Bitcoin Liquidity

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Abstract

Bitcoin is emerging as a popular financial asset and means of transacting. However, little is known about its liquidity. This paper addresses this deficit. We find there is both substantial variation in the level of liquidity across different exchanges and currency pairs and a strong systematic aspect to bitcoin liquidity. Moreover, changes in currency liquidity influence bitcoin liquidity. The pricing of bitcoin is less efficient than stock pricing and liquidity plays an important role, with the inefficient pricing being more prevalent on days with less liquidity. Liquidity declines also contribute to bitcoin crash risk.

JEL Classification Codes: G11, G23
Keywords: Bitcoin, Liquidity, Cryptocurrency

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1. Introduction

The popularity of the bitcoin as a financial asset and means of transacting is rapidly increasing. Easley, O'Hara, and Basu (2017) note that an estimated 100,000 companies worldwide accept payment in bitcoin and a likely 10 million individuals hold a non-trivial amount of bitcoin as an asset. By early 2018, the market capitalization of bitcoin exceeded the market capitalization of a number of developed equity markets that attract global investment flows[1], and Foley, Karlsen, and Putnins (2018) note that there are now in excess of one hundred hedge funds solely focusing on bitcoin and related "cryptocurrencies." Moreover, in late 2017, the CME launched a bitcoin futures contract in response to demand from traders and hedgers.

However, relatively little is known about the liquidity of the bitcoin market, which is in sharp contrast to the many studies that highlight the importance of liquidity in equity, bond, currency, and commodity markets.[2] The bitcoin market has a number of features that differentiate it from most other markets, such as continuous trading, no regulation, and a lack of transparency, so it is unclear whether liquidity findings from other markets will apply in bitcoin or not. We contribute to several strands of the liquidity literature. First, we add to the work (e.g. McInish and Wood, 1992) on intraday variation in transaction costs by considering an environment of continuous trading. Second, we consider whether liquidity commonality (e.g. Chordia, Roll, and Subramanyam, 2000) is prevalent despite the fragmented nature of the bitcoin market and the fact that the correlated trading by institutional investors explanation of Koch, Ruenzi, and Starks (2016)

[1] Developed markets in this category include New Zealand and Ireland.

[2] An incomplete list of the many important papers in this area includes Amihud (2002), Chordia, Roll, and Subrahmanyam (2000), Lee (2011), and Karolyi, Lee, and van Dijk (2012) for stocks, Chen, Lesmond, and Wei (2007) and Schestag, Schuster, and Uhrig-Homburg (2016) for bonds, Mancini, Ranaldo, and Wrampelmeyer (2013) and Karnaukh, Ranaldo, and Soderlind (2016) for currencies, and Marshall, Nguyen, and Visaltanachoti (2012) for commodities.

is likely to be less of a feature. Third, we investigate whether there is liquidity spillover between currency and stocks and bitcoin, using the framework of Chordia, Sarkar, and Subrahmanyam (2005). Fourth, we follow Brunnermeier, Nagel, and Pedersen (2008) and consider whether variables such as VIX and the TED Spread, which have been shown to influence stock liquidity, are determinants of bitcoin liquidity. Fifth, we document the role that liquidity plays in the efficient pricing of bitcoin using the framework of Chordia, Roll, and Subramanyam (2008). Last, we consider whether liquidity contributes to crash risk in bitcoin.

Using a comprehensive database of intraday bitcoin data that spans 14 exchanges and includes prices against 13 currencies, we provide insight into bitcoin liquidity. We show there is considerable variation across the different bitcoin pairs, with the average effective spread ranging from 0.04% for bitcoin priced in Chinese Yuan to 1.28% for bitcoin in Canadian Dollars. The Okcoin and Btcc exchanges have the lowest effective spreads, while the Huobi and Kraken exchanges have the largest effective spreads. The average effective (quoted) spread across all 35 pairs is 0.30% (0.38%). These spreads are lower than average stock spreads (e.g. Fong, Holden, and Trzcinka (2017)), but higher than currency spreads (e.g. Mancini, Ranaldo, and Wrampelmeyer (2013)) and commodity spreads (e.g. Marshall, Nguyen, and Visaltanachoti (2012)).

These findings will be of interest to a number of parties. For instance, those wishing to diversify portfolios by adding bitcoin exposure can use these costs to estimate whether there are net benefits to bitcoin diversification. De Roon, Nijman, and Werker (2001) note that what appears to be diversification benefits can disappear when transaction costs are accounted for. Active traders of bitcoin can also use these costs to assess the net gains to their strategies. Papers such as Lesmond, Schill and Zhou (2004) show that transaction costs are an important consideration when determining whether market timing techniques add value. Finally, exchanges can also make use of these results. Harris (2003) points out that transaction cost levels are an important aspect that exchanges use when competing for business.

There is a well-documented pattern of intraday variation in stock spreads (e.g. McInish and Wood, 1992) with spreads being higher at the start of the trading day due to higher levels of information asymmetry (e.g. Foster and Viswanathan, 1992). Intraday variation also exists in currency spreads (e.g. Bollerslev and Domowitz, 1993), despite the fact these are traded continuously during the business week. We find no evidence of intraday variation in bitcoin transaction costs. The continuous trading leads to largely uniform costs over the course of the day.

Chordia, Roll, and Subramanyam (2000) show that stock liquidity has a systematic component. A change in the liquidity of stocks across the entire market impacts on the liquidity of individual stocks. We find this phenomenon is also prevalent in bitcoin despite the fragmented nature of the bitcoin market. There is a strong link between individual bitcoin liquidity and the aggregate bitcoin market liquidity in 12 of the 13 bitcoin-currency pairs.

Changes in the liquidity of currency markets are correlated with changes in bitcoin liquidity and currency market liquidity changes Granger cause changes in bitcoin liquidity. However, changes in bitcoin liquidity do not influence liquidity in currency markets. Bitcoin liquidity is not strongly influenced by factors that have been shown to affect stock liquidity. Brunnermeier and Pedersen (2009) develop a model that links the liquidity of assets to the liquidity of funding markets. Their premise is that the ability of traders to provide market liquidity is dependent on their ability to obtain funding. We follow Brunnermeier, Nagel, and Pedersen (2008) and use the TED spread, which is the difference between the London Interbank Offered Rate (LIBOR) and the risk-free T-Bill rate, as a proxy for funding liquidity. We find there is some evidence that increases in the TED spread reduce the liquidity of bitcoin. However, this is not consistent across liquidity proxies and bitcoin exchange and currency pairs. We also find that movements in the VIX, which is regularly used as a proxy for uncertainty and investor fear, does not have a strong consistent impact on bitcoin liquidity.

Another contribution we make, is documenting that liquidity plays an important role in price discovery and the efficient pricing of bitcoin. Unlike stocks, which Chordia, Roll, and Subramanyam (2005) show have efficient pricing over intervals between 5 - 60 minutes, over 40% of bitcoin pair returns are predictable from lag order imbalance at 60-minute horizons. Moreover, the predictive ability of lag order imbalance is stronger (i.e. the pricing is less efficient) in all 13 bitcoin currency pairs on days when liquidity is lower. Bitcoin returns are much more volatile than stock returns and there are frequent crashes. We show that changes in bitcoin liquidity contribute to bitcoin return crashes.

The remainder of the paper is as follows. Section 2 provides more detail on the bitcoin market and summarises related literature. The data and liquidity measures we adopt are in Section 3. Section 4 contains the results and Section 5 concludes the paper.

2. The Bitcoin Market and Related Literature

2.1. Bitcoin

Bitcoin is a digital or cryptocurrency, which was first discussed by Nakamoto (2008)[3]. As Yermack (2014) notes, Bitcoin differs from fiat money in that its growth rate is linked to

[3] The author(s) of this paper have never been identified.

mathematics, which is applied in a decentralized manner by transparent computer code. As Easley, O'Hara, and Basu (2017) point out, "miners" create new bitcoins by solving mathematical problems and receiving new bitcoins as payment. Yermack (2014) highlights that the rate of growth in bitcoin slows over time with the last bitcoin due to be released in the year 2140, bringing the total to 21 million units. Harvey (2014) mentions that bitcoin differs to fiat money in that the history of every transaction is known. A ledger, known as a "blockchain" records transactions, with new blocks added as new transactions happen. Yermack (2017) notes that blockchain technology is a major advance in financial record keeping and that stock exchanges around the world have started evaluating this technology as a mechanism by which company shares can be listed and traded. However, Huberman, Leshno and Moallemi (2017) highlight that bitcoin cannot provide some services such as reversing fraudulent transactions. While the use of bitcoin for legal transactions and as an investment asset is rapidly increasing, bitcoin is also a popular means of transacting for those involved in illegal activity. Foley, Karlsen, and Putnins (2018) estimate that one quarter of bitcoin users are involved in illegal activity, although they note (p. 1) that "declines with mainstream interest in bitcoin and with the emergence of more opaque cryptocurrencies". This is consistent with Tasca, Liu, and Hayes (2016) who conclude that the bitcoin market has progressed away from being dominated by "sin" activities toward legitimate business activity.

