Fragmentation and Price Discovery in Bitcoin Markets

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Abstract

This study uses existing research on competitive fragmentation and price discovery to test its applicability to cryptocurrency markets. Bitcoin (BTC) transaction and order book data is collected across six exchanges for both United States Dollar (USD - $) and Euro (€) order books (2017-2019). A panel-regression model on a multivariate version of Hasbrouck's (1995) information share is employed. Results confirm that market share has a positive relationship with the informativeness of exchange prices (Madhavan, 1995). This is attributed to informed investors migrating to competing exchanges to better conceal and profit on their superior information. This, in turn, increases events of information asymmetry as exchange prices become more informative and dispersed across an increasing number of exchanges.

JEL Classification: G12, G15

Keywords: cryptocurrency, fragmentation, price discovery, Bitcoin

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1.0 Introduction

Financial markets exist to facilitate the exchange of investable assets. The formulation of explicit rules that govern and control this process are of crucial importance to efficiently pricing traded assets. If prices are to be efficient, the price formation process must incorporate new information as quickly and accurately as possible. This study investigates the applicability of established microstructure theory in equity markets to cryptocurrency markets. Existing research on this topic is limited due to how new cryptocurrency markets are. However, both markets operate pre-trade transparent (lit) order books and facilitate transactions in a similar way. Much like events of competitive fragmentation in equity markets, fragmentation in cryptocurrency is also partly motivated by the desire to reduce levels of information asymmetry. Therefore, using established research in equity markets, this study investigates the following: How does competitive market fragmentation affect the cryptocurrency market's ability to efficiently price assets and convey price disseminating information to the public?

The degree to which information is freely available influences price formation. Differences in the distribution of information, that is, when participants are denied equal access to information, result in information asymmetry. Such flaws tend to make prices inefficient. Thus, price discovery is sensitive to structure of markets. Any regulations that affect any of these rules would, in turn, affect the price discovery process.

In equity markets, new exchanges attract informed trades from the dominant exchange making collecting all necessary price adjusting information more difficult. The result is a deterioration in the price discovery process. Bornholdt and Sneppen (2014) argues that cryptocurrencies are prone to similar effects of competition as new exchanges and currencies are introduced into the market. However, with its large levels of volatility, a low number of daily transactions, and relatively small trading volume, Bitcoin and other competing cryptocurrencies do not yet share the characteristics of sovereign currencies. As a result, their exchanges can be looked upon as having more similarity to equity-based exchanges offering access to pre-trade transparent liquidity than those that trade currencies. Therefore, much of the exchange-based discussion for cryptocurrencies draws on our knowledge of equity markets. The cryptocurrency market resembles current equity markets in that is consists of a series of exchanges. This study investigates the effects of increased competitive market fragmentation in the cryptocurrency market and tests whether equity market theories surrounding price discovery, such as those based in rational expectations theory and the efficient market hypothesis, are applicable.

As it stands, most financial market participants have not embraced cryptocurrencies. Due to their limited market share compared to other financial assets, cryptocurrencies currently have a negligible influence on the global economy. However, infrastructural developments demonstrate that it is feasible to use distributed ledgers in order to facilitate peer-to-peer transactions, thus negating the need for an established intermediary. Also, the incorporation distributed ledgers into general investment practices open the door for the development of new investment techniques and strategies, including those that require simultaneous access to multiple sovereign marketplaces.

Investors are beginning to see the potential benefits of cryptocurrencies and are beginning to invest heavily in start-ups looking to further the technology. As of November 2016, $1.4 billion have been invested in digital currency start-ups[1]. R3CEV, for example, is a consortium of forty-two of the largest banks whose goal is to develop blockchain technology further. Another example is the Open Ledger Project, which involves some of the largest names in the computing industry including IBM, Intel, Cisco and the Linux Foundation. The goal of the Open Ledger Project is to foster the deployment and adoption of the distributed ledger technology by focusing on innovation and security. As a result, cryptocurrency markets have experienced numerous fragmenting events. The focal point of this study, competitive market fragmentation, can have a significant impact on the supply of cryptocurrencies in the market, as well as the stability of the market itself. The empirical study presented in this paper examines the impact of competitive market fragmentation on the dissemination of key price adjusting information, specifically, the introduction of new exchanges for facilitating transactions.

