomes costlier. However, Schultz (2000) do not find conclusive evidence supporting the hypothesis. As such, evidence from stock splits suggest that larger tick sizes lead to reduced market quality, higher profits made by market makers but overall improvements in liquidity provision.

However, the effects of tick sizes change when the pre-change conditions are different. On Euronext Paris, which has an electronic limit order book and small relative tick sizes (which facilitates undercutting), Bourghelle and Declerck (2004) find no effect of tick size changes on quoted or effective spreads. The authors argue that the results are different from other markets because the spreads are unconstrained prior to the change, the relative tick reduces but the spread to tick ratio increases and the tick sizes are smaller than on American exchanges. Bourghelle and Declerck (2004) conclude an increasing but convex relation between the relative tick size and relative spread, where spreads are wide at extremely small tick sizes, tighten as tick sizes increase and then widens as ticks become a binding constraint. This conclusion is consistent with Cordella and Foucault (1999) and is supported by Meling and Odegaard (2017) who find that a tick size reduction leads to narrower spreads for tick constrained stocks, but wider spreads for tick unconstrained stocks.

As previous literature has focused on equity exchanges, the extant literature is relatively silent on the effects of tick sizes under different market conditions. Bourghelle and Declerck (2004) and Meling and Odegaard (2017) show that when the tick sizes are small, and the spreads are unconstrained the effects of changing the tick size deviates from previous findings. This paper extends the literature by analyzing a market which is similarly structured to foreign exchange markets (being open 24-hours), exhibits no fundamental value, extremely small tick sizes and unconstrained spreads.

3 Testable hypotheses

The high frequency trade and quote data from Kraken allows us to test several hypotheses regarding how trading behavior and liquidity is affected by tick size increases. Based on the findings of Harris (1996; 1997) and Buti et al. (2015) we expect that when tick sizes are increased, undercutting orders becomes more costly as traders now have to improve the price by a larger amount, resulting in less undercutting. With reduced undercutting behavior, the best bid and offer will update less frequently, leading to our first hypothesis.

H1: Larger tick size leads to fewer price revisions at the best prices.

Reduced undercutting behavior makes liquidity provision more attractive as the risks of exposing trading intentions is reduced (Bourghelle & Declerck, 2004; Harris, 1996; Harris, 1997). When undercutting is reduced, liquidity providers also earn the entire spread, collecting profits which would otherwise have gone to the undercutting trader. We therefore expect liquidity providers to post more and larger limit orders, leading to hypothesis two.

H2: Larger tick size increases liquidity provision, increasing the proportion of limit orders and the average limit order volume.

The larger tick size will also affect the price clustering of limit orders as traders cannot disperse their orders across as many price steps. Because the tick size is very small on Kraken it is rare to observe more than two orders at the same price, as traders can enjoy price priority with inconsequential price improvement. Increasing the tick size will increase the number of limit orders posted to the same price step which improves the average trading price for large volume orders, leading to hypothesis three.

H3: Larger tick size increases the number of resting limit orders at the same price step.

If reduced undercutting behavior improves liquidity provision, particularly narrowing spreads, it is also likely to affect the behavior of liquidity demanding traders. Given the extremely small tick size on Kraken, large orders frequently 'walk the book', executing against limit orders at multiple price points. This supports the theory by Werner, Wen, Rindi, Consonni, and Buti, (2015) who document that for illiquid stocks when tick sizes are small and undercutting prevalent, spreads widen and traders use market orders instead of limit orders incurring higher trading costs. A tick size increase should thus reverse this effect as traders post more and larger limit orders at the same price step, increasing depth, narrowing spreads and reducing the cost of demanding large quantities. We therefore expect the size of market orders to increase. More limit orders at the same price points will also result in market orders trading through fewer price steps. However, when an order is large enough to execute against multiple (larger) price steps the cost will be greater as the price steps are now further apart due to the increased tick size. The price difference of limit orders within an executed market order is thus likely to increase after the larger tick size is implemented. This leads to hypothesis four, five and six.

H4: Larger tick size increases the average market order volume.

H5: Larger tick size lead to market orders executing against fewer price levels.

H6: Larger tick size lead to market orders executing against a wider range of prices.

The tick size has a mechanical effect on spreads as it determined how narrow it can possibly be, but when spreads are unconstrained the direct effect is less certain. Evidence from stock splits shows that trading costs increase when tick sizes increase, as spreads become wider (Conroy et al., 1990; Gray et al., 2003; Schultz, 2000). However, Bourghelle and Declerck (2004) show that when tick sizes are very small and spreads are unconstrained before the change, there is no effect on spreads. In the case of Kraken, none of the currency pairs are tick constrained prior to the tick size increase. The relative tick size is also extremely small prior to the tick size increase, 0.0015 basis points for Litecoin-USD. However, the tick size increase is large, so the relative tick size increases to 1.49 basis points for Litecoin-USD. The spread is therefore likely to become more constrained. This context is somewhat similar to that of Bourghelle and Declerck (2004). We therefore expect the spread to remain unchanged but become more constrained as the tick size increases leading to hypothesis seven.

H7: Larger tick size constrains spreads more frequently, but does not change quoted spreads.

As the incentive to post limit orders is affected by a tick size change, the depth at the best bid and offer is also likely to be affected. Tick size increases have resulted in more depth at the best prices (Conroy et al., 1990; Gray et al., 2003; Schultz, 2000) so a tick size increase at Kraken is therefore expected to have the same effect and consolidate depth at the best prices, reducing execution costs for large trades. Goldstein and Kavajecz (2000) find that a tick size decerase leads to a reduction in cumulative depth. This leads us to expect that a tick size increase will increase both the depth at best and cumulative depth, leading to hypothesis eight.

H8: Larger tick size leads to greater cumulative and BBO depth.

Tick size changes affect the precision of prices, impacting short-term volatility, but the direction of the effect is unclear. Both Angel et al. (2004) and Koski (1998) find that volatility increases after a stock split, suggesting Kraken should experience higher short-term volatility after the tick size increase. However, the reduced price precision is expected to decrease undercutting, making prices more stable. Short-term volatility is therefore expected to increase due to lower price precision and decrease due to less undercutting. We anticipate that the stabilizing effect to be more prevalent, resulting in an overall reduction in short-term volatility, leading to hypothesis nine.

H9: Larger tick size leads to decreased volatility of midpoint returns.

4 Institutional detail

The first cryptocurreny, Bitcoin, was introduced by Satoshi Nakamoto and began trading in 2009. Unlike traditional currencies, the production and accounting of bitcoins is not controlled by a central authority but rather a distributed network of market participants. Bitcoin transactions are recorded on a public ledger by miners using cryptographic principles to minimize the risk of double spending.[2] Miners incorporate transactions into a block by solving a complex cryptographic

[2] For more information about how bitcoin and the blockchain is structured and a discussion on the implications and governance see Böhme, Christin, Edelman, & Moore (2015) Dwyer (2015) Nian & Chuen (2015)

puzzle. This public ledger (known as the blockchain) records bitcoin creation, transfer and ownership. One can therefore track every bitcoin in existence back to its creation. With each block processed, new bitcoins are released as a reward to miners, which compensates them for costs such as computing power and electricity. As more miners compete to solve each cryptographic puzzle, the difficulty increases to ensure that the average block time is ten minutes, creating a constant growth in the supply of bitcoins. In addition to the block reward, users can incentivize miners to include their transaction in the next block by attaching a small fee. This mechanism becomes increasingly important through time, as the block reward is halved approximately every two years. Easley, O'Hara, & Basu (2017) model the determinants of the transaction fee and find that the waiting time is the primary driver. Thus, the longer it takes a transaction to be added to the blockchain, the larger the transaction fee it is necessary to pay to jump the queue.

The cryptocurrency exchange Kraken, founded in 2011 (Kraken, 2018), allows market participants to trade 58 different cryptocurrencies against other cryptocurrencies or fiat currencies such as the US dollar, Euro, Canadian dollar or Japanese yen. Trading resembles modern equity markets, with electronic order books which accommodate algorithmic trading.

Facilitating liquidity provision is important on exchanges like Kraken, as it is order driven, without designated market makers and with a large number of cryptocurrencies listed with varying levels of liquidity. Consequently, Kraken incentivizes liquidity provision in two ways. First, liquidity providers pay lower explicit transactions costs.[3] Second, Kraken has advanced order types available to liquidity providers such as stop-loss and take-profit order types which are easily cancelled and resubmitted.

We use the tick size increase as a natural experiment to test if larger tick sizes facilitate more liquidity provision and improved market quality under these market conditions. The tick size was increased on two occasions on August 30th and September 6th, 2017 at 06:00, see Table 1.[4] The tick size increase was substantial for some of the currency pairs. For example, Litecoin to USD increased from 1E-05 (0.0015 bps) to 1E-02 (1.4867 bps) which is a 99,900% increase. The tick size increase brings the tick size into line with competing venues such as Gemini and Gdax.