Hileman and Rauchs (2017) state that while the second cryptocurrency, "Namecoin", did not emerge until April 2011, there are now hundreds of cryptocurrencies traded. However, Hileman and Rauchs (2017) estimate that in March 2017 that market capitalization of bitcoin was in excess of 3.5 times the market capitalization of the other cryptocurrencies combined.

2.2. Related Literature

In addition to papers that explain the features of the bitcoin market, a number of authors consider various dynamics of the bitcoin market. Detzel, Liu, Strauss, Zhou, and Zhu (2018) show that bitcoin returns are largely unpredictable by economic variables. However, simple technical trading strategies based on moving average rule generate returns that are statistically significantly greater than those to a buy-and-hold strategy. Scaillet, Treccani, and Trevisan (2017) show that jumps occur frequently, have a short-term positive impact on market activity, and cause a persistent price change. Brandvold, Molnar, Vagstad, and Vagstad (2015) consider the role of various exchanges in price discovery and show the information share of different exchanges has changed significantly through time. Easley, O'Hara, and Basu (2017) show that the level of transaction fees in the bitcoin market will over time play an important role in influencing both bitcoin miners and those transacting in bitcoin. Elendner, Trimborn, Ong, Lee (2016) consider the co-movement between bitcoin and assets such as stock indices, real estate, gold, and U.S. Treasury Bills. They find consistently low correlations, which indicates including Bitcoin in a portfolio provides important diversification benefits.

3. Measuring Bitcoin Liquidity

3.1. Data

We obtain data from Kaiko (https://www.kaiko.com/), which provides trade and order book data representing the leading cryptocurrency exchanges. Both the trade and book data are are reported at one second intervals. The exchanges we consider are Bitfinex, Bitflyer, Bitstamp, Btcbox, Btcc, Btce, Coinbase, Gatecoin, Gemini, Huobi, Kraken, Okcoin, Quoine, and Zaif. We focus on bitcoin trades against currencies including the Australian Dollar (AUD), Canadian Dollar (CAD), Chinese Yuan (CNY), Euro (EUR), Great Britain Pound (GBP), Hong Kong Dollar (HKD), Indian Rupee (INR), Indonesian Rupee (IDR), Japanese Yen (JPY), Philippine Peso (PHP), Russian Rubee (RUB), Singapore Dollar (SGD), and United States Dollar (USD). Kaiko have increased their data coverage over time and continue to do so. Our data end point is March 2017 and we source all data that was available when we obtain the data soon after this month. The earliest series commence in October 2015 and the latest series start in October 2016. An exchange pair month is excluded if the average number of trades per day is less than ten and we require that three or more months of data for an exchange pair to be included in our analysis.[4] Our sample comprises 38 exchange pairs. Eleven of these pairs involve the USD, six involve the EUR, five involve the JPY, four involve the CNY, two involve the JPY and SGD, and the other currencies are represented once. The pairs we include represent in excess of 95% of Bitcoin volume over the five years ending September 2017.[5] The unregulated nature of the Bitcoin exchanges raises the possibility that some exchanges may engage in practises which distorts their data.[6] We therefore report our core results at the exchange level so the reader can have confidence that the overall results are consistent with those from the individual exchanges.

[4] We also remove trade observations that fall outside the prevailing bid-ask quote by 1% or more at the time of the trade, and only included a quoted spread observation for a day if there is at least one trade during the day.
[5] http://data.bitcoinity.org/markets/exchanges/all/5y#volume_desc
[6] For instance, it has been alleged that some exchanges use trading bots to artificially inflate trading volume: https://medium.com/@sylvainartplayribes/chasingfake-volume-a-crypto-plague-ea1a3c1e0b5e

3.2. Liquidity Measures

The high-frequency trade and order book data allows us to calculate these measures directly rather than rely on some of the many liquidity proxies that have developed (e.g., Goyenko, Holden, and Trzcinka (2009). The first of these is effective spread, as specified in equation 1.

$$\textit{Effective Spread (ESP)} = 2 \cdot |\ln(P_k) - \ln(M_k)|, \tag{1}$$

where P_k and M_k are the price and the midpoint of bid and ask quotes when the kth trade occurs. We calculate average daily effective spreads by weighting intraday spreads by dollar volume.

We calculate quoted spread as per equation 2:

$$\textit{Quoted Spread (QSP)} = (A_k - B_k)/M_k, \tag{2}$$

where A_k, B_k, and M_k are ask price, bid price, and midpoint of these two prices, respectively. The daily average quoted spread is calculated by time weighting the intraday spreads.

We calculate the one-minute price impact as per equation 3:

$$\textit{Price Impact}\ (PI) = \begin{cases} 2\ \cdot \left(\ln(M_{k+1min}) - \ln(M_k)\right) \text{ when the } k^{th} \text{ trade is a buy,} \\ 2\ \cdot \left(\ln(M_k) - \ln(M_{k+1min})\right) \text{ when the } k^{th} \text{ trade is a sell,} \end{cases} \tag{3}$$

where $M_{k+1mins}$ (M_k) are the midpoints one minute after the *k*th trade (at the time of the *k*th trade). We use the Lee and Ready (1991) algorithm to classify trades, and daily averages are calculated using the same approach as for effective spreads.[7]

Depth is calculated as the value bitcoin available at the best bid and ask quote as per equation 4:

$$Depth = (A_k \times Unit\_A_k + B_k \times Unit\_B_k) / 2 \tag{4}$$

where A_k and B_k are the ask price and bid price respectively, and $Unit\_A_k$ and $Unit\_B_k$ are the amount of bitcoin available at the best ask and bid price respectively. The average daily depth is then calculated.

The fifth liquidity measure we compute is *Order Imbalance*. As Chordia, Roll, and Subrahmanyam (2002) note, order imbalances influence liquidity and can signal the presence of private information. Our measure of *Order Imbalance* is stated in equation 5.

$$Order\ Imbalance = (Bitcoin\_Buy_k - Bitcoin\_Sell_k) / (Bitcoin\_Buy_k + Bitcoin\_Sell_k) \tag{5}$$

[7] The lack of regulation of cryptocurrency exchanges and the opaqueness of their operations raises the possibility of variation in latency, which may impact analysis including the assigning of buy and sell trades. If there are delays between a quote being updated or a trade occurring and this being reported to market participants in some or all exchanges the Lee and Ready (1991) algorithm may result in inaccurate trade classifications. However, transaction cost measures such as quoted spread are not impacted by this.

where $Bitcoin\_Buy_k$ and $Bitcoin\_Sell_k$ are the total bitcoin purchased in buyer-initiated trades and seller-initiated trades over a five-minute interval respectively. Daily averages are then calculated.[8] Our sixth liquidity measure is the number of trades occurring in a day.

3.3. Liquidity Across Bitcoin Currency and Exchange Pairs

We present mean liquidity measures for each bitcoin-currency-exchange pair in Table 1. Mean quoted spreads range from 0.011% for bitcoin traded in Chinese Yuan on the Okcoin exchange to 1.950% for bitcoin traded on the Kraken exchange in Great Britain Pounds. The average quoted spread across all bitcoin-currency-exchange pairs is 0.300%, compared to 1.7% for global stocks (e.g. Fong, Holden, and Trzcinka, 2017), 0.015% - 0.083% for currencies (e.g. Mancini, Ranaldo, and Wrampelmeyer (2013)), median commodity spreads of 0.176% (e.g. Marshall, Nguyen, and Visaltanachoti (2012)), and mean spreads of 1.286% for bonds (e.g. Schestag, Schuster, and Uhrig-Homburg (2016)). The currency pairs with the smallest transaction costs are bitcoin against the Chinese Yuan, Hong Kong Dollar, and Singapore Dollar, while the pairs with the largest transaction costs are bitcoin against the Canadian Dollar, Great Britain Pound, and Indian Rupee. The smallest transaction costs are evident on Okcoin and Btcc and the largest costs are on Huobi and Kraken.