The results suggest that increased market fragmentation either leads to an increased concentration of informed investors on the dominant cryptocurrency exchange or the introduction of informed investors on smaller satellite cryptocurrency exchanges. The implication is that investors can no longer look towards a single exchange to gather all relevant price adjusting information. The process of price discovery, that is, the process of forming an accurate opinion of prices levels, becomes more difficult. The more the market becomes fragmented the more investors protect themselves against the risk of information asymmetry and adverse selection by widening bid-ask

[1]$1.4 Billion Invested in Blockchain, says PwC Executive - Bitcoin: https://news.bitcoin.com/1-1-billion-invested-blockchain-pwc/

spreads. This leads to a reduction of market quality factors such as bid-ask spreads. The widening of bid-ask spreads is seen as a negative outcome to cryptocurrency market fragmentation as it increased the cost of a round-trip transaction for investors.

The lower Frag coefficients for less liquid exchanges also explains supports the notion that these exchanges find it more difficult to locate a counterparty for the informed traders when compared to more liquid exchanges (Mendelson, 1987). So, when markets fragment, and smaller exchanges entice some investors to transact in their order books, the increases in fragmentation they cause is able to support some trading activity.

The remainder of this paper is structured as follows. Section 2 discusses existing research and identifies our contributions to the field. Section 3 details the contributions and hypotheses. Section 4 provides information on the data used in the study. Section 5 outlines the methodology and discusses the relevant findings, including our hypothesised results. Section 6 presents the results while Section 7 presents a discussion on the results and future research. Finally, Section 8 is the conclusion.

2.0 Existing Literature

There is a recent limited but growing cryptocurrency research literature. Some studies investigate the validity of Bitcoin and other cryptocurrencies as a replacement for traditional fiat currency (Lots & Vasselin, 2013). Other studies focus on price discovery and volatility transmission (Eun & Sabherwal, 2003; Pascual, Pascual-Fuster, & Climent, 2006). Others study the price dynamics and their relationship to the market structure of Bitcoin markets (Brandvold, Molnár, Vagstad, & Valstad, 2015; Fink & Johann, 2014). This study extends this latter body of research and investigates the price dynamics and market microstructure.

A key contribution of this study is to test the applicability of equity-based research surrounding rational expectations theory and the efficient market hypothesis to a new asset class, cryptocurrencies. In summary, the results surrounding the benefits of fragmentation within lit order books are mixed. Recent studies find that fragmentation is beneficial to the price discovery process (Battalio, 1997; Boehmer & Boehmer, 2003; Colliard & Foucault, 2012; Foucault & Menkveld, 2008). However, benefits observed across the consolidated global order book come at the expense of degradation to the local exchange and retail investors (Degryse, De Jong, & Kervel, 2015; Gresse, 2017).

Cryptocurrency

The state of cryptocurrency exchanges is not stagnant. Rather, it involves the formation and closure of several exchanges over time. Exchanges close for various reasons including illiquidity, fraud and theft, among others. Moore and Christin (2013) are among the first to research Bitcoin exchanges. They gather data on 40 different markets and study the factors that influence their sustainability. Of the 40 exchanges included in the study, they find that 18 of those exchanges ceased operations during the three-year study period. Of the 11 exchanges for which Moore and Christin (2013) were able to retrieve information regarding reimbursement, six of exchange closures resulted in customers losing the balances contained within their accounts, with the most famous closure being Mt. Gox. Mt. Gox is widely viewed as the first major Bitcoin exchange and accounts for roughly 80% of all trading activity during the early stages of the Bitcoin trading (Fink & Johann, 2014). The exchange filed for bankruptcy in February 2014 following the revelation of the theft of USD 350 million worth of Bitcoins from the exchange.