[3] Differential pricing of 16 basis points for liquidity provision (limit order) versus 26 basis points for liquidity consumption (market order) when trading less than 50,000 USD in a 30-day period (Kraken, 2018b). As volume increases the explicit fee decreases, for example a liquidity provider (demander) pays 14 bps (24 bps) when trading less than 100,000 USD in a 30-day period.

[4] On each of the days where the tick size was increased, 46 currency pairs were affected. The same currency pairs were not necessarily affected by both changes. The analysis is limited to six currencies due to data availability.

Additionally, Figure 1 indicates that after the tick size changes the relative tick size for each of the currency pairs become relatively similar, suggesting that the various tick sizes converge towards an optimal (or perceived optimal) relative tick size for the market.

< Table 1 here >

< Figure 1 here >

Cryptocurrency exchanges remain almost entirely unregulated. Whilst some countries have banned all trading, most developed countries only consider cryptocurrencies in relation to taxes, and do not regulate trading conduct. This lack of regulation combined with the infancy and volatility of the market has anecdotally limited participation by institutional investors, though we are unable to verify the involvement of institutions or market makers with the available data.

Kraken facilitates margin trading and operates a dark pool. The availability of dark pool trading may have an implication for the results as traders who observe increasingly constrained spreads may reroute their order flow to the dark pool. Data on dark pool trading on Kraken is however not available.

5 Research design

5.1 Data

We use a unique dataset of high-frequency order-level data obtained directly from Kraken's Application Programming Interface (API). The API is polled twice a second to get a snapshot of the top 50 levels of the order book. The data spans the week before and after the tick size changes, from 23 August, 2017 to 13 September, 2017 and encompasses the currency pairs Bitcoin to US Dollar (BTC-USD), Ethereum to Bitcoin (ETH-BTC), Litecoin to US Dollar (LTC-USD), Ethereum -Classic to US Dollar (ETC-USD), Ethereum-Classic to Ethereum (ETC-ETH) and Ethereum-Classic to Bitcoin (ETC-BTC).[5] Trades and quotes are time stamped to the millisecond, with an indicator provided for trade initiator.

Trade aggregation is complicated by Kraken's relatively slow matching engine. Appendix A1 documents the time distribution between trades. We find that the central messaging engine delays consecutive interactions of market orders with limit orders by up to 20 milliseconds, with such a filter capturing 80% of the observed trade durations. As such, trades which occur within 20

[5] Obvious pricing errors were corrected (eg misplacement of decimal points surrounding the tick size changes). Kraken was offline for one hour on August 25 and an hour and a half on August 26 due to maintenance during which time there are no quotes or trades observed.

milliseconds or less of each other in the same direction are considered to be a part of one market order. Trade volumes are then aggregated and assigned the average price of the trade.

5.2 Trading behavior metrics

As small tick sizes allow traders to undercut standing limit orders to gain execution priority, we introduce novel metrics to measure and analyze this trading behavior. All metrics are calculated in event time and are averaged over 15-minute buckets per pair.

$Price\ changes\ at\ best$ measures undercutting by counting how often prices are changed. If undercutting is frequent, the best prices will not be displayed for long before an order improves the price.

$Limit\ order\ volume$ measures the average unit volume (BTC, ETH, ETC, LTC) of each limit order. $Market\ order\ volume$ measures the average unit volume in a market order. $Limit\ order/Market\ order$ measures the number of limit orders per market order to determine if more limit orders are posted.

As the tick size is very small it is uncommon to see more than one limit order placed at the same price step. We cannot observe how many orders are posted at each price step without a market order executing, as we only observe aggregated volume. $Resting\ limit\ orders$ measure how many limit orders within a trade are resting at the same price step. To make sure that we count all limit orders within a price step we exclude trades that execute against only one limit order and also exclude the last price step of a market order that executes against multiple price steps.

$Price\ Differential$ measures the average price difference of executed limit orders within each market order following Eq. (1):

$$Price\ Difference_{jit} = Max\ Price_{jit} - Min\ Price_{jit} \quad (1)$$

where $Price\ Difference_{ijt}$ is the difference between the maximum price and minimum price of limit orders in market order j for currency pair i at time t.

$Price\ steps\ per\ market\ order$ counts how many price steps a market order goes through, indicating if volume is consolidated at fewer price steps after the tick size increase.

These trading behavior metrics indicate if the tick size increase is successful at attracting more liquidity providers who post larger limit orders, consolidating depth at fewer price steps and stabilizing the best quotes by letting them stand for longer

5.3 *Liquidity metrics*

We explore the effect of the tick size changes on several liquidity measurements. Quoted spread measures the cost of a small round-trip trade calculated using Eq. (2):

$$Quoted\ Spread_{it} = \frac{(Ask_{it} - Bid_{it})}{m_{it}} \quad (2)$$

where Ask_{it} and Bid_{it} are the best ask and bid quotes at time t for currency pair i and the midpoint at time t is $m_{it} = (Ask_{it} + Bid_{it})/2$. Due to extremely small tick and lot sizes undercutting is common among traders. Consequently, the best prices do not always have meaningful volume attached. During the sample period approximately 85% of all market orders are executed against one price step. To capture the cost of market orders which consume more than one price level, we construct an "adjusted spread" using the prices quoted at level three. During our sample, 96% of market orders were executed against three price levels or less. The adjusted spread follows Eq. (1) but uses the bid and offer of level three. Both the quoted and adjusted spread are time weighted.

The variable constrained measures the proportion of time the spread is equal to one tick, represented as a percentage of the 15-minute bucket. If the spread is constrained for all 15 minutes, the variable takes the value of 100.

The quoted spread can underestimate the cost of demanding liquidity, as trades can execute against orders within or outside the spread. The volume weighted effective spread captures the cost of liquidity when it is demanded, and is calculated using Eq. (3).

$$Effective\ Spread_{it} = 2q_{it}(P_{it} - m_{it})/m_{it} \quad (3)$$

where q_{it} is the direction of the trade, taking +1 for a buyer and -1 for a seller initiated order. P_{it} is the price of the trade at time t for currency pair i. m_{it} is the midpoint at time t. The volume weighted realized spread captures the returns to liquidity provision, and is calculated using Eq. (4).

$$Realized\ Spread_{it} = 2q_{it}(P_{it} - m_{it+Xmin})/m_{it} \quad (4)$$

where the trade price, P_{it}, is compared to the midpoint after the price impact has been realized $m_{it+Xmin}$.[6]

The time weighted depth at the best bid and offer is calculated following Eq. (5).

$$Depth_{it} = \ Best\ bid\ price_{it} * Bid\ size_{it} + Best\ ask\ price_{it} * Ask\ size_{it} \quad (5)$$

[6] The lead time of the midpoint is estimated for each currency pair as we cannot expect this market to follow equity markets. ETC-BTC, ETC-ETH and ETH-BTC are compared to the midpoint after 10 seconds and LTC-USD, BTC-USD and ETC-USD after 20 seconds. Further details on the VAR model and results are provided in Appendix A2.

As the tick sizes for these cryptocurrencies can be extremely small, analyzing only depth at the best prices will likely understate available depth. We employ the depth measure constructed in Van Kervel (2015) in Eq. (6) - (8). The metric sums the depth at X bps on either side of the midpoint. This creates a fair comparison of the change in depth, particularly when the tick size changes. The depth metric is calculated in the base currency (USD, BTC or ETH).

$$Depth\ Ask(X)_{it} = \sum_{i=1}^{I} P_{i,t}^{Ask} Q_{i,t}^{Ask} 1\left(P_{i,t}^{Ask} < m_{it}(1+X)\right) \tag{6}$$

$$Depth\ Bid(X)_{it} = \sum_{i=1}^{I} P_{i,t}^{Bid} Q_{i,t}^{Bid} 1\left(P_{i,t}^{Bid} < m_{it}(1+X)\right) \tag{7}$$

$$Depth\ at\ (X)\ bps_{it} = Depth\ Ask(X)_{it} + Depth\ Bid(X)_{it} \tag{8}$$

where $P_{i,t}^{Ask}$ is the ask price for currency pair i at time t, $Q_{i,t}^{Ask}$ is the ask quantity, m_{it} is the midpoint and X is the basis point cut off. The cutoff varies between currency pairs to reflect their varying levels of liquidity.[7] The bps cutoff (X) is determined as the average spread in basis points, adding two standard deviations and dividing by two.

Volatility is measured as the standard deviation of midpoint returns using Eq. (9):

$$Short-term\ volatility_{it} = SD\left(\frac{(m_{it}-m_{it-1})}{m_{it-1}} * 10{,}000\right) \tag{9}$$

where m_{it} is the midpoint for currency i at time t and m_{it-1} is the preceding midpoint. The return is calculated in bps before calculating the standard deviation.