Effective spreads show a similar pattern to their quoted spread counterparts, which is unsurprising given the correlation between these two liquidity measures is 0.691. Effective spreads range from 0.092% for bitcoin in Japanese Yen traded on Zaif to 1.706% for bitcoin in Great Britain Pounds traded on the Kraken exchange. The average effective spread across all currency-

[8] We also calculate order imbalance based on the value of the bitcoin purchased and sold but the results are qualitatively similar so we do not report these.

exchange pairs is 0.382%, with bitcoin against the Chinese Yuan and Great Britain Pounds having the smallest and largest effective spreads respectively.

The price impact and number of trade results also point to bitcoin traded in Chinese Yuan as being the most liquid. There are an average of 701,045 trades per day in bitcoin against the Chinese Yuan compared to an average 8,242 trades per day for bitcoin in USD, and just 132 trades per day on average for bitcoin against the Canadian Dollar. Bitcoin against Japanese Yen has the lowest level of order imbalance (in absolute terms), while there is relatively large levels of order imbalance on average in bitcoin priced against the Russian Rupee. Bitcoin priced in Chinese Yuan traded on Okcoin and Huobi are the least volatile currency-exchange pairs, while bitcoin priced in Japanese Yen on Kraken and the Philippine Peso traded on Quoine are the most volatile.

In Appendix 1 we present equivalent results for medians. These indicate that median quoted and effective spreads, and price impacts are 0.234%, 0.337%, and 0.178% respectively, compared to 0.300%, 0.382%, and 0.191% for means. However, the median results are consistent with the mean numbers in that they indicate bitcoin in Chinese Yuan has the lowest transaction costs, while bitcoin in the Great Britain Pound and Canadian Dollar have the largest transaction costs.

In the last two columns of Table 1, we present bitcoin returns and standard deviations based on daily data. It is evident that bitcoin priced in Chinese Yuan and Hong Kong dollars traded on the Quoine exchange are the most volatile, while bitcoin priced in USD and Euros traded on the Gatecoin exchange are the least volatile. However, all bitcoin series are materially more volatile than the S&P 500. The average volatility across all bitcoin currency exchange pairs is over four times the volatility of the S&P 500 over an equivalent period.

[Please Insert Table 1 About Here]

In Figures 1 and 2, we present the average daily effective spreads, quoted spreads, and price impact through time. Figure 1 includes averages across all bitcoin-currency-exchange pairs, while Figure 2 is limited to USD exchange pairs. This means that while Figure 1 is more comprehensive, it is influenced by new bitcoin-currency-exchange pairs being added over time. Both figures indicate that while daily liquidity is relatively volatile through time, there is no clear time trend of liquidity increasing or decreasing over the period we consider. Some of the instances of illiquidity spiking higher can be attributed to events in the bitcoin market. For instance, in August 2016 the Bitfinex exchange was hacked and bitcoin was stolen. However, there do not appear to be any bitcoin market specific catalysts on other occasions.

[Please Insert Figures 1 and 2 About Here]

Accurate measures of liquidity and transaction costs have been an important aspect of advances in our understanding of other financial markets and we hope that the results in this paper for bitcoin liquidity and transaction costs are of similar assistance to the growing number of researchers who are investigating the bitcoin market. For example, Detzel, Liu, Strauss, Zhou, and Zhu (2018) show that simple moving average technical trading rules are effective in the bitcoin market. Part of their analysis involves estimating breakeven transaction cost levels that would remove any alpha compared to buy-and-hold strategy. Our results indicate that actual transaction costs are lower than their estimates, which suggests that there are economic gains after costs to the strategies they test.

Stock spreads tend to be higher at the beginning and end of the trading day and lower in the middle of the day. (e.g. McInish and Wood, 1992). A similar pattern is evident in futures markets (e.g. Ferguson and Mann, 2001) and there is also evidence of intraday variation in currency spreads (e.g. Bollerslev and Domowitz, 1993). There are a number of possible explanations for these effects, including variation in the level of information asymmetry throughout the trading day (e.g. Foster and Viswanathan, 1992) and differing intraday levels of market maker risk aversion (e.g. Ferguson and Mann, 2001). Bitcoin is similar to foreign exchange in that it is traded continuously. However, unlike in the foreign exchange market, there are no market makers in bitcoin markets. These aspects suggest against intraday variation in bitcoin transaction costs, and the results in Figure 3 indicate that this is the case. There are largely uniform costs over the course of the day for bitcoin in general and, in unreported results, we find that this also holds in different bitcoin currency pairs.

[Please Insert Figure 3 About Here]

4. Results

4.1. Liquidity Commonality

Chordia, Roll, and Subrahmanyam (2000) show that there is a market-wide systematic dimension to stock liquidity. Changes in aggregate liquidity have an important impact on the liquidity of individual stocks. Establishing the existence, or otherwise, of liquidity commonality is an important pursuit as the existence of a common market-wide aspect to liquidity motivates investigation into the factors that influence changes in liquidity across all securities in the market. As such, researchers establish the presence of liquidity commonality in other markets, such as currencies (e.g. Mancini, Ranaldo, and Wrampelmeyer (2013)) and commodities (e.g. Marshall, Nguyen, and Visaltanachoti (2012)). However, it is not clear whether one should expect to see common movements in bitcoin liquidity or not. First, the bitcoin market is more fragmented and segmented than other markets. Second, Koch, Ruenzi, and Starks (2016) show there is a demand-side explanation for commonality in stocks, due to correlated trading in number of stocks by mutual funds. However, while institutional investor interest in bitcoin has grown over time, it seems unlikely that this would be at the same level as mutual fund ownership in stocks, and, as such, there seems less likelihood of demand-side factors resulting in liquidity commonality in bitcoin.

We follow Chordia, Roll, and Subrahmanyam (2000) and regress the liquidity measure for a bitcoin-currency-exchange pair on the daily percentage change in the liquidity measure for the market, as given below in equation 6.

$$DL_{i,t} = \alpha_i + \beta_{1i} DL_{M,t} + \beta_{2i} DL_{M,t-1} + \beta_{3i} DL_{M,t+1} + Controls + \varepsilon_{i,t} \tag{6}$$

where $DL_{i,t}$ is the daily percentage change in liquidity measure L during day t for bitcoin exchange pair i and $DL_{M,t}$ is the change in bitcoin market liquidity L during day t. However, we exclude the bitcoin-currency-exchange pair that is the dependant variable from this market liquidity measure. $DL_{M,t-1}$ and $DL_{M,t+1}$ are the lag and lead changes in bitcoin market liquidity for L respectively. We follow Chordia, Roll, and Subrahmanyam (2000), and include the contemporaneous, lead and lag market returns and the individual bitcoin-currency-exchange pair squared return as control variables. We run equation 6 for effective spread, quoted spread, and price impact and report the results in Table 2.

The results indicate that a one unit movement in market liquidity results in an average contemporaneous movement in liquidity of the bitcoin-currency-exchange pair of 0.90, 0.74, and

0.48 units for effective spread, price impact, and quoted spread respectively. There is also a one-day lead and lag influence which brings the cumulative influence of a one-unit change in market liquidity on individual bitcoin-currency-exchange pair liquidity to 0.97, 0.95, and 0.74 units respectively.

The currency- and exchange-pair results, which are based on effective spreads, indicate that the liquidity of bitcoin priced in Hong Kong Dollars, Singapore Dollars, Japanese Yen, Chinese Yuan, is the most sensitive to changes in market liquidity, while bitcoin priced in the Russian Ruble and Indian Rupee is the least sensitive. Bitcoin priced in Australian Dollars and Great Britian Pounds are the only pairs that show no evidence of commonality. Bitcoin traded on the Bitflyer and Zaif exchanges is the most sensitive to changes in market liquidity, while bitcoin traded on Btce and Gatecoin is the least sensitive.

[Please Insert Table 2 About Here]

4.2. Determinants of Bitcoin Liquidity

We now investigate the influence, if any, that currency liquidity has on bitcoin liquidity. Our currency liquidity series is based on closing bid-ask spreads for G10 spot currency data. We calculate a weighted average series based on the currency weights in the US Dollar index. The Panel A results indicate weekly correlation coefficients of 0.191, 0.136, and 0.186 for effective spread, quoted spread, and price impact respectively, with the effective spread and price impact coefficients being statistically significantly different to zero at the 10% level.