In support of the theory presented by Pagano (1989), Moore and Christin (2013) find that exchanges which maintain healthy levels of transactional volume are most likely to continue operating (Figure 1-1). These exchanges thrive as customers value the ability to transact quickly and finding a suitable counterparty in a timely fashion is easier when presented with a larger investor pool. Technological advancements provide critical support in improving the timeliness of transactions.

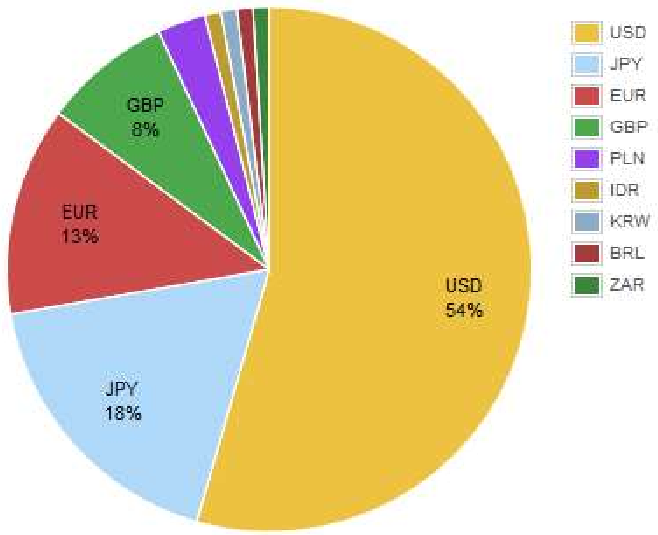


Figure 1-1: Cryptocurrency Volume Distribution (Fiat Currency)

Source: Bitcoincharts.com (March 2019)

However, Moore and Christin (2013) find that operating a popular exchange attracts the attention of criminals as popular exchanges are more likely to experience security breaches. Fraudulent activity is another factor responsible for the closure of a Bitcoin exchange. This provides further support that technological shocks are highly motivational in the formation of new exchanges. Exchange operators use advancements in security technology as a means of promoting themselves and differentiating their offerings from competitors.

Fink and Johann (2014) study the pricing dynamics and their relation to the microstructure of Bitcoin markets. The authors focus on the following major exchanges, with their respective currencies presented in parentheses, to determine the extent to which they contribute to price discovery: Bitstamp (USD), Btce (USD and EUR), Btcn (CNY) and Mt. Gox (USD and EUR). Using a vector-error-correction-model (VECM), they conclude that before the bankruptcy of Mt. Gox (nearly) all exchanges have at least a 10% level of influence on the prices of their competitors. The one exception to this is Mt. Gox (USD) which does not appear to be noticeably influenced by any of its competitors. The absence of external influences leads to the conclusion that they are a price leader. Being the market leader in transactional volume at the time is consistent with theory by Hasbrouck (1995) who argues that the dominant exchange is the source of the majority of price forming information. New exchanges contribute to the process of maintaining efficient price levels across cryptocurrencies. Therefore, reductions to information asymmetry play a supporting role in motivating exchange-based fragmentation in cryptocurrency markets.

Adapting Gonzalo and Granger's (1995) component share (CS) measure Fink and Johann (2014) find confirmation that Mt. Gox (USD) dominates its competitors in terms of its contribution of permanent price adjusting information. Mt. Gox (USD) displayed a CS of 33.14 %, implying that the other exchanges adjust their prices to the information presented by the dominant exchange. Fink and Johann (2014) exclude results on Hasbrouck's (1995) information share (IS) from analysis as the large discrepancy between lower and upper bounds do not allow for drawing of dependable interpretation.

Brandvold et al. (2015) also focus on price discovery in Bitcoin exchanges. They select five major exchanges as well as two minor ones in an attempt to account for differences in behaviour resulting from exchange size. The major exchanges included in the study are Bitfinex, Bitstamp, Btce, Btcn and Mt. Gox, and all but Btcn trade in USD currency pairs; Btcn is a Chinese Yuan exchange. Except for Bitfinex, these exchanges match those used in Fink and Johann (2014), though the latter study also includes some Euro pairs as well. The two minor cryptocurrency exchanges are the Canadian Virtex and the Polish Bitcurex exchanges and, while smaller, are still apart of the ten largest exchanges at the time of the study.