5.4 *Econometric specification*

Identifying the effect on liquidity and trading behavior is explored by firstly calculating the pre and post averages of each of the metrics, taking the difference and testing the significance using a two-sided *t*-test. Secondly the effect of the tick size increase is measured by an ordinary least squares regression following Eq. (10).

$$Metric_{it} = \alpha_i + \alpha_t + \beta_1 Post_{it} + \beta_2 \$Volume_{it} + \beta_3 Trades_{it} + \beta_4 Volatility_{it} + \beta_5 MeanPrice_{it} + \varepsilon_t \tag{10}$$

where $Metric_{it}$ is a liquidity or trading behavior measure of currency pair i in 15-minute interval t, where α_i and α_t are currency pair and intraday fixed effects, $Post_{it}$ is a post tick size change dummy which takes the value of one after the tick size is increased and zero otherwise, $\$Volume_{it}$ is the dollar volume, $Trades_{it}$ is the number of trades, $Volatility_{it}$ is the currency pair minute high-low price range divided by the sum over two, $MeanPrice_{it}$ is the average price and ε_t is the error

[7] The currency pairs take the following values for X: ETH-BTC = 10 bps, LTC-USD = 28 bps, BTC-USD = 7.5 bps, ETC-ETH = 125 bps, ETC-USD = 55 bps, and ETC-BTC = 70 bps.

term. Dollar volume and average price are calculated in the base currency which can be USD, BTC or ETH.

In addition to the above model it is necessary to look at how the changes to the relative tick affects trading behavior and liquidity on the exchange. Harris (1994, 1996, 1997) find that the relative tick is what affects trading behavior and not the absolute tick. The relative tick shows the tick size proportional to the price and gives more information about the dollar value of the tick size. The relative tick size is included in a two-stage least squared regression to account for potential endogeneity between tick size and the constructed metrics, many of which are directly influenced by the tick size. The first stage of the regression follows Eq. (11). The second stage includes the estimated variable $\widehat{Relative\ Tick}_{it}$ as an independent variable which is the variable of interest in Eq. (12).

$$\widehat{Relative\ Tick}_{it} = \alpha_i + \alpha_t + \beta_1 PercentChange_{it} + \beta_2 \$Volume_{it} + \beta_3 Trades_{it}$$
$$+\beta_4 Volatility_{it} + \beta_5 MeanPrice_{it} + \varepsilon_t \tag{11}$$
$$Metric_{it} = \alpha_i + \alpha_t + \beta_1 \$Volume_{it} + \beta_2 Trades_{it} + \beta_3 Volatility_{it} + \beta_4 MeanPrice_{it}$$
$$+\beta_5 \widehat{RelativeTick}_{it} + \varepsilon_t \tag{12}$$

where $Relative\ Tick_{it}$ is the tick size relative to the price in basis points for currency pair i in 15-minute interval t, α_i and α_t are currency pair and intraday fixed effects, $PercentChange_{it}$ is the percent change in the tick size which takes the value of 0 before the increase and the percentage change after the tick size increase, $\$Volume_{it}$ is the dollar volume in base currency, $Trades_{it}$ is the number of trades, $Volatility_{it}$ is the currency pair 15-minute high-low price range divided by the sum over two, $MeanPrice_{it}$ is the average price in base currency and ε_t is the error term.

6 Empirical results

The currency pairs in our sample differ significantly in terms of trading activity and overall liquidity. Table 2 shows summary statistics for trading behavior, liquidity metrics and control variables for the most traded currency pair (BTC-USD) and the least traded fiat pair (ETC-USD). The average daily number of trades is significantly higher for BTC-USD (at over 11,000) than for ETC-USD (with just over 2,400 trades daily). Given the higher trading activity in Bitcoin, the number of price changes at best is also significantly higher. The average market and limit order volume is also higher for BTC-USD however only 1.5 limit orders are posted at the same price point on average for BTC-USD versus 1.2 for ETC-USD. This is one of the central issues for these markets as liquidity providers do not post orders to the same price step, but rather create new price steps by undercutting the price by a single tick. This results in the average depth at the best prices being just over $24,000 USD for bitcoin and just under $6,000 USD for Ethereum Classic.

Transaction costs can vary widely between currency pairs, where Bitcoin has an average quoted spread of 8.5 basis points (which is below most equity markets), Ethereum classic has an average quoted spread of 78 basis points. The spreads are rarely constrained, with BTC-USD being constrained at most 15.9% of the day over the sample period. Level three quoted spread is 25.3 basis points for Bitcoin however, so a trade large enough to go through multiple levels experiences substantial transaction costs in addition to the 26 basis points fixed taker fee. This is also visible when looking at the mean and standard deviation of the effective spread. Figure 2 shows a scatterplot between effective spread in basis points and the dollar volume of the individual trade. Most trades clearly experience low transaction costs, but larger trades can incur significant transaction costs when they 'walk the book'. These transaction costs increase when trading in less liquid currency pairs such as ETC-USD. These statistics show that Kraken is liquid for trades smaller than $24,000 but larger trades incur substantial transaction costs.

< Table 2 here >

< Figure 2 here >

Table 3 provides a univariate comparison of liquidity and trading behavior metrics around the tick size increase on Kraken, whose main motivation was to reduce the excessive activity caused by undercutting. It appears that this reduction in activity was achieved, with the number of price changes at the best decreasing 4.2%. The number of trades decreases by 15%, but the size of individual market and limit orders increases substantially (38-42%) following the tick size increase suggesting there are fewer, larger trades in the post period. The ratio of limit orders to market orders also increases, consistent with more passive liquidity and the observed increase in the number of resting limit orders per price step. This result suggests that traders post more, larger limit orders, and cluster them at fewer price steps.

The results in Table 3 show that overall liquidity improved after the tick-size increase on Kraken. Transaction costs decreased after the tick size increase, which reduced quoted spreads. Traders are no longer able to undercut by an insignificant incremental amount, but rather have to improve the price by a larger amount, reducing spreads at the best bid and offer. As expected the increased tick size results in spreads being constrained for a greater proportion of the day. These results are consistent with Meling and Odegaard (2017) who find increases in spreads for unconstrained stocks following a tick size reduction. The results however contradict previous literature on stock splits (Conroy et al., 1990; Gray et al., 2003; Schultz, 2000). Depth at both the best prices and lower levels shows significant increases, which is expected as volume will consolidate at fewer price steps after a tick size increase. However, the Depth at best X metric shows increases of a similar magnitude, although it should be unaffected by this aggregating, suggesting that traders are more willing to post passive liquidity.

< Table 3 here >

Table 4 reports the impact of the tick size increase on trading. Consistent with a reduction in undercutting, we observe a significant decline in the number of price chances at the best, and an increase in the average size of limit orders, consistent with the arguments of Harris (1997). The number of limit orders per market order increases by 3 limit orders, indicative of market participants posting more liquidity. We also observe increases in the number of resting limit orders at each price point. Overall, our measures of liquidity provision improve after the tick size increase.

Consistent with Foucault et al. (2005), the reduced spreads encourage more impatient traders towards market orders, with the average market order volume increasing by six percent after the tick size change. However, despite the existence of more, larger limit orders at each price point, the number of limit orders executed by each market order does not change significantly. This indicates that the tick size increase does not cluster enough limit orders at the same price steps to accommodate large trades. In addition, when a market order executes against multiple price steps, the price difference of limit orders within a market order increases due to the wider tick size, confirming hypothesis six. Our evidence suggests that the tick size increase on Kraken successfully reduces undercutting behavior, facilitating increased liquidity provision, but not by enough to reduce the cost of executing large trades.

< Table 4 here >

Table 5 examines the effect of the tick size increase on liquidity. The results show that quoted spread decreased by 8.4 basis points and became 2% more constrained. Whilst this result conflicts with early research on stock splits and tick size increases, Foucault et al. (2005) argue that investors who want to price improve will have to post larger price improvements to gain queue priority, decreasing spreads. Additionally, the effect of a tick size change depends on the relative tick size and liquidity of the asset (Aitken & Comerton-forde, 2006; Angel, 1997). The higher relative tick size documented in Figure 1 may be optimal for the currency pairs in the sample, improving liquidity. Level three quoted spreads do not change, indicating that transaction costs are not reduced for market orders which go through more than one price level. Our finding therefore suggests that for assets with small tick sizes and unconstrained spreads, transaction costs for small trades can be decreased by increasing the tick size. Similar the results for quoted spreads, transaction costs (effective spreads) reduce by 6.3 basis points, while realized spreads decrease by 7.5 basis points after the tick size increase on Kraken, reducing the profits to liquidity provision

Consistent with Conroy et al., (1990), Gray et al., (2003) and Schult,(2000) we observe an increase in depth at the best prices following the tick size, which is somewhat mechanical given a tick size increase consolidates volume at fewer price steps. However, unlike Goldstein and Kavajecz (2000), cumulative depth does not significantly change, indicating that the same overall level of depth is displayed but is now concentrated around the best prices. This supports our previous findings of more and larger limit orders at each price point.