We follow Chordia, Sarkar, and Subrahmanyam (2005) and consider bidirectional causalities using the following vector auto-regression:

$$X_t = Y_{t-1} + X_{t-1} + u_t \tag{7}$$

$$Y_t = X_{t-1} + Y_{t-1} + v_t \tag{8}$$

where X and Y represent the bitcoin and currency liquidity pairs. We adopt one lag for each variables in our core tests. However, we also generate results with the optimal lags calculated based on the corrected AIC number and obtain consistent results. The Panel B results indicate that there is strong evidence that the currency spread Granger causes the bitcoin effective and quoted spread and price impact. However, there is no evidence that the causality also runs in the opposite direction.

[Please Insert Table 3 About Here]

We now turn our attention to addressing the question of the extent to which bitcoin liquidity influenced by factors that have been shown to affect stock liquidity. Brunnermeier and Pedersen (2009) suggest that the ability of traders to obtain funding influences the provision of liquidity. They use the TED spread, which is the difference between the London Interbank Offered Rate (LIBOR) and the risk-free T-Bill rate, as a proxy for funding liquidity. We follow this approach and find mixed evidence regarding the link between the TED spread and bitcoin liquidity. There is a consistent positive relation between the TED spread and overall liquidity when the quoted spread liquidity proxy is used. However, this is not evident in either the effective spread or price impact proxies. Moreover, there is no clear pattern of increases in the TED spread leading to reduced liquidity in the bitcoin-currency pairs or bitcoin-exchange pairs based on the effective spread liquidity proxy. In fact, there is evidence of TED spread increases leading to increased liquidity in some of these. Our results perhaps indicate that the absence of market makers in bitcoin markets contribute to a lesser role for the TED spread in bitcoin liquidity. We also consider the link between movements in the VIX, which is regularly used as a proxy for uncertainty and investor fear (e.g. Nagel, 2012), and bitcoin liquidity. As with the TED spread, we find no consistent link. While there is a positive relation between VIX and liquidity when price impact is the liquidity proxy, this is not the case with the other two proxies.

[Please Insert Table 4 About Here]

4.3. Liquidity and Market Efficiency

We consider whether there is a link between the liquidity of bitcoin and price efficiency within this market. Chordia, Roll, and Subrahmanyam (2008) find that short-horizon return predictability, which they point out is an inverse measure of market efficiency, declines when liquidity is higher. Higher liquidity appears to stimulate arbitrage activity which results in markets becoming more efficient.

We investigate the influence of liquidity on returns using the predictive regression specified in equation 9.

$$Return_t = \alpha_t + \beta_{1t} OIB_{t-1} + \beta_{2t} OIB_{t-1} * ILD_{t-1} + \varepsilon_t \tag{9}$$

where $Return_t$ is return in a five-minute interval, OIB_{t-1} is the order imbalance in Bitcoin units in interval $t-1$, and ILD_{t-1} is a dummy variable that equals 1 if the daily effective spread is at least one standard deviation above the detrended expected effective spread for the trading day, otherwise zero.

We run equation 9 separately for each of the 38 Bitcoin – exchange pairs and report the average coefficients, *t*-statistics, and Adjusted R^2 in Table 5. The results indicate there is strong evidence that OIB have a stronger predictive impact on days when the market is relatively more illiquid. The average *t*-statistic for the interaction variable across the 35 pairs is 7.14 and 25 of the 27 exchange or currency combinations have an average t-statistic that is statistically significant at the 10% level or greater.

Chordia, Roll, and Subramanyam (2005) show stocks have efficient pricing over intervals between 5 - 60 minutes. However, as shown in Appendix 2, over 40% of bitcoin pair returns are predictable from lag order imbalance at 60-minute horizons, which indicates that bitcoin prices are much less efficient than stock prices.

[Please Insert Table 5 About Here]

4.4. Liquidity and Crash Risk

Crash risk has attracted the attention of researchers in recent times due to sharp declines in the prices of a range of prominent financial assets. Papers such as Callen and Fang (2015) present evidence of crash risk in stock returns, while Chernov, Graveline, and Zivadadze (2018) document crash risk in currency returns. There is also evidence of a link between liquidity and extreme volatility or price crashes. For instance, Dow and Han (2018) suggest that when informed market participants are liquidity constrained prices become less informative which leads to a decrease in valuations by uninformed investors who become reluctant to provide capital to support the price. This can then lead to fire sales and sharp declines in price.[9] We consider whether there is a link between bitcoin crash risk and bitcoin liquidity and liquidity risk as follows.

$$CRASH_t = \alpha_t + \beta_{1t} ILLIQ_t + \beta_{2t} ILLIQ\_RISK_t + \varepsilon_t \tag{10}$$

where $CRASH_t$ is a dummy that equals one if the bitcoin return on day t is less than 2 standard deviations below its time series return average, and $ILLIQ_t$ and $ILLIQ\_RISK_t$ are the liquidity measure and standard deviation of the liquidity measure on day t respectively.

Crashes occur much more frequently than in stocks, with crashes in bitcoin over 30% more common than crashes in the U.S. equity market over the same period. The Table 6 results indicate that an increase in illiquidity corresponds with an increase in crash risk across all pairs when either effective spread or price impact are the liquidity proxies. This is also evident in nine of the currency pairs and nine of the exchange pairs. Illiquidity risk also plays an important role in crash risk. An increase in illiquidity risk coincides with an increase in crash risk in across all currency – exchange pairs in all three liquidity proxies. This relation is also evident in 11 currency pairs and 12 exchange pairs. Overall, we conclude that illiquidity contributes to crash risk.

[9] Another paper suggests a positive relation between stock liquidity and crash risk. However, this explanation appears to be specific to stock markets. Chang, Chen, and Zolotoy (2017) suggest that liquidity leads to managers withholding bad news in the fear this will lead to transient investor selling. Then when the bad news is ultimately released prices crash.

[Please Insert Table 6 About Here]

5. Conclusions

Bitcoin is growing in popularity as a financial asset and means of transacting. However, little is known about its liquidity. Using a database of intraday bitcoin data that spans 14 exchanges and includes prices against 13 currencies, we document considerable variation across the different bitcoin pairs, with the average effective spread ranging from 0.04% for bitcoin priced in Chinese Yuan to 1.28% for bitcoin in Canadian Dollars. Unlike most other financial markets, there is no evidence of intraday variation in bitcoin transaction costs. The continuous trading leads to largely uniform costs over the course of the day.

There is strong evidence of a systematic component to bitcoin liquidity despite the fragmented nature of the market and changes in bitcoin liquidity are Granger caused by changes in the liquidity of currencies. However, changes in bitcoin liquidity do not influence currency liquidity. Moreover, bitcoin liquidity is not strongly influenced by factors that have been shown to affect stock liquidity, such as changes in the TED spread and VIX.

We also show that liquidity plays an important role in price formation in the bitcoin market. Price discovery is generally slower in bitcoin than what has been documented in stock markets and liquidity plays a role here. Inefficient pricing last for longer when the bitcoin market is more illiquid. Liquidity also contributes to bitcoin crash risk. Increases in both illiquidity and illiquidity risk are associated with higher incidences of crash risk.

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Table 1
Liquidity Measure Means