Brandvold et al. (2015) find that Btce and Mt. Gox prices are more correlated future market returns compared to past market returns. Correlations with future returns indicates that Btce and Mt. Gox are price leaders. Btce and Mt. Gox transactions also trade at more informative price points. Positive covariances between fundamental price changes and idiosyncratic shocks, the basis for the IS measurement, indicate price informativeness. Mt. Gox was the overall leader with a starting IS of 0.667. This result at least partially conforms with the findings of Fink and Johann (2014) who also find Mt. Gox to be a price leader. Two of the three foreign currency pairs do not lead the market in terms of correlation with future returns with Virtex and Btcn proving themselves to be price followers. However, Btcn saw its IS increase from 0.040 in April 2013 to 0.325 in December 2013 as Chinese firms began to accept Bitcoin as payment. This figure would subsequently drop to 0.124 following the Chinese government's ban on such payments in January 2014, thus providing further support for Madhavan (1995) who states that the price discovery occurs in the most dominant and active exchanges.

Equity

Findings regarding the benefits of fragmentation within lit order books are mixed; however recent studies find that fragmentation is beneficial to the price discovery process (Battalio, 1997; Boehmer & Boehmer, 2003; Colliard & Foucault, 2012; Foucault & Menkveld, 2008). Studies also acknowledge that benefits observed across the consolidated global order book come at the expense of the local exchange (Degryse et al., 2015; Gresse, 2017)[2].

Traditional studies view exchanges as natural monopolies where participants benefit from economies of scale. Transaction costs in a monopolistic environment are reduced through the superior matching of buyers and sellers (Chowdhry & Nanda, 1991; Mendelson, 1987; Pagano, 1989). Critics of market fragmentation in traditional lit exchanges argue that adverse selection risk increases and price discovery deteriorates as investor access to exchanges with pre-trade transparency increases. Mendelson (1987) states that participants face more difficulty finding a counterparty to their trade in a fragmented clearinghouse market compared to a consolidated clearinghouse market. Trade execution speeds decrease, leading to increased price variance and lower returns on trades, when finding a counterparty becomes more difficult. Greater participation by a wide array of investors improves both the probability and speed of execution.

[2] The local exchange refers to the dominant sovereign exchange (primary exchange) while the the global order book is comprised of orders across all exchanges trading in a particular stock.

As a result, investors favour and tend to concentrate on the most liquid market, resulting in a positive feedback loop (Pagano, 1989).

Chowdhry and Nanda (1991) extend the work of Kyle (1985) by incorporating multiple exchanges into their model. They find that adverse selection risk increases along with an increase in the number of exchanges listing a particular asset. The increase in adverse selection risk hinders a market's ability to formulate accurate prices (Chowdhry & Nanda, 1991; Madhavan, 1995). When there exists a greater proportion of large liquidity traders who can simultaneously access multiple exchanges, exchanges experience an increase in volume but also a decrease in the informativeness of prices. Prices become less informative as market makers, who compete by offering investors more favourable transaction costs than their competitors, release price information to the market in order to deter informed trading. Smaller liquidity traders tend to concentrate on exchanges that offer lower transaction costs. Consequently, the actions of smaller liquidity traders attract large liquidity traders and informed traders, thereby concentrating the market around a single dominant venue (Chowdhry & Nanda, 1991).

Madhavan (1995) argues that differences in trade disclosure rules are largely responsible for the fragmentation of markets and that markets with similar requirements across exchanges tend to consolidate. Fragmented markets allow dealers to be less competitive. Fragmented markets also help informed traders conceal their trades from certain participants of the overall consolidated market. Less competition among dealers and more dispersed informed trading can contribute to price volatility (Madhavan, 1995). Easley, Kiefer, and O'Hara (1996) and Bessembinder and Kaufman (1997) also conclude that increased fragmentation, caused by the listing shares on multiple exchanges, deteriorates the price discovery process of the primary exchange. This occurs as the most profitable uninformed trades are picked off by informed traders, often referred to in the literature as 'cream-skimming'.