Midpoint return volatility decreases after the tick size increase, suggesting that unlike other markets which exhibited increased volatility after a tick size increase (Angel et al., 2004; Koski, 1998), the prices on Kraken become more stable after eliminating the excessive trading activity generated by undercutting activity. Overall, our results suggest that the increase in tick sizes on Kraken improve both market quality and pricing efficiency by encouraging traders to enter more, larger liquidity providing orders.

< Table 5 here >

As the effect of a tick size change depends on the relative tick size (Aitken & Comerton-forde, 2006; Angel, 1997), we use the relative tick size as an instrumental variable in a two-stage least squared regression to account for potential endogeneity. Table 6 reports the first stage results which controls for variation in the dollar volume, trading activity, volatility and average price between currency pairs. $PercentChange_{it}$ takes a value of zero prior to the tick size increase, and the percent change in the tick size after. The F-statistic of the regression is 130.29 which rejects the null hypothesis of a weak instrument using the critical values by Stock and Yogo (2003).

< Table 6 here >

The estimated relative tick variable is then included in the second stage regression reported in Tables 7 and 8. The two-stage least squared approach reports results consistent with our initial findings, but of a larger magnitude. Table 8 shows that undercutting is reduced by 1.3 price changes. Limit order volume increases by 0.06 units similar to the initial estimation, but the number of resting limit orders increases by one limit order which is higher than the initial result. Market order volume also increases by 8.4 units suggesting that the larger tick size also facilitates increased liquidity demand. The average price difference between limit orders within a market order becomes insignificant, suggesting that larger orders do not incur higher costs, however the average number of price steps a market order executes against marginally increases, consistent with Harris (1996, 1997).

Table 8 presents the impact of the tick size increase on liquidity, with quoted, effective and realized spreads all decreasing while the tick size becomes more constraining. Level three quoted spreads increase, however in the presence of wide and unconstrained absolute spreads, it is not surprising that the larger tick size increases the distance of the third best quotes from the BBO. Our results suggest that tick size increases intensify competition between liquidity providers at the best, narrowing the spread and increasing depth. We also document reductions in short-term volatility. The results of our two-stage least squared regression confirm that increased tick sizes in cryptocurrency markets improve liquidity provision, lowering transaction costs for small trades and reducing volatility.

< Table 7 here >

< Table 8 here >

7 Conclusion

We investigate the importance of tick sizes in a market with significantly unconstrained spreads, extremely small tick sizes, 24-hour trading and limited fundamental value. We examine how two tick size increases on the American cryptocurrency exchange Kraken affects undercutting behavior transactions costs and depth. We also construct novel trading behavior metrics, finding an improvement in liquidity provision, with more, larger limit orders submitted at each price point reducing the frequency of price changes at the best. This is consistent with Harris' (1996) argument that larger tick sizes will increase quoted volume.

Additionally, we find that spreads improve after the tick size increase, consistent with the model developed by Foucault et al. (2005). When tick sizes are very small, liquidity providers cannot improve the spread substantially which disincentivizes price improvement. Given a wide enough spread, an increased tick size rewards price improvement. This shows that exceedingly small tick sizes can be detrimental to market quality by facilitating undercutting, essentially rendering time priority redundant. Larger tick sizes are also found to improve depth and lower volatility, suggesting reduced tick sizes can facilitate increased transitory volatility due to undercutting.

This paper also adds to our understanding of the cryptocurrency markets by examining both the transaction costs and liquidity of a variety of cryptocurrencies. We show that implicit transaction costs are relatively low for Bitcoin, but grow substantially with trade sizes due to the relatively shallow depth available at the best prices. In addition, explicit trading costs form a substantial proportion of total costs, making it costly to trade both large and small amounts.

Our findings have implications for market design and how we think about the benefits from small tick sizes. We show that exceedingly small tick sizes are undesirable and can be detrimental to market quality. This has relevenace for equity markets, which have seen tick sizes consistently reduce over the last 20 years. Our findings have particular implications for cryptocurrency and foreign exchange markets, which operate with extremely small tick sizes. As such we add to the discussion about optimal tick sizes for small cap assets which is currently being investigated following the tick size pilot in the US.

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Figure 1
Relative tick size of currency pairs over time

This graph shows the relative tick size of the currency pairs on Kraken over the two weeks 23 August to 13 September 2017. The relative tick size is the tick size divided by the price and calculated in basis points. The relative tick is then averaged per day.

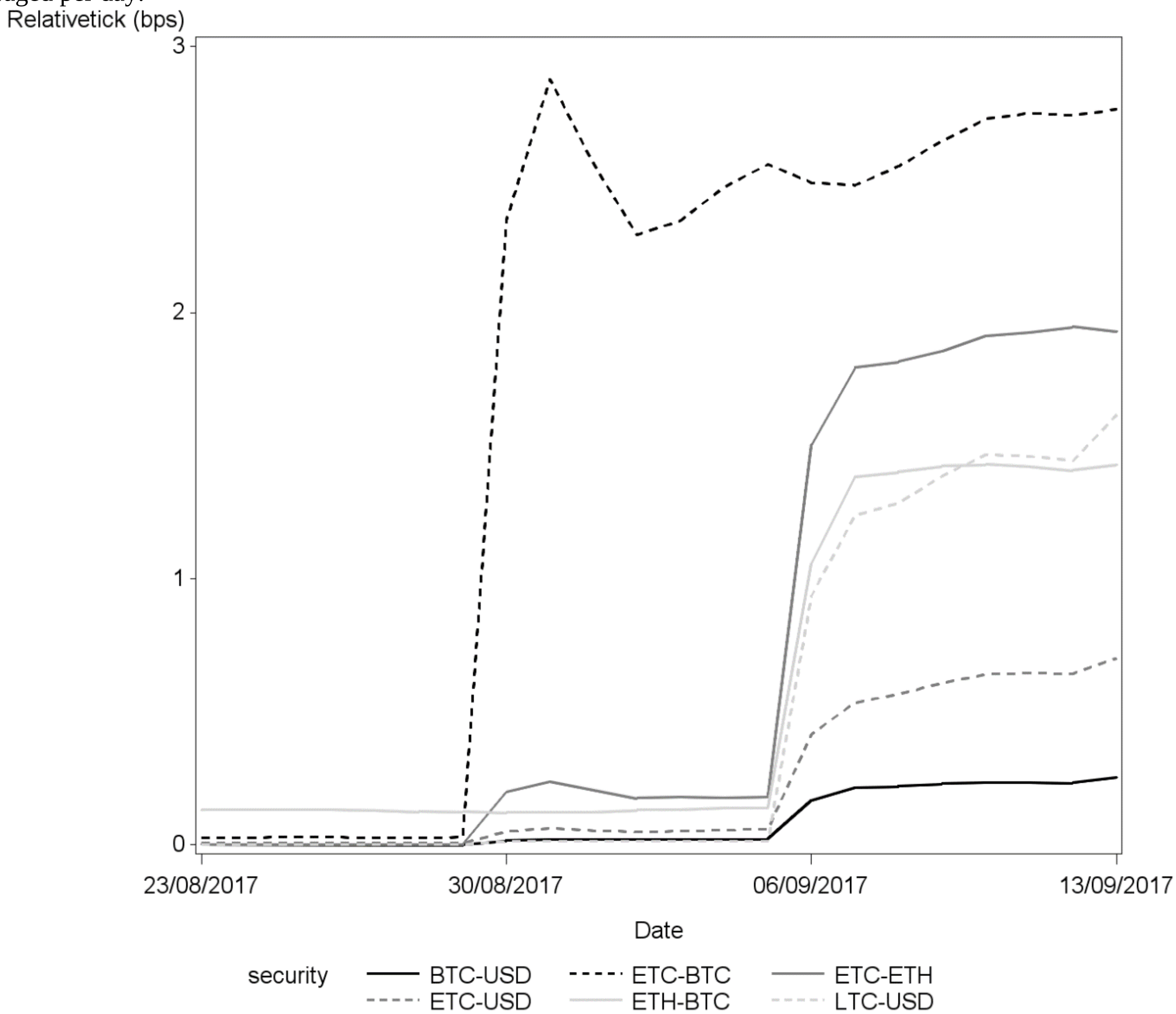


Figure 2
Scatterplot of effective spread and dollar volume for BTC-USD

This graph shows the effective spread in basis points for individual trades by dollar volume of over the sample period 23 August to 13 September 2017.