		Start Date	*QSP*	*ESP*	*PI*	*OIB*	*DEPTH*	*No. Trades*	*Return*	*Std. Dev.*
BTCAUD	Quoine	20161001	0.149	0.322	0.407	-0.044	5.673	374	0.394	4.149
BTCCAD	Kraken	20161001	1.284	1.263	0.378	-0.012	2.979	132	0.312	3.632
BTCCNY	Btcc	20151001	0.032	0.140	0.067	-0.008	2.339	136361	0.281	3.431
BTCCNY	Huobi	20151110	0.005	0.125	0.079	0.296	6.437	966990	0.252	3.402
BTCCNY	Okcoin	20151001	0.011	0.130	0.073	0.013	2.206	1700597	0.322	3.084
BTCCNY	Quoine	20161101	0.093	0.265	0.400	-0.029	4.952	233	0.280	4.358
BTCEUR	Bitstamp	20160425	0.378	0.475	0.154	0.078	8.000	909	0.250	3.034
BTCEUR	Btce	20151001	0.628	0.663	0.198	0.000	2.471	577	0.281	2.938
BTCEUR	Coinbase	20151101	0.114	0.287	0.109	0.211	2.391	3302	0.230	3.184
BTCEUR	Gatecoin	20160218	0.208	0.215	0.135	-0.169	4.173	1908	0.049	1.459
BTCEUR	Kraken	20151101	0.116	0.222	0.12	0.059	10.321	8012	0.231	3.139
BTCEUR	Quoine	20161001	0.176	0.301	0.267	0.043	6.589	514	0.350	3.593
BTCGBP	Coinbase	20161001	0.398	0.497	0.124	0.489	1.627	1319	0.319	3.286
BTCGBP	Kraken	20161001	1.950	1.706	0.581	-0.022	2.412	101	0.325	3.503
BTCHKD	Quoine	20161101	0.097	0.272	0.324	-0.033	5.287	200	0.312	4.155
BTCIDR	Quoine	20161001	0.105	0.214	0.210	0.018	4.49	714	0.311	3.437
BTCINR	Quoine	20161101	0.443	0.427	0.340	-0.286	5.22	247	0.237	4.037
BTCJPY	Bitflyer	20160530	0.039	0.124	0.070	-0.050	6.706	24514	0.226	3.505
BTCJPY	Btcbox	20160530	0.265	0.290	0.058	-0.011	5.236	4593	0.220	3.532
BTCJPY	Kraken	20160613	1.449	1.190	0.294	0.041	10.855	271	0.157	3.548
BTCJPY	Quoine	20160530	0.069	0.247	0.092	-0.039	8.488	8522	0.230	3.285
BTCJPY	Zaif	20160530	0.018	0.092	0.063	0.020	1.579	89308	0.226	3.494
BTCPHP	Quoine	20161101	0.143	0.223	0.402	0.020	4.938	307	0.318	4.103
BTCRUB	Btce	20161001	0.417	0.524	0.202	0.217	2.414	1601	0.260	2.980
BTCSGD	Quoine	20161001	0.112	0.227	0.279	0.092	4.947	907	0.319	3.387
BTCUSD	Bitfinex	20151001	0.039	0.273	0.168	0.002	16.985	9456	0.298	3.208
BTCUSD	Bitstamp	20151001	0.132	0.302	0.136	0.062	14.096	5071	0.275	3.052
BTCUSD	Btce	20151001	0.121	0.277	0.116	0.077	9.001	14704	0.282	3.010
BTCUSD	Coinbase	20151001	0.021	0.172	0.098	0.073	5.72	17234	0.280	3.273
BTCUSD	Gatecoin	20160218	0.194	0.212	0.129	-0.191	4.983	1366	0.093	1.367
BTCUSD	Gemini	20151101	0.112	0.234	0.131	0.213	40.585	1022	0.225	3.214
BTCUSD	Huobi	20151110	0.740	0.697	0.026	0.186	3.545	17745	0.234	3.499
BTCUSD	Kraken	20151101	0.332	0.373	0.154	0.031	10.961	1571	0.231	3.192
BTCUSD	Okcoin	20151001	0.035	0.187	0.107	-0.171	5.89	11922	0.273	3.214
BTCUSD	Quoine	20161001	0.071	0.190	0.211	0.035	6.006	2333	0.301	3.411

Table 1 contains means for various liquidity measures. Start date refers to first date a particular currency exchange pair appears on our sample rather than the first day of trading in that pair. Intraday measures are calculated and daily averages are computed as described in Section 3.2. Return and Standard Deviation relate to daily returns.

Table 2
Liquidity Commonality

	Concurrent	*Lag*	*Lead*	*Sum*	R^2
Panel A: All Pairs					
All - ESP	**0.899**	0.017	0.058	**0.974**	0.128
All - QSP	**0.478**	**0.090**	**0.175**	**0.743**	0.071
All - PI	**0.740**	0.029	0.183	**0.952**	0.112
Panel B: Currency Pairs – Effective Spread					
BTCAUD	0.409	-0.361	-0.294	-0.250	0.008
BTCCAD	**0.659**	-0.084	0.299	**0.870**	0.109
BTCCNY	**1.243**	-0.075	0.046	**1.213**	0.289
BTCEUR	**0.734**	-0.045	0.087	**0.777**	0.159
BTCGBP	0.264	0.080	0.197	0.545	0.061
BTCHKD	**1.668**	0.036	0.714	**2.420**	0.108
BTCIDR	**0.937**	0.159	0.044	**1.140**	0.220
BTCINR	**0.742**	-0.345	0.032	**0.430**	0.030
BTCJPY	**1.016**	0.144	0.091	**1.248**	0.249
BTCPHP	**1.115**	0.009	-0.499	**0.630**	0.081
BTCRUB	**0.223**	0.082	-0.060	0.240	0.059
BTCSGD	**1.141**	0.397	-0.080	**1.460**	0.022
BTCUSD	**0.958**	0.040	0.030	**1.029**	0.205
Panel C: Exchange Pairs – Effective Spread					
Bitfinex	**1.169**	**-0.162**	**0.270**	**1.280**	0.261
Bitflyer	**1.258**	**0.151**	**0.255**	**1.660**	0.397
Bitstamp	**0.754**	0.017	**0.134**	**0.905**	0.240
Btcbox	**0.623**	**0.227**	-0.029	**0.820**	0.166
Btcc	**1.029**	0.067	0.004	**1.100**	0.373
Btce	**0.342**	0.036	0.001	**0.377**	0.102
Coinbase	**0.676**	0.007	0.175	**0.857**	0.200
Gatecoin	**0.454**	0.150	-0.041	**0.560**	0.134
Gemini	**1.567**	-0.059	-0.391	**1.120**	0.077
Huobi	**0.949**	**0.169**	0.056	**1.170**	0.273
Kraken	**0.637**	0.063	0.088	**0.788**	0.112
Okcoin	**1.115**	0.116	0.070	**1.300**	0.316
Quoine	**1.189**	-0.117	0.040	**1.113**	0.117
Zaif	**1.142**	**0.206**	0.104	**1.450**	0.339

Liquidity commonality is estimated using the following regression $DL_{i,t} = \alpha_i + \beta_{1i} DL_{M,t} + \beta_{2i} DL_{M,t-1} + \beta_{3i} DL_{M,t+1} + Controls + \varepsilon_{i,t}$, where DL is the liquidity of the bitcoin-currency-exchange pair and DM is the liquidity of the market respectively. The controls include the contemporaneous, lead and lag market returns and the individual bitcoin-currency-exchange pair squared return. Coefficients that are statistically significant at the 10% level or more are in bold.

Table 3
Link to Currency Liquidity

	Panel A: Correlations		
		Bitcoin	
	ESP	*QSP*	*PI*
Currency Index	**0.191**	0.136	**0.186**

		Panel B: Granger Causality	
Variable 1	*Variable 2*	*Variable 1 GC Variable 2*	*Variable 2 GC Variable 1*
Currency Spread	Bitcoin ESP	**4.850**	1.690
Currency Spread	Bitcoin PI	**2.710**	1.910
Currency Spread	Bitcoin QSP	**7.740**	1.220

	Panel C: VAR	
Dependent Variable	*Estimate*	*t-statistic*
Bitcoin ESP	**11.620**	2.193
Bitcoin PI	**12.817**	2.780
Bitcoin QSP	**4.135**	1.637

Table 3 contains results relating to the link between weekly bitcoin and currency liquidity, where currency liquidity is calculated using closing spot market bid-ask spreads. Correlation coefficients are in Panel A, results for the the following vector auto-regression: $X_t = Y_{t-1} + X_{t-1} + u_t$ and $Y_t = X_{t-1} + Y_{t-1} + v_t$ are in Panel B, where X and Y represent the Variable 1 and 2 pairs, and VAR results are in Panel C. Coefficients that are statistically significant at the 10% level or more are in bold.