One drawback of the studies mentioned up to this point is their use of specialist markets. In specialist markets, market makers or dealers take on the responsibility of providing quotes and matching purchase and sale requests. In contrast, electronic limit order books allow market participants to trade with each other directly without the need for an intermediary. Hasbrouck (1995) develops a widely used measure of price discovery, the information share (IS). Hasbrouck (1995) concludes that, for those shares whose primary listing is on the New York Stock Exchange (NYSE), the primary exchange is responsible for over 90% of price discovery when compared to regional satellite exchanges on which the asset is cross-listed. Barclay, Hendershott, and Jones

(2008) later find that consolidating orders aids in producing efficient prices and is particularly important when the demand for liquidity is high.

Empirically, critics of market fragmentation in displayed order books show that price efficiency is inversely related to the level of fragmentation in the market. Bennett and Wei (2006) study 39 stocks that transfer their primary listing from a fragmented market (NASDAQ) to a consolidated market (NYSE) between 2002 and 2003. They find that the transition to a consolidated market improves price efficiency and liquidity provisions. They also observe improvements to price efficiency through reduced volatility and a contraction of quoted, effective and realised spreads. Gajewski and Gresse (2007) confirm the improvements to price efficiency. They find that consolidated order books offer lower trading costs compared to orders which are shared between a limit order book and a group of competing dealers.

Foucault and Menkveld (2008) examine the launch of the Frankfurt Stock Exchange (FSE) operated EuroSets into the Dutch stock market alongside the existing EuroNext exchange and present mixed results. The authors investigate whether liquidity improves upon the introduction of a new market and conclude that the consolidated global limit order book deepens following the introduction of EuroSets. However, higher trade-through rates in the newly formed market highlight the need for policies protecting the price priority of limit orders in order to preserve the quality of transactions (Foucault & Menkveld, 2008).

In contrast, Riordan, Storkenmaier, and Wagener (2011) find that price protection policies are not necessary to protect all investors. They study the events surrounding the introduction of three new Multilateral Trading Facilities (MTFs) operating lit order books: Chi-X, BATS and Turquoise. They find that a lack of price protection policies did not prevent investors from executing orders at the best price level. Riordan et al. (2011) argue that given the importance of price competition, investors prioritise the need to stay informed by autonomously monitoring multiple markets. However, Riordan et al. (2011) concede that some investor protection policies are necessary. Not all market participants, particularly retail investors, can afford to employ the monitoring techniques needed to avoid the increase in trade-through rates.

Advocates of market fragmentation argue that it has positive market effects and increases investor welfare. Monopolistic trading environments often result in non-competitive behaviour. Increased competition improves trading costs in the form of tighter primary market bid-ask spreads as liquidity suppliers improve their prices (Battalio, 1997; Boehmer & Boehmer, 2003; Colliard & Foucault, 2012; Foucault & Menkveld, 2008). Battalio (1997) study the New York

Stock Exchange (NYSE) after the introduction of a third-market broker deal and the results support trading cost benefits of fragmentation. Boehmer and Boehmer (2003) study the NYSE following the listing of Exchange Traded Funds (ETFs) on the competing American Stock Exchange (ASE) and also support the positive benefits of fragmentation.

O'Hara and Ye (2011) are among the first studies to directly compare the effects of fragmentation on liquidity. Using data on 265 stocks over six months in 2008, they find that higher levels of fragmentation are inversely related to both transaction costs and the speed of execution. While the authors acknowledge that more fragmented assets experience greater short-term volatility, this comes with the benefit of improved market efficiency. Using data for 100 FTSE stocks from 2008 to 2011, Boneva, Linton, and Vogt (2016) find that volatility is lower in a fragmented lit order book. Volatility also remains more constant over the study period when compared to the effects of dark order book fragmentation. One drawback to the study by O'Hara and Ye (2011) is that the data does not allow for the comparison between global consolidated and local primary order books. However, O'Hara and Ye (2011) argue that the positive effects are because the overall market acts as a single source of liquidity with multiple entry points. This concept is explored in future studies by Degryse et al. (2015) and Gresse (2017).