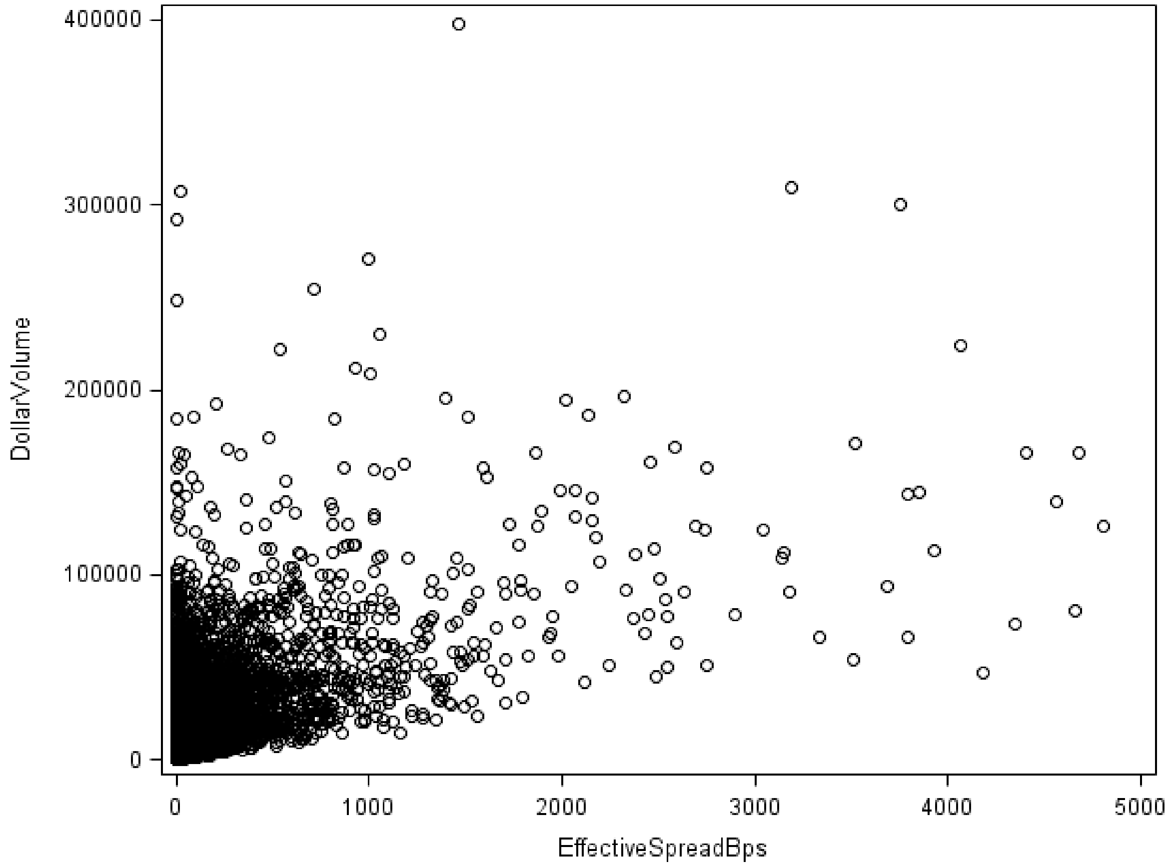


Table 1
Currency pairs and tick sizes at Kraken

The tick sizes are presented in decimal places and in bps relative to the average daily price in the sample period 23rd August to 13th September 2017.

	Pre 30 August		Post 30 August		Post 6 September	
Currency pair	Tick	Tick (bps)	Tick	Tick (bps)	Tick	Tick (bps)
BTC-USD	1E-03	0.0023	1E-02	0.0226	1E-01	0.2261
ETH-BTC	1E-06	0.1330	1E-06	0.1330	1E-05	1.3297
LTC-USD	1E-05	0.0015	1E-04	0.0149	1E-02	1.4867
ETC-ETH	1E-08	0.0020	1E-06	0.1984	1E-05	1.9841
ETC-USD	1E-05	0.0060	1E-04	0.0598	1E-03	0.5882
ETC-BTC	1E-08	0.0265	1E-06	2.6517	1E-06	2.6517

Table 2

Summary statistics of trading behavior and liquidity metrics

The table shows summary statistics of trading behavior, liquidity and control variables for the most traded currency pair BTC-USD and one of the least traded currency pair ETC-USD over the period 23rd August to 13th September 2017 on Kraken. All metrics are daily. *The number of price changes at best* counts the number of times within the day where the best prices are changed. *Limit order / market order* shows the proportion of limit orders to market orders. The *average market order and limit order volume* shows the volume in USD. The *average price difference* is the difference between limit order prices within a market order scaled by 100. The *average price steps* is how many price steps a market order goes through on average. The *number of resting limit orders* shows how many limit orders are resting at the same price step on average. *Quoted spread* is time weighted and in basis points. *Level three quoted spread* is the spread of prices at price level three time weighted and in basis points. *Effective and realized spread* are volume weighted and in basis points. *Constrained* is the percent of the day where the spread is equal to one tick. *Depth at best* and *depth at X bps* sums the depth at X bps on either side of the midpoint where X takes the value of 7.5 basis points for BTC-USD and 28 basis points for ETC-USD. *Short – term volatility* is the average 15-minute midpoint return volatility. The *number of trades* is the daily total. *Dollar volume* is the daily total displayed in 10,000 USD. *Volatility* is the currency-time high-low price range divided by the sum over two in basis points. The *mean price* shows the average price. The *relative tick* is the tick size divided by the trading price in basis points averaged in 15-minute buckets.

	BTC-USD					ETC-USD				
	Mean	Median	Std	Minimum	Maximum	Mean	Median	Std	Minimum	Maximum
Panel 1: Trading behavior metrics										
The number of price changes at best	11.53	10.30	2.16	9.28	15.66	8.67	8.53	0.69	7.77	10.10
Limit order / market order	1.68	1.71	0.15	1.30	1.87	1.82	1.85	0.25	1.24	2.18
Average market order volume	2.24	2.34	10.02	3.87	1.52	0.03	0.03	0.04	0.18	0.01
Average limit order volume	4.00	4.22	18.76	5.90	2.83	0.06	0.06	0.13	0.32	0.03
Average price difference (scaled)	46.14	42.31	21.04	13.87	97.24	0.68	0.63	0.36	0.19	1.61
Average price steps	1.25	1.27	0.05	1.12	1.32	1.52	1.54	0.18	1.17	1.91
Number of resting limit orders	1.51	1.48	0.09	1.33	1.66	1.20	1.21	0.07	1.08	1.31
Panel 2: Liquidity metrics										
Quoted spread (bps)	8.54	8.70	3.22	3.97	17.49	78.33	79.87	15.80	51.48	108.29
Level three quoted spread (bps)	25.32	25.44	8.70	12.36	47.61	137.24	141.97	25.98	85.90	183.18
Effective spread (bps)	16.67	16.46	6.94	7.23	34.60	84.66	85.80	19.79	52.54	125.09
Realized spread (bps)	14.89	13.07	6.80	6.05	33.35	77.15	78.52	19.25	47.79	116.66
Constrained (%)	8.79	9.51	3.31	3.84	15.88	2.68	2.56	1.67	0.16	6.52
Depth at best (1,000 USD)	24.3	22.36	9.14	11.41	48.8	5.78	5.52	2.65	1.04	12.02
Depth at X bps (1,000 USD)	235.36	225.85	50.57	179.18	376.06	21.97	22.23	10.33	7.9	55.54
Short – term volatility	1.94	1.98	0.76	0.9	3.88	5.56	5.31	2.5	2.73	10.48
Panel 3: Control variables										
Number of trades	11,388.36	10,968.00	2,962.98	7,773.00	21,203.00	2,416.86	2,144.00	1,320.05	736.00	5,026.00
Dollar volume (10,000 USD)	2,320.94	2,088.78	873.70	975.49	4,330.73	154.11	96.65	132.97	17.94	472.34
Volatility (bps)	0.01	0.01	0.00	0.00	0.01	0.01	0.01	0.01	0.00	0.02
Mean price	4,422.12	4,367.25	207.71	3,943.44	4,806.66	16.72	15.84	1.70	14.28	20.57
Relative tick (bps)	0.09	0.02	0.11	0.00	0.25	0.24	0.05	0.28	0.01	0.70

Table 3
Difference in averages between market quality metrics

This table reports the average liquidity and trading behavior measures in the week before and the week after the tick size increase. All the metrics are averaged over 15-minute time buckets, calculated in event time and standardized by the pre-period average (August 23-29). The metrics are then averaged across the ten events (four currency pairs change twice and two once yielding ten events). The $number\ of\ price\ changes\ at\ best$ counts the number of times within the day where the best prices are changed. The $number\ of\ trades$ is the daily total. $Limit\ order\ /\ market\ order$ shows the proportion of limit orders to market orders. The $average\ market\ order\ and\ limit\ order\ volume$ shows the volume in USD. The $average\ price\ difference$ is the difference between limit order prices within a market order scaled by 100. The $average\ price\ steps$ is how many price steps a market order goes through on average. The $number\ of\ resting\ limit\ orders$ shows how many limit orders are resting at the same price step on average. $Dollar\ volume$ is the daily total displayed in 10,000 USD. $Quoted\ spread$ is time weighted and in basis points. $Level\ three\ quoted\ spread$ is the spread of prices at price level three time weighted and in basis points. $Effective\ and\ realized\ spread$ are volume weighted and in basis points. $Constrained$ is the percent of the day where the spread is equal to one tick. $Depth\ at\ best$ is the dollar volume depth at the best prices. $Depth\ at\ X\ bps$ sums the depth at X bps on either side of the midpoint where X takes different values (see section 1.3). $Short-term\ volatility$ is the average 15-minute midpoint return volatility. The last two column reports the difference in means pre and post tick size increase and the p-value of the difference using a two-tailed t-test. ***, ** and * indicate the statistical significance at 1%, 5% and 10% levels respectively.