Table 4
Liquidity Determinants

	(1)	(2)	(3)		(4)		
	TED$_{t-1}$	*VIX$_{t-1}$*	*TED$_{t-1}$*	*VIX$_{t-1}$*	*TED$_{t-1}$*	*VIX$_{t-1}$*	*LIQ$_{t-1}$*
			Panel A: All Pairs				
All - ESP	0.06	**-0.01**	-0.06	**-0.01**	0.00	0.00	**0.82**
All - QSP	**0.39**	**-0.01**	**0.28**	**-0.01**	**0.04**	0.00	**0.93**
All - PI	**0.07**	**0.00**	0.00	**0.00**	-0.01	0.00	**0.79**
			Panel B: Currency Pairs – Effective Spread				
BTCAUD	**0.70**	0.03	**0.63**	**0.03**	0.19	0.02	**0.54**
BTCCAD	**-2.00**	**-0.04**	-1.61	-0.03	-0.37	-0.01	**0.57**
BTCCNY	**-0.11**	**0.00**	**-0.26**	**-0.01**	**-0.06**	**0.00**	**0.85**
BTCEUR	**-0.75**	**0.01**	**-0.71**	0.00	**-0.24**	0.00	**0.72**
BTCGBP	**-3.42**	**-0.04**	**-3.16**	-0.02	-0.90	-0.01	**0.59**
BTCHKD	-0.52	-0.04	-0.63	-0.04	-0.27	**-0.05**	**0.21**
BTCIDR	**-0.59**	**-0.01**	**-0.48**	-0.01	-0.15	0.00	**0.68**
BTCINR	-0.92	**0.16**	**-1.11**	**0.16**	0.05	**0.04**	**0.72**
BTCJPY	-0.07	-0.01	-0.09	**-0.01**	0.01	0.00	**0.69**
BTCPHP	-0.08	0.04	-0.04	0.04	0.02	0.01	**0.49**
BTCRUB	**-0.59**	0.00	**-0.59**	0.00	**-0.37**	0.00	**0.50**
BTCSGD	-0.25	0.00	-0.24	0.00	-0.17	0.00	**0.50**
BTCUSD	**-0.19**	0.00	**-0.22**	0.00	-0.08	0.00	**0.74**
			Panel C: Exchange Pairs – Effective Spread				
Bitfinex	**-0.70**	**0.01**	**-0.68**	0.00	**-0.37**	0.00	**0.48**
Bitflyer	**-0.71**	**0.01**	**-0.70**	**0.00**	**-0.19**	0.00	**0.75**
Bitstamp	-0.07	0.00	-0.08	0.00	-0.04	0.00	**0.63**
Btcbox	-0.54	-0.01	**-0.57**	**-0.01**	**-0.27**	0.00	**0.61**
Btcc	-0.10	**0.00**	**-0.22**	**-0.01**	**-0.06**	**0.00**	**0.84**
Btce	-0.62	**0.01**	**-0.58**	0.00	**-0.35**	0.00	**0.45**
Coinbase	-0.19	0.00	**-0.24**	**0.00**	-0.07	0.00	**0.72**
Gatecoin	0.05	0.00	**0.37**	**0.01**	0.12	0.00	**0.73**
Gemini	**-0.43**	**0.01**	**-0.44**	0.00	**-0.28**	0.00	**0.37**
Huobi	**1.12**	**-0.03**	**0.76**	**-0.02**	0.08	0.00	**0.85**
Kraken	**1.34**	**-0.03**	**0.81**	**-0.02**	**0.25**	0.00	**0.83**
Okcoin	-0.05	**0.00**	**-0.13**	**0.00**	**-0.07**	**0.00**	**0.64**
Quoine	**-0.64**	**0.01**	**-0.62**	0.01	-0.15	0.00	**0.69**
Zaif	**-0.60**	**0.01**	**-0.59**	**0.00**	**-0.12**	0.00	**0.83**

Table 4 contains results for liquidity proxies are regressed on VIX, the TED spread, and lag liquidity Coefficients that are statistically significant at the 10% level or more are in bold.

Table 5
Liquidity and Market Efficiency

	No.	*OIB*	*t-stat*	*OIB*ILD*	*t-stat*	R^2
		Panel A: All Pairs				
All	35	**0.0007**	20.09	**0.0006**	8.00	3.64%
		Panel B: Currency Pairs				
BTCAUD	1	**0.0015**	21.03	**0.0017**	7.51	9.55%
BTCCAD	1	**0.0015**	15.49	**0.0010**	4.26	5.69%
BTCCNY	4	**0.0006**	13.39	**0.0004**	5.02	3.28%
BTCEUR	6	**0.0005**	27.33	**0.0006**	11.57	3.51%
BTCGBP	2	**0.0013**	19.32	**0.0011**	5.10	4.42%
BTCHKD	1	**0.0019**	16.68	**0.0012**	3.96	9.87%
BTCIDR	1	**0.0010**	28.87	**0.0009**	10.64	9.02%
BTCINR	1	**0.0019**	21.08	**0.0007**	2.19	9.74%
BTCJPY	5	**0.0004**	12.04	**0.0004**	5.66	1.03%
BTCPHP	1	**0.0021**	22.02	**0.0012**	4.02	10.67%
BTCRUB	1	**0.0004**	26.54	**0.0005**	13.22	3.25%
BTCSGD	1	**0.0009**	23.67	**0.0010**	11.49	7.25%
BTCUSD	10	**0.0003**	21.16	**0.0003**	9.46	1.44%
		Panel C: Exchange Pairs				
Bitfinex	1	**0.0002**	24.14	**0.0002**	7.27	0.64%
Bitflyer	1	**0.0002**	10.85	**0.0002**	5.22	0.27%
Bitstamp	2	**0.0003**	23.37	**0.0003**	11.58	1.24%
Btcbox	1	**0.0001**	6.40	**-0.0001**	-2.39	0.05%
Btcc	1	**0.0001**	11.95	**0.0002**	8.30	0.25%
Btce	3	**0.0004**	30.44	**0.0004**	11.98	2.81%
Coinbase	3	**0.0004**	22.30	**0.0002**	7.41	0.93%
Gatecoin	2	**0.0004**	15.55	**0.0002**	3.13	2.14%
Gemini	1	**0.0004**	31.16	**0.0005**	15.60	2.33%
Huobi	2	**0.0001**	6.460	**-0.0001**	-2.95	0.05%
Kraken	5	**0.0011**	21.52	**0.0011**	12.42	4.10%
Okcoin	2	**0.0002**	16.72	**0.0002**	9.28	0.42%
Quoine	10	**0.0014**	21.67	**0.0011**	7.58	8.42%
Zaif	1	**0.0002**	12.12	**0.0003**	7.75	0.42%

Table 5 contains results for the following regression: $Return_t = \alpha_t + \beta_{1t}OIB_{t-1} + \beta_{2t}OIB_{t-1}*ILD_{t-1} + \varepsilon$, where $Return_t$ is return in a five-minute interval, OIB_{t-1} is the order imbalance in Bitcoin units in interval *t-1*, and ILD_{t-1} is a dummy variable that equals 1 if the daily effective spread is at least one standard deviation above the detrended expected effective spread for the trading day, otherwise zero. Coefficients that are statistically significant at the 10% level or more are in bold.

Table 6
Liquidity and Crash Risk

	Intercept		*ILLIQ*		*ILLIQ_RISK*		
	Coeff.	*Std. Err.*	*Coeff.*	*Std. Err.*	*Coeff.*	*Std. Err.*	R^2
			Panel A: All Pairs				
All - ESP	**-3.432**	0.060	**0.750**	0.071	**0.001**	0.000	0.031
All - QSP	**-3.264**	0.055	0.045	0.107	**0.106**	0.023	0.014
All - PI	**-3.510**	0.062	**2.156**	0.174	**0.000**	0.000	0.041
			Panel B: Currency Pairs				
BTCAUD	**-4.240**	1.034	-2.667	3.348	**0.103**	0.047	0.131
BTCCAD	**-5.469**	1.025	**0.846**	0.443	**0.070**	0.032	0.185
BTCCNY	**-6.385**	1.034	**13.323**	3.680	**0.014**	0.065	0.235
BTCEUR	**-8.065**	1.493	**1.997**	3.834	**0.654**	0.256	0.290
BTCGBP	**-6.196**	1.257	-1.337	1.513	**0.800**	0.226	0.271
BTCHKD	**-4.553**	1.000	**4.811**	1.945	0.000	0.014	0.191
BTCIDR	**-5.937**	1.138	**4.880**	3.023	**0.001**	0.001	0.272
BTCINR	**-4.102**	0.837	0.700	0.698	**0.007**	0.004	0.096
BTCJPY	**-6.513**	1.122	**5.601**	3.241	**0.064**	0.031	0.276
BTCPHP	**-6.365**	1.561	**5.869**	2.490	**0.018**	0.009	0.287
BTCRUB	**-10.385**	2.574	**17.124**	4.622	**-0.090**	0.052	0.476
BTCSGD	**-5.186**	1.002	2.628	3.383	**0.091**	0.062	0.167
BTCUSD	**-8.089**	1.336	**3.238**	3.643	**0.541**	0.190	0.306
			Panel C: Exchange Pairs				
Bitfinex	**-7.424**	0.978	-3.382	2.984	**0.371**	0.089	0.269
Bitflyer	**-6.340**	1.018	**10.517**	4.141	0.022	0.019	0.289
Bitstamp	**-10.896**	1.699	2.067	2.228	**0.600**	0.139	0.442
Btcbox	**-5.871**	0.847	3.410	3.045	0.012	0.009	0.215
Btcc	**-6.382**	0.788	**12.204**	3.174	**0.054**	0.027	0.212
Btce	**-8.870**	1.583	**9.095**	2.889	**0.311**	0.126	0.313
Coinbase	**-7.926**	1.174	**1.879**	2.507	**1.059**	0.284	0.369
Gatecoin	**-8.337**	3.153	-3.871	13.319	**1.317**	0.775	0.208
Gemini	**-4.422**	0.449	**3.644**	0.978	0.018	0.030	0.136
Huobi	**-7.753**	1.268	**10.213**	2.529	**0.157**	0.071	0.261
Kraken	**-6.580**	1.031	**1.744**	1.139	**0.284**	0.073	0.256
Okcoin	**-8.324**	1.177	**14.904**	3.958	**0.346**	0.178	0.370
Quoine	**-5.347**	1.094	**3.590**	2.684	**0.039**	0.031	0.213
Zaif	**-8.206**	1.709	6.619	6.222	**0.266**	0.119	0.335