Some authors acknowledge that fragmentation is beneficial to the market only up to a certain point. Degryse et al. (2015) find that visible fragmentation follows an inverted U-Shape showing with the marginal benefit of fragmentation decreasing over time. They determine that the ideal level of fragmentation of 32% as measured by one minus the Herfindahl-Hirschman Index. They find that fragmentation improves liquidity about the midpoint but has a lesser effect deeper in the visible order book.

In summary, the results surrounding the benefits of fragmentation within lit order books are mixed. Recent studies find that fragmentation is beneficial to the price discovery process (Battalio, 1997; Boehmer & Boehmer, 2003; Colliard & Foucault, 2012; Foucault & Menkveld, 2008). However, benefits observed across the consolidated global order book come at the expense of degradation to the local exchange and retail investors (Degryse et al., 2015; Gresse, 2017).

3.0 Contribution and Hypotheses

Many Bitcoin (BTC) exchanges allow for trading across multiple fiat currencies. However, they operate separate order books for each fiat currency in which investors can transact. Exchanges also restrict customers to the order books which use their local currency. This results in the fragmentation of BTC investors into pools based on their home currency as identified by the country in which they are currently a resident. This study investigates two fiat based, USD and Euro, BTC markets determine if they react similarly to competitive market fragmenting events. This study investigates the research question by testing the applicability of equity-based research principles, such as rational expectations theory and the efficient market hypothesis, to instances of competitive market fragmentation in a relatively new asset class, cryptocurrencies.

This study is the first to measure the level of fragmentation in the cryptocurrency market and study its relationship to the price discovery process. It is also the first study to apply established research surrounding rational expectations theory and the efficient market hypothesis to cryptocurrency markets. Therefore, it is the first to apply these techniques, largely used for equity markets, and test the extent to which they, and existing theory on competition, applies to the cryptocurrency market.

Pagano (1989) argues if two similar exchanges exist with unequal trading costs, some investors will concentrate on one exchange while others migrate to the alternative exchange. Chowdhry and Nanda (1991) extend the work of Kyle (1985) and find that adverse selection risk increases along with an increase in the number of exchanges listing a particular asset. Glosten and Milgrom (1985) deduce that increased participation from informed competitive traders is proportional to bid-ask spreads due to adverse selection. The increase in adverse selection risk results from increased competitive market fragmentation and hinders a market's ability to formulate accurate prices (Chowdhry & Nanda, 1991; Madhavan, 1995). Also, Hasbrouck (1995) concludes that, for those shares whose primary listing is on the New York Stock Exchange (NYSE), the primary exchange is responsible for over 90% of price discovery when compared to regional satellite exchanges on which the asset is cross-listed. However, any informed activities that leave the market take with them some permanent price-adjusting information. This leads to the first two hypotheses for the study:

H1: When multiple exchanges offer the ability to transact in the same asset, price adjusting information is spread across multiple exchanges and does not originate from a single source.

H2: Market share is positively related to the informational content of prices on an exchange.

When there exists a greater proportion of large liquidity traders who can simultaneously access multiple exchanges, markets experience an increase in volume but also a decrease in the informativeness of prices (Chowdhry & Nanda, 1991; Madhavan, 1995). Greater fragmentation affords informed investors the ability to more easily conceal their trades from investors wishing to take advantage of their superior information Madhavan (1995). This results in the migration of critical price-adjusting information across exchanges and leads to the following hypothesis.

H3: Market fragmentation is positively related to the informational content of prices on an exchange.