Variable	Pre	Post	Difference	t-statistic
$The\ number\ of\ price\ changes\ at\ best$	98.2	94.0	-4.2	(-4.46)***
$Number\ of\ trades$	104.6	89.4	-15.2	(-6.06)***
$Limit\ order\ /\ market\ order$	104.8	109.9	5.2	(6.11)***
$Average\ market\ order\ volume$	143.0	185.7	42.7	(5.90)***
$Average\ limit\ order\ volume$	144.7	183.1	38.4	(7.08)***
$Average\ price\ difference\ (scaled)$	147.5	179.5	32.0	(4.54)***
$Average\ price\ steps$	102.9	104.1	1.2	(2.00)**
$Number\ of\ resting\ limit\ orders$	101.5	106.8	5.3	(8.62)***
$Dollar\ volume\ (10{,}000\ USD)$	192.7	234.8	42.1	(3.56)***
$Quoted\ spread\ (bps)$	106.2	102.2	-4.0	(-2.50)**
$Level\ three\ quoted\ spread\ (bps)$	108.9	111.4	2.5	(1.69)*
$Effective\ spread\ (bps)$	112.7	114.8	2.0	(0.89)
Realized spread (bps)	112.1	113.9	1.8	(0.69)
$Constrained\ (\%)$	110.2	144.9	34.7	(6.79)***
$Depth\ at\ best\ (1{,}000\ USD)$	153.2	193.3	40.1	(7.34)***
$Depth\ at\ X\ bps\ (1{,}000\ USD)$	134.3	172.5	38.2	(6.82)***
$Short-term\ volatility$	106.4	95.4	-10.9	(-5.41)***

Table 4
Impact of tick size increase on trading behavior

This table reports the estimates of the ordinary least squares regression: $Metric_{it} = \alpha_i + \alpha_t + \beta_1 Post_{it} + \beta_2 \$Volume_{it} + \beta_3 Trades_{it} + \beta_4 Volatility_{it} + \beta_5 MeanPrice_{it} + \varepsilon_t$. Where α_i and α_t are currency pair and time fixed effects. The control variables are $Post_{it}$ which is the tick size change dummy which takes the value of one after the tick size increase come into effect and zero otherwise. $\$Volume_{it}$ measures the dollar volume in 10,000 USD traded for currency i in 15-minute interval t. $Trades_{it}$ is the total number of trades. $Volatility_{it}$ is the currency-time high-low price range divided by the sum over two in basis points and $MeanPrice_{it}$ which is the average price. The dependent variables $Metric_{it}$, are measures of trading behavior for each currency and 15-minute interval in event time. The $number\ of\ price\ changes\ at\ best$ counts the number of times within the day where the best prices are changed. $Limit\ order\ /\ market\ order$ shows the proportion of limit orders to market orders. The $average\ market\ order\ volume$ and $limit\ order\ volume$ is the volume in units. The $average\ price\ difference$ is the difference between limit order prices within a market order scaled by 100. The $average\ price\ steps$ is how many price steps a market order goes through on average. The $number\ of\ resting\ limit\ orders$ shows how many limit orders are resting at the same price step on average. T-statistics are reported in parentheses. ***, ** and * indicate the statistical significance at 1%, 5% and 10% levels respectively. The trading behavior measures have fewer observations as not all 15-minute intervals observe trades. Resting limit orders per price steps exclude trades that only interact with one depth level and excludes the last limit orders on the last price step the market order interacted with to ensure that all price steps are filled.

Variable	*Price changes at best$_{it}$*	*Limit order / market order$_{it}$*	*Market order volume$_{it}$*	*Limit order volume$_{it}$*	*Price difference$_{it}$*	*Price steps$_{it}$*	*Resting limit orders$_{it}$*
Post$_{it}$	-0.325	0.055	6.092	2.987	1.87	-0.001	0.066
	(-4.99)***	(5.05)***	(5.99)***	(7.87)***	(5.28)***	(-0.19)	(9.6)***
Intercept	23.668	2.356	-1.146	-4.647	186.286	1.882	1.032
	(9.89)***	(15.05)***	(-0.17)	(-1.73)*	(10.83)***	(26.29)***	(5.97)***
\$Volume$_{it}$	-0.012	0.010	0.550	0.218	0.640	0.004	0.003
	(-3.15)***	(16.66)***	(8.03)***	(7.77)***	(12.06)***	(18.61)***	(5.96)***
Trades$_{it}$	0.003	-0.003	-0.117	-0.026	-0.085	-0.002	0.001
	(2.42)**	(-19.47)***	(-7.63)***	(-4.83)***	(-9.52)***	(-29.48)***	(4.98)***
Volatility$_{it}$	0.001	0.001	0.047	0.013	0.019	0.001	0.000
	(2.41)**	(16.75)***	(7.32)***	(6.09)***	(14.04)***	(16.96)***	(1.42)
Mean Price$_{it}$	-0.003	-0.000	-0.002	-0.000	-0.032	-0.000	0.000
	(-5.51)***	(-5.01)***	(-1.13)	(-0.45)	(-8.49)***	(-8.28)***	(1.69)*
Observations	13450	12803	12803	12803	12803	12803	11242
Adjusted R^2	18.5%	9.9%	8.7%	13.7%	54.4%	14.1%	14.5%

Table 5

Impact of tick size increase on liquidity

This table reports the estimates of the ordinary least squares regression: $Metric_{it} = \alpha_i + \alpha_t + \beta_1 Post_{it} + \beta_2 \$Volume_{it} + \beta_3 Trades_{it} + \beta_4 Volatility_{it} + \beta_5 MeanPrice_{it} + \varepsilon_t$. Where α_i and α_t are currency pair and time fixed effects. The control variables are $Post_{it}$ which is the tick size change dummy which takes the value of one after the tick size increase come into effect and zero otherwise. $\$Volume_{it}$ measures the dollar volume in 10,000 USD traded for currency i in 15-minute interval t. $Trades_{it}$ is the number of trades. $Volatility_{it}$ is the currency-time high-low price range divided by the sum over two in basis points and $MeanPrice_{it}$ which is the average price. The dependent variables $Metric_{it}$, are measures of liquidity for each currency and 15-minute interval in event time. $Quoted\ spread$ is time weighted and in basis points. $Level\ three\ quoted\ spread$ is the spread of prices at price level three time weighted and in basis points. $Effective\ and\ realized\ spread$ are volume weighted and in basis points. $Constrained$ is the percent of the day where the spread is equal to one tick. $Depth\ at\ best$ is the dollar volume depth at the best prices in 1,000 USD. $Depth\ at\ X\ bps$ sums the dollar volume depth at X bps on either side of the midpoint where X takes different values (see section 1.3) and is calculated in 1,000 USD. $Short-term\ volatility$ is the average 15-minute midpoint return volatility. T-statistics are reported in parentheses. ***, ** and * indicate the statistical significance at 1%, 5% and 10% levels respectively. The number of observations for effective and realized spread is lower as not all 15-minute intervals have trades and any trades with negative effective spreads due to sequencing error is excluded. Depth X has fewer observations as the exchange was offline for a few hours on August 25 and August 26.