Table 6 contains results for the following regression: $CRASH_t = \alpha_t + \beta_{1t} ILLIQ_t + \beta_{2t} ILLIQ\_RISK_t + \varepsilon_t$, where $CRASH_t$ is a dummy that equals 0 if the bitcoin return on day *t* is less than 2 standard deviations below its time series return average, and $ILLIQ_t$ and $ILLIQ\_RISK_t$ are the liquidity measure and standard deviation of the liquidity measure on day *t* respectively. Coefficients that are statistically significant at the 10% level or more are in bold.

Figure 1
Liquidity Measures Through Time For All Bitcoin Pairs

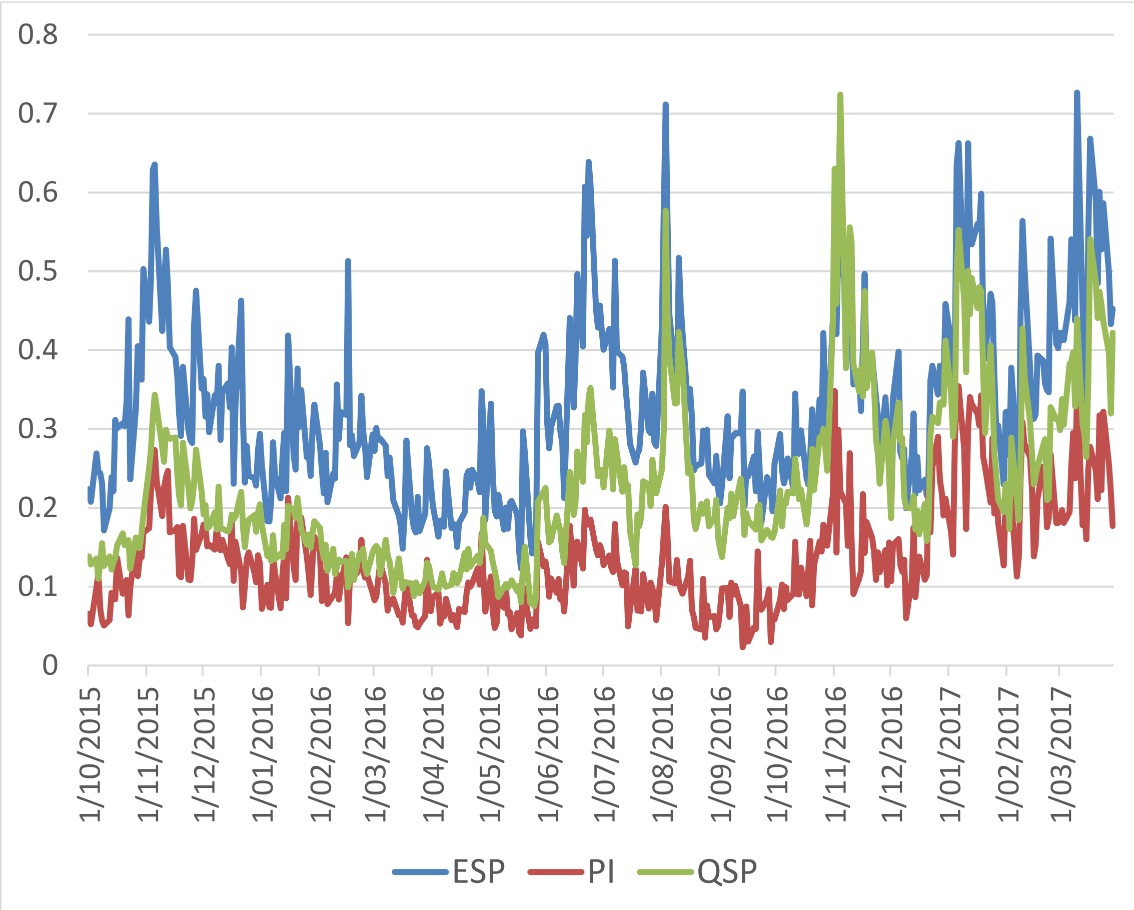

Figure 1 contains the cross-section average bitcoin transaction costs through time.

Figure 2
Liquidity Measures Through Time For USD Bitcoin Pairs

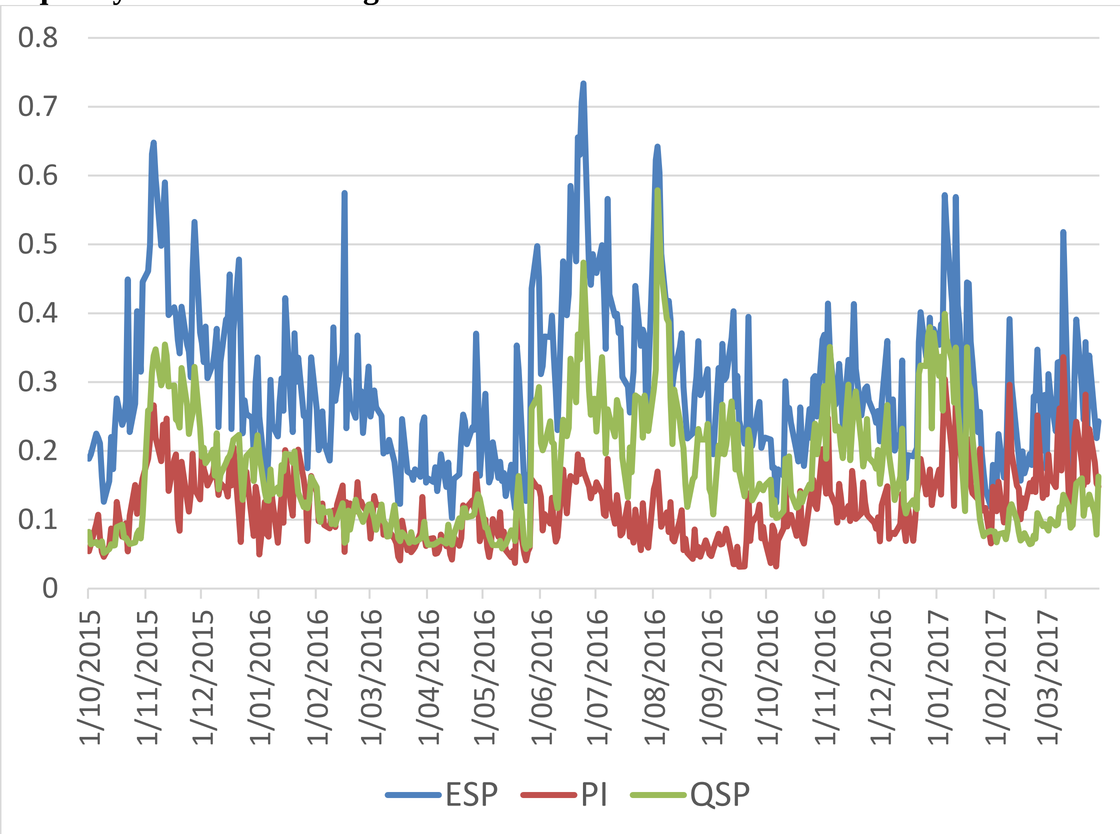

Figure 2 contains the cross-section average transaction costs for bitcoin against the USD through time.