Local exchanges, those that operate within the same country as a particular order book currency, will contain more price discovery than foreign exchange. Noronha, Sarin, and Saudagaran (1996) find that informed trading increases following international cross-listing, leading to more efficient and informative prices. However, the primary market is still believed to provide the majority of price disseminating information. Ultimately, price discovery occurs in the primary domestic exchange (Su & Chong, 2007) which leads to the final hypothesis for the study:

H4: USD (Euro) exchanges contribute more information to USD (Euro) transactions than Euro (USD) transactions.

4.0 Data

This section utilises tick level transaction data and order book data obtained from CoinMarketCap. It also references data from BitcoinCharts.com for supporting information regarding market totals. Bitcoin (BTC) data is chosen as it is the largest and most liquid cryptocurrency with regards to market capitalisation and trading volume, respectively. BTC is also the oldest and most recognisable cryptocurrency whose name is used as an eponym for all cryptocurrencies.[3]

BTC data is collected from January 1st, 2017 to March 31st, 2019. The data is not only recent at the time of the writing of this thesis, it also corresponds to a highly liquid period of the BTC market. This allows for the use of more granular data in constructing the necessary variables due to the frequency of transactions.

BTC data is collected for the following seven exchanges: Bitbay, Bitfinex, Bitstamp, Coinbase, Exmo, Gemini and Kraken. These exchanges are among the most liquid BTC exchanges with regards to trading volume. Both USD and Euro data is used as they represent the two most active BTC markets when we consider the fragmentation of investors by their respective fiat currency.

[3] People refer to cryptocurrencies as Bitcoin akin to the way in which they use Kleenex when referring to facial tissue, or Q-tips when referring to cotton swabs.

Bitbay, Bitstamp, Exmo, and Kraken operate both USD and Euro order books while Bitfinex, Coinabase and Gemini only allow for USD trading. During the study period, these markets represent 81% and 74% of total BTC trading volume in USD and Euro, respectively (see **Error! Reference source not found.**).

Millisecond time-stamped transactional data is used to calculate the various dependent and independent variables used in the analysis. Order-book data utilises 1-minute snapshots of the order book.

5.0 Methodology

This section introduces the methods used to conduct the study. Section 5.1 introduces the methods used to calculate price discovery, the dependent variable. Section 5.2 discusses independent variables. Section 5.3 discusses the regression models used to test the hypotheses.

5.1 Measuring Price Discovery

This section outlines the key measure of price discovery used in this study. The measure is calculated for each exchange in the study for each trading day. Exchange prices, and subsequent returns, are calculated on 5-minute intervals. This follows the findings of Anderson (2000) who suggests that this time frame is short enough to account for the granularity of the data but long enough to avoid capturing a meaningful number of observations and minimise noise. The construction of the price discovery metric follows the approach modelled by de Jong (2001) and applied to the cryptocurrency market by Brandvold et al. (2015). This multivariate time-series model is designed to measure the degree to which an exchange contributes permanent price adjusting information to a market comprised of several exchanges.

Similar to the information share (Hasbrouck, 1995) and component share (Gonzalo and Granger, 1995) price discovery measures assume that prices are comprised of the efficient price and an idiosyncratic noise component. This allows a single, unobserved, efficient price to be the basis for the prices found on each exchange with deviations from that price being a result of exchange specific factors. Separating idiosyncratic factors from the efficient price was first introduced by Hasbrouck (1995).

Exchanges and markets are defined in order to measure price discovery. An exchange consists of a single order book where investors can buy and sell BTC. A market refers to all other exchanges (order books). Price discovery is therefore calculated for *n* exchanges across *m* markets where *n=m*.

Order books operate separately for each fiat currency and that customers rarely have access to order books for fiat currencies outside of their local currency. Therefore, price discovery measures are calculated separately for USD and Euro markets. This not only helps differentiate between subsets of investors but also eliminates the risks associated with exchange rates and cross-currency transactions. As a result, there are *n=7* USD exchanges and *n=4* Euro exchanges.

Let P be a vector of prices where P^e is a vector of exchange prices and P^m is a vector of market prices. Also, let U be a vector of idiosyncratic components with U^e and U^m referring to the idiosyncratic components for the exchange and the market, respectively. Element *i* of P^e and U^e refer to exchange *i* while element *j* of P^m and U^m refer to market *j*. Finally, denote P^* as the efficient price.