Variable	*Quoted spread$_{it}$*	*Level three quoted spread$_{it}$*	*Effective spread$_{it}$*	*Realized spread$_{it}$*	*Constrained$_{it}$*	*Depth at best$_{it}$*	*Depth at X bps$_{it}$*	*Short-term volatility$_{it}$*
Post$_{it}$	-8.406	-1.759	-6.311	-7.521	2.015	1.544	-0.410	-0.502
	(-8.71)***	(-1.58)	(-5.69)***	(-6.11)***	(12.67)***	(4.61)***	(-0.34)	(-8.77)***
Intercept	63.763	63.409	71.268	80.291	-18.406	-124.268	-755.885	-1.9
	(6.84)***	(7.33)***	(6.66)***	(6.95)***	(-4.36)***	(-5.75)***	(-11.25)***	(-2.82)***
\$Volume$_{it}$	0.227	0.054	0.248	0.253	-0.134	0.398	1.116	-0.033
	(8.75)***	(1.66)*	(6.18)***	(5.79)***	(-11.76)***	(10.63)***	(10.73)***	(-8.8)***
Trades$_{it}$	-0.353	-0.215	-0.442	-0.476	0.066	0.078	0.126	0.019
	(-25.14)***	(-12.30)***	(-24.60)***	(-24.32)***	(16.89)***	(8.66)***	(4.71)***	(9.93)***
Volatility$_{it}$	0.181	0.321	0.406	0.404	-0.003	-0.015	-0.079	0.026
	(18.84)***	(31.78)***	(31.31)***	(24.96)***	(-3.51)***	(-9.15)***	(-16.95)***	(51.29)***
Mean Price$_{it}$	-0.007	-0.008	-0.008	-0.010	0.005	0.029	0.215	0.000
	(-4.30)***	(-5.89)***	(-3.81)***	(-4.0-)***	(5.53)***	(6.05)***	(14.30)***	(2.04)**
Observations	13450	13450	12703	12703	13450	13450	13416	13450
R^2	55.2%	64.4%	55.2%	49.2%	19.4%	22.0%	65.2%	57.3%

Table 6
First stage regression of relative tick size

This table shows the results of the first stage regression following the equation $\widehat{Relative}\,Tick_{it} = \alpha_i + \alpha_t + \beta_1 PercentChange_{it} + \beta_2 \$Volume_{it} + \beta_3 Trades_{it} + \beta_4 Volatility_{it} + \beta_5 MeanPrice_{it} + \varepsilon_t$ where α_i and α_t are currency pair and time fixed effects. The control variables are $PercentChange_{it}$ which takes the value of zero before the tick size change and the value of the percent change in tick size after. $\$Volume_{it}$ measures the dollar volume in 10,000 USD traded for currency i in 15-minute interval t. $Trades_{it}$ is the number of trades. $Volatility_{it}$ is the currency-time high-low price range divided by the sum over two in basis points and $MeanPrice_{it}$ which is the average price. The dependent variable $\widehat{Relative}\,Tick_{it}$ is the tick size in cents over the price averaged in the 15-minute buckets. T-statistics are reported in parentheses. ***, ** and * indicate the statistical significance at 1%, 5% and 10% levels respectively. The number of observations is lower as not all 15-minute buckets have trades.

Variable	$RelativeTick_{it}$
$PercentChange_{it}$	0.975
	(15.89)***
Intercept	0.000
	(55.42)***
$\$Volume_{it}$	0.001
	(4.04)***
$Trades_{it}$	-0.001
	(-11.67)***
$Volatility_{it}$	-0.001
	(-12.53)***
$Mean\ Price_{it}$	-0.000
	(-19.50)***
Observations	12803
R^2	52.9%

Table 7

Impact of relative tick size on trading behavior

This table reports the estimates of the two stage least squares regression: $Metric_{it} = \alpha_i + \alpha_t + \beta_1 \$Volume_{it} + \beta_2 Trades_{it} + \beta_3 Volatility_{it} + \beta_4 MeanPrice_{it} + \beta_5 \widehat{RelativeTick}_{it} + \varepsilon_t$ where relative tick is the estimate of the first stage regression $Relative\ Tick_{it} = \alpha_i + \alpha_t + \beta_1 \$Volume_{it} + \beta_2 Trades_{it} + \beta_3 Volatility_{it} + \beta_4 MeanPrice_{it} + \varepsilon_t$. The model has currency and intraday time fixed effects. The control variables are $\$Volume_{it}$ which measures the dollar volume in 10,000 USD traded for currency i in 15-minute interval t in base currency. $Trades_{it}$ is the number of trades. $Volatility_{it}$ is the currency-time high-low price range divided by the sum over two in basis points. $MeanPrice_{it}$ is the average price in base currency. The dependent variables $Metric_{it}$, are measures of trading behavior for each currency and 15-minute interval in event time. The $number\ of\ price\ changes\ at\ best$ counts the number of times within the day where the best prices are changed. $Limit\ order\ /\ market\ order$ shows the proportion of limit orders to market orders. The $average\ market\ order\ volume$ and $limit\ order\ volume$ is the volume in units. The $average\ price\ difference$ is the difference between limit order prices within a market order scaled by 100. The $average\ price\ steps$ is how many price steps a market order goes through on average. The $number\ of\ resting\ limit\ orders$ shows how many limit orders are resting at the same price step on average.. T-statistics are reported in parentheses. ***, ** and * indicate the statistical significance at 1%, 5% and 10% levels respectively. The trading behavior measures have fewer observations as not all 15-minute intervals observe trades. Resting limit orders per price steps exclude trades that only interact with one depth level and excludes the last limit orders on the last price step the market order interacted with to ensure that all price steps are filled.

Variable	*Price changes at best*$_{it}$	*Limit order / market order*$_{it}$	*Market order volume*$_{it}$	*Limit order volume*$_{it}$	*Price difference*$_{it}$	*Price steps*$_{it}$	*Resting limit orders*$_{it}$
$\widehat{RelativeTick}_{it}$	-1.281	0.055	8.410	4.419	0.117	-0.019	0.100
	(-18.17)***	(3.51)***	(4.90)***	(6.53)***	(0.83)	(-1.78)*	(10.30)***
Intercept	25.006	2.288	-10.957	-9.753	185.742	1.90	0.918
	(10.53)***	(14.61)***	(-1.64)	(-3.63)***	(10.81)***	(26.19)***	(5.31)***
*$Volume*$_{it}$	-0.011	0.010	0.554	0.220	0.645	0.004	0.003
	(-2.93)***	(16.9)***	(8.00)***	(7.78)***	(12.09)***	(18.66)***	(6.07)***
Trades$_{it}$	0.000	-0.003	-0.106	-0.020	-0.087	-0.002	0.001
	(0.25)	(-18.89)***	(-6.53)***	(-3.48)***	(-9.76)***	(-28.77)***	(6.14)***
Volatility$_{it}$	-7.831	0.336	51.459	27.027	0.737	-0.113	0.61
	(-18.17)***	(3.52)***	(4.91)***	(6.54)***	(0.85)	(-1.78)*	(10.3)***
Mean Price$_{it}$	-0.003	-0.000	0.001	0.001	-0.032	-0.000	0.000
	(-6.11)***	(-4.42)***	(0.70)	(1.93)*	(-8.42)***	(-8.44)***	(2.43)**
Observations	12803	12803	12803	12803	12803	12803	11242
Adjusted R^2	19.6%	9.8%	8.7%	13.7%	54.3%	14.1%	14.6%

Table 8

Impact of relative tick size increase on liquidity

This table reports the estimates of the two stage least squares regression: $Metric_{it} = \alpha_i + \alpha_t + \beta_1 \$Volume_{it} + \beta_2 Trades_{it} + \beta_3 Volatility_{it} + \beta_4 MeanPrice_{it} + \beta_5 \widehat{RelativeTick}_{it} + \varepsilon_t$ where relative tick is the estimate of the first stage regression $Relative\ Tick_{it} = \alpha_i + \alpha_t + \beta_1 \$Volume_{it} + \beta_2 Trades_{it} + \beta_3 Volatility_{it} + \beta_4 MeanPrice_{it} + \varepsilon_t$. The model has currency and intraday time fixed effects. The control variables are $\$Volume_{it}$ which measures the dollar volume in 10,000 USD traded for currency i in 15-minute interval t in base currency. $Trades_{it}$ is the number of trades. $Volatility_{it}$ is the currency-time high-low price range divided by the sum over two in basis points. $MeanPrice_{it}$ is the average price in base currency. The dependent variables $Metric_{it}$, are measures of liquidity for each currency and 15-minute interval in event time. $Quoted\ spread$ is time weighted and in basis points. $Level\ three\ quoted\ spread$ is the spread of prices at price level three time weighted and in basis points. $Effective\ and\ realized\ spread$ are volume weighted and in basis points. $Constrained$ is the percent of the day where the spread is equal to one tick. $Depth\ at\ best$ is the dollar volume depth at the best prices in 1,000 USD. $Depth\ at\ X\ bps$ sums the dollar volume depth at X bps on either side of the midpoint where X takes different values (see section 1.3) and is calculated in 1,000 USD. $Short-term\ volatility$ is the average 15-minute midpoint return volatility. T-statistics are reported in parentheses. ***, ** and * indicate the statistical significance at 1%, 5% and 10% levels respectively. The number of observations for effective and realized spread is lower as not all 15-minute intervals have trades and any trades with negative effective spreads due to sequencing error is excluded. Depth X has fewer observations as the exchange was offline for a few hours on August 25 and August 26.