Figure 3
Intraday Liquidity Measures

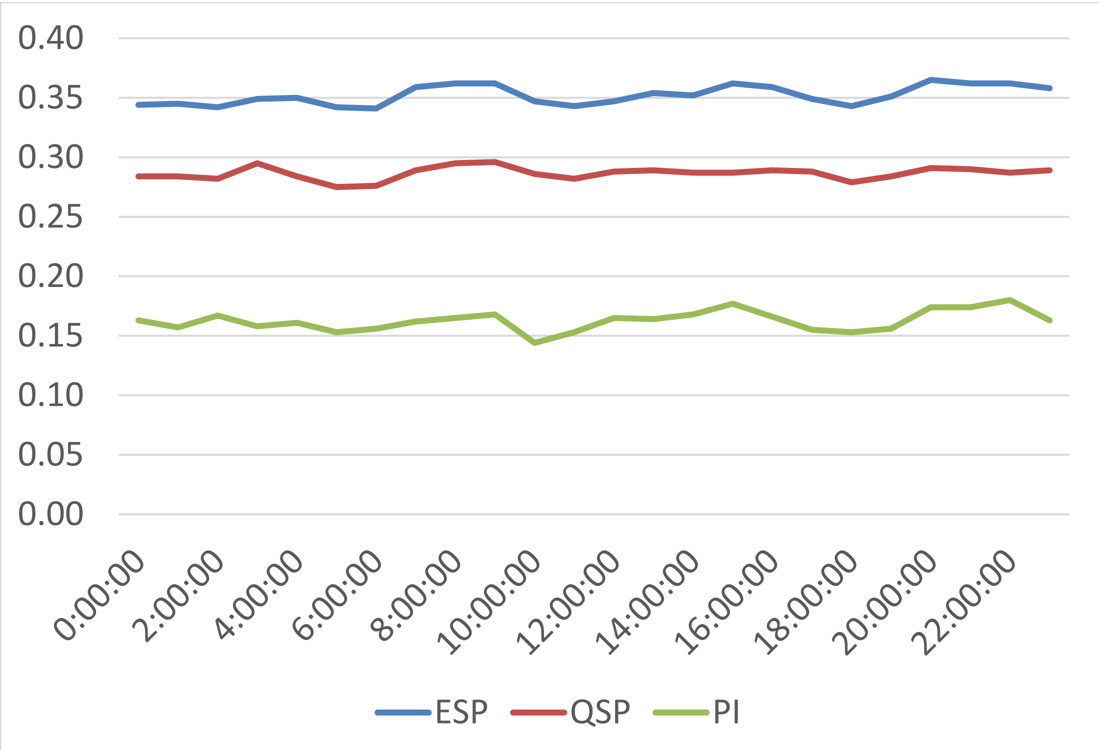

Figure 3 contains the cross-section average bitcoin transaction costs throughout the day.

Appendix 1
Liquidity Measure Medians

		Start Date	QSP	ESP	PI	OIB	DEPTH	No. Trades
BTCAUD	Quoine	20161001	0.061	0.304	0.409	-0.008	4.659	160
BTCCAD	Kraken	20161001	1.069	1.068	0.361	0.042	2.853	92
BTCCNY	Btcc	20151001	0.018	0.119	0.060	-0.007	2.041	109085
BTCCNY	Huobi	20151110	0.005	0.112	0.071	0.019	6.294	877245
BTCCNY	Okcoin	20151001	0.003	0.116	0.065	-0.008	1.858	1770584
BTCCNY	Quoine	20161101	0.066	0.229	0.373	-0.006	4.148	64
BTCEUR	Bitstamp	20160425	0.374	0.466	0.143	0.103	7.787	669
BTCEUR	Btce	20151001	0.605	0.645	0.179	-0.003	2.222	387
BTCEUR	Coinbase	20151101	0.102	0.265	0.100	0.223	2.263	2314
BTCEUR	Gatecoin	20160218	0.164	0.209	0.129	-0.202	3.650	1972
BTCEUR	Kraken	20151101	0.109	0.197	0.106	0.061	10.053	6059
BTCEUR	Quoine	20161001	0.066	0.250	0.210	-0.004	4.358	172
BTCGBP	Coinbase	20161001	0.380	0.466	0.116	0.501	1.421	1134
BTCGBP	Kraken	20161001	1.600	1.521	0.555	-0.052	2.371	77
BTCHKD	Quoine	20161101	0.070	0.218	0.292	0.001	4.528	54
BTCIDR	Quoine	20161001	0.059	0.191	0.202	0.009	3.724	512
BTCINR	Quoine	20161101	0.065	0.264	0.293	-0.189	4.429	56
BTCJPY	Bitflyer	20160530	0.034	0.102	0.061	-0.053	6.548	19174
BTCJPY	Btcbox	20160530	0.175	0.255	0.048	-0.023	5.188	4754
BTCJPY	Kraken	20160613	1.151	0.994	0.280	0.020	9.901	59
BTCJPY	Quoine	20160530	0.051	0.219	0.072	-0.018	8.053	5938
BTCJPY	Zaif	20160530	0.012	0.067	0.054	0.015	1.457	74543
BTCPHP	Quoine	20161101	0.066	0.210	0.380	-0.001	4.030	121
BTCRUB	Btce	20161001	0.403	0.509	0.194	0.235	2.198	1391
BTCSGD	Quoine	20161001	0.060	0.209	0.272	0.012	3.545	334
BTCUSD	Bitfinex	20151001	0.035	0.244	0.166	0.008	16.673	6846
BTCUSD	Bitstamp	20151001	0.129	0.267	0.127	0.065	13.317	4389
BTCUSD	Btce	20151001	0.129	0.269	0.112	0.116	8.593	12224
BTCUSD	Coinbase	20151001	0.017	0.146	0.088	0.073	5.464	14579
BTCUSD	Gatecoin	20160218	0.143	0.211	0.117	-0.235	4.172	1215
BTCUSD	Gemini	20151101	0.033	0.170	0.112	0.217	31.063	627
BTCUSD	Huobi	20151110	0.600	0.602	0.021	0.086	3.375	18710
BTCUSD	Kraken	20151101	0.257	0.317	0.135	0.027	9.394	1064
BTCUSD	Okcoin	20151001	0.030	0.171	0.099	-0.138	5.005	10374
BTCUSD	Quoine	20161001	0.054	0.176	0.214	0.038	4.648	1639

Appendix 1 contains means for various liquidity measures. Intraday measures are calculated and daily averages are computed as described in Section 3.2.

Appendix 2
Order Imbalance and Returns

	1	5	10	15	30	60
Panel A: All Pairs						
All	100%	97%	80%	63%	51%	43%
Panel B: Currency Pairs						
BTCAUD	100%	100%	100%	100%	100%	100%
BTCCAD	100%	100%	100%	100%	100%	100%
BTCCNY	100%	100%	50%	25%	25%	25%
BTCEUR	100%	100%	100%	83%	50%	33%
BTCGBP	100%	100%	100%	100%	50%	50%
BTCHKD	100%	100%	100%	100%	100%	100%
BTCIDR	100%	100%	100%	100%	100%	100%
BTCINR	100%	100%	100%	100%	100%	100%
BTCJPY	100%	100%	40%	40%	40%	20%
BTCPHP	100%	100%	100%	100%	100%	100%
BTCRUB	100%	100%	100%	100%	100%	0%
BTCSGD	100%	100%	100%	100%	100%	100%
BTCUSD	100%	90%	80%	40%	30%	30%
Panel C: Exchange Pairs						
Bitfinex	100%	100%	100%	0%	0%	0%
Bitflyer	100%	100%	0%	0%	0%	0%
Bitstamp	100%	100%	100%	50%	0%	0%
Btcbox	100%	100%	0%	0%	0%	0%
Btcc	100%	100%	100%	0%	0%	0%
Btce	100%	100%	67%	67%	67%	33%
Coinbase	100%	100%	100%	67%	33%	0%
Gatecoin	100%	100%	100%	50%	0%	0%
Gemini	100%	100%	100%	100%	100%	100%
Huobi	100%	50%	0%	0%	0%	0%
Kraken	100%	100%	100%	100%	80%	80%
Okcoin	100%	100%	50%	0%	0%	0%
Quoine	100%	100%	100%	100%	100%	90%
Zaif	100%	100%	0%	0%	0%	0%

Appendix 2 contains results for the following regression: $Return_t = \alpha_t + \beta_{1t} OIB_{t-1} + \varepsilon_t$ where $Return_t$ is return in a five-minute interval, OIB_{t-1} is the order imbalance in bitcoin units in interval $t-1$, and ILD_{t-1} is a dummy variable that equals 1 if the daily effective spread is at least one standard deviation above the detrended expected effective spread for the trading day, otherwise zero. Coefficients that are statistically significant at the 10% level or more are in bold.