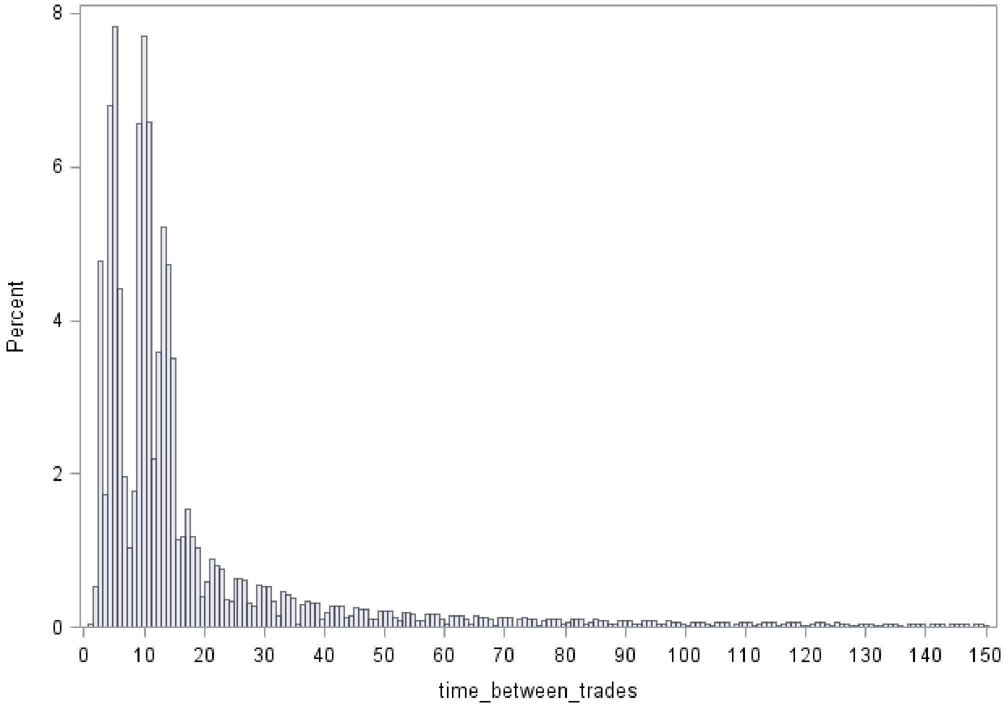
Variable	*Quoted spread$_{it}$*	*Level three quoted spread$_{it}$*	*Effective spread$_{it}$*	*Realized spread$_{it}$*	*Constrained$_{it}$*	*Depth at best$_{it}$*	*Depth at X bps$_{it}$*	*Short-term volatility$_{it}$*
$\widehat{RelativeTick}_{it}$	-4.255	8.789	-4.313	-4.954	3.76	1.821	0.366	-0.304
	(-2.50)**	(4.37)***	(-2.13)**	(-2.19)**	(14.49)***	(7.00)***	(0.48)	(-2.89)***
Intercept	70.037	55.229	77.068	87.015	-22.597	-126.44	-756.161	-1.476
	(7.44)***	(6.15)***	(7.11)***	(7.43)***	(-5.30)***	(-5.85)***	(-11.25)***	(-2.13)**
\$Volume$_{it}$	0.211	0.038	0.237	0.240	-0.134	0.399	1.114	-0.034
	(8.24)***	(1.15)	(5.89)***	(5.48)***	(-11.91)***	(10.66)***	(10.73)***	(-8.94)***
Trades$_{it}$	-0.350	-0.192	-0.443	-0.477	0.072	0.079	0.127	0.019
	(-24.17)***	(-10.56)***	(-24.06)***	(-23.95)***	(18.23)***	(8.83)***	(4.72)***	(9.62)***
Volatility$_{it}$	-25.829	54.048	-25.962	-29.878	22.981	11.115	2.158	-1.835
	(-2.49)**	(4.39)***	(-2.10)**	(-2.16)**	(14.49)***	(6.99)***	(0.46)	(-2.85)***
Mean Price$_{it}$	-0.010	-0.007	-0.010	-0.012	0.006	0.030	0.215	0.000
	(-5.84)***	(-4.99)***	(-4.70)***	(-4.96)***	(6.61)***	(6.18)***	(14.30)***	(0.86)
Observations	13450	13450	12703	12703	13450	13450	13416	13450
R^2	55.0%	64.4%	55.1%	49.1%	20.4%	22.0%	65.2%	57.1%

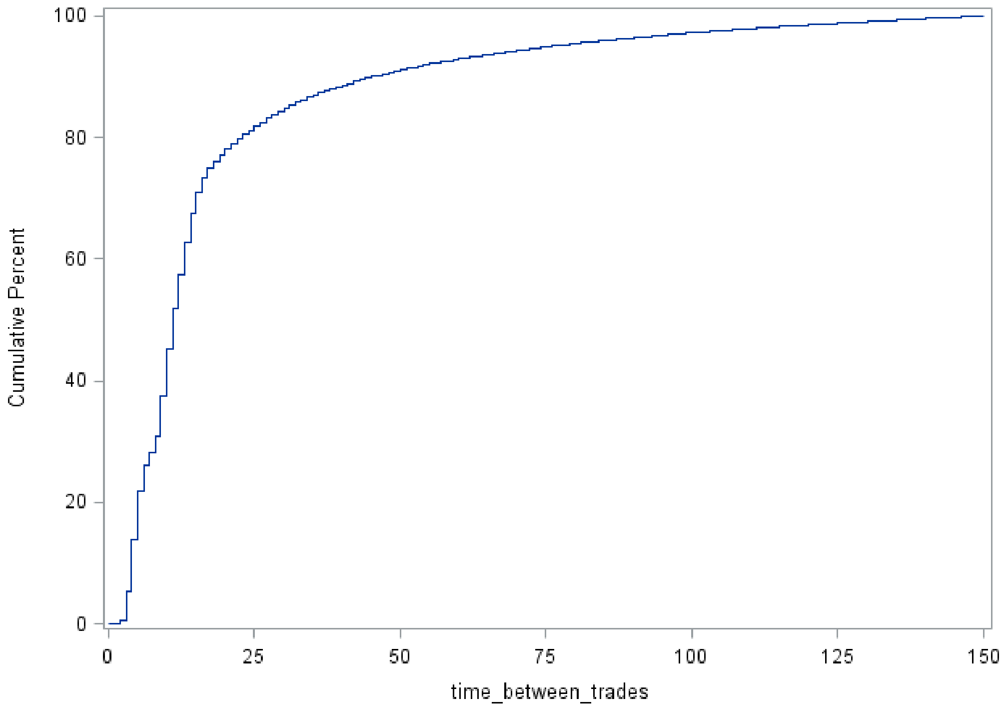
Appendix A1: Trade aggregation

Appendix figure 1

Histogram and cumulative distribution function of time between trades

The graphs show the distribution and cumulative distribution of the time between trades in milliseconds for all six currencies on Kraken between August 1, 2017 and October 21, 2017. For the purposes of this graph observations greater than 0.15 seconds have been omitted to clearly show the skewed distribution.





Appendix A2: Realized spread lead time estimation

When calculating which midpoint to compare the price of a trade to when calculating the realized spread it is important to use the correct lead time. If the lead time is too short, the inventory effect will be included and the price impact will be overstated. If the lead time is too long other trades may have occurred and the price impact will therefore include responses by other information which will give a biased estimate. To estimate the correct lead time a vector auto regression is estimated following the structural form shown in Eq. (a) and (b).

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

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

where individual currency pair and date subscripts are suppressed, t is one second intervals, x_t is signed dollar volume of trades in the one second interval t, r_t is the log midpoint change in the t^{th} interval, ε_t^x is unanticipated signed dollar volume and ε_t^r is a midpoint innovation that is not caused by order flow. All variables are converted to USD using the daily trade price on Gemini so the shock is of equal size. Gemini is used as it is the only exchange for which we have all USD denominated exchange rates. Each Eq. contains 180 lags of signed dollar volume and midpoint changes.

A reduced form VAR is estimated following Eq. (c) and (d).

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

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

where $e_t^x = \varepsilon_t^x$ and $e_t^r = b_1 e_t^x + \varepsilon_t^r$. The error terms are serially uncorrelated and i.i.d. and contemporaneously correlated across equations.

To identify how long it takes for the price impact to converge, a shock to e_0^x is introduced representing a 200-dollar volume buyer-initiated trade. The impulse response functions are then graphed to observe when the price converges. Appendix Figure 2 shows that most currency pairs converge after 10-20 seconds. Its looks as though the USD denominated currency pairs take longer to converge than the cryptocurrency cross rates. When introducing a 200-dollar seller-initiated trade as a shock the same results are produced. Based on these results the price of a trade will be compared to the midpoint 10 seconds after for ETC-BTC, ETC-ETH and ETH-BTC and 20 seconds after for LTC-USD, ETC-USD and BTC-USD.

Appendix figure 2

Impulse response function of a 200 USD buyer-initiated trade on the midpoint return

The figure shows the impulse 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 using the daily traded price on Gemini. Gemini is used as it is the only exchange for which we have all USD denominated exchange rates.