If $p^e = lnP^e$, $u^e = lnU^e$ and $p^* = lnP^*$ the n-vector of exchange prices is

$$p_t^e = p_t^* + u_t^e \tag{1}$$

and the m-vector of market prices is

$$p_t^m = p_t^* + u_t^m \tag{2}$$

If p^* is a random walk it is assumed that you cannot predict the efficient price (Hasbrouck, 1995). Since prices across all exchanges and markets are centred around the same efficient price, p^*, by design the prices are cointegrated.

Changes in the efficient price from period *t-1* to period *t* are defined as

$$r_t = p_t^* - p_{t-1}^* \tag{3}$$

The model assumes that unconditional serial covariances are stable across r_t, u_t^e and u_t^m. This allows for the following definitions where ψ, γ_l and Ω are (n x 1) matrices:

$$E[r_t^2] = \sigma^2 \tag{4a}$$

$$E[r_t u_{it}^e] = \psi_i \tag{4b}$$

$$E[r_t u_{jt}^m] = \psi_j \tag{4c}$$

$$E\left[r_t u^e_{i,t+1}\right] = \gamma_{li},\ l \geq 0 \qquad (4d)$$

$$E\left[r_t u^m_{j,t+1}\right] = \gamma_{lj},\ l \geq 0 \qquad (4e)$$

$$E\left[r_t u^e_{i,t-k}\right] = 0,\ k > 0 \qquad (4f)$$

$$E\left[r_t u^m_{j,t-k}\right] = 0,\ k > 0 \qquad (4g)$$

$$E[u^e_{it}] = \Omega^e \qquad (4h)$$

$$E\left[u^e_{it} u^m_{jt}\right] = \Omega,\ i = j \qquad (4i)$$

$$E\left[u^e_{i,t-k}\right] = 0,\ k \neq 0 \qquad (4j)$$

$$E\left[u^e_{it} u^m_{j,t-k}\right] = 0,\ k \neq 0 \qquad (4k)$$

de Jong et al. (2001) define r_t as the price adjusting component that leads to changes in the efficient price, p^*. Since r_t is the return corresponding to changes in p^*, and p^* is a random walk, r_t is serially uncorrelated.

p is the only variable that can be observed. Therefore, it is critical in helping calculate the measure of price discovery. Let

$$y_{it} = p_{it} - p_{it-1} = p^*_t + u_{it} - p^*_{t-1} + u_{it-1} = r_t + u_{it} - u_{it-1} \qquad (5)$$

and let the vectors of prices for exchanges and markets be

$$Y^e_t = \iota r_t + u^e_t - u^e_{t-1} \qquad (6a)$$

$$Y^m_t = \iota r_t + u^m_t - u^m_{t-1}$$

ι

i

s

ι is a vector of ones of size n. Using the definitions listed in $Er⍰t⍰2⍰⍰ = \sigma^2$ a

(

4

a

)

$$E[Y_t Y_t'] = \sigma^2 \iota\iota' + \iota\psi' + \psi\iota' + 2\Omega \qquad (7a)$$

v

e

$$E[Y_t Y_{t-1}'] = -\psi\iota' - \Omega + \gamma\iota' \qquad (7b)$$

c

t

o

r

t

o

o

$$E[Y_tY'_{t-2}] = -\gamma\iota' \tag{7c}$$

The covariance between exchanges and their markets are key to the final results and are defined as the covariance between and element and its counterpart in vectors Y^e and Y^m, respectively. Given this information and Equations (7a) to (7c)

$$E[y_{jt}y_{it}] = \sigma^2 + 2\omega_{ij} + \psi_j + \psi_i \tag{8a}$$

$$E[y_{jt}y_{i,t-1}] = -\omega_{ij} - \psi_j + \gamma_j \tag{8b}$$

$$E[y_{jt}y_{i,t-2}] = -\gamma_j \tag{8c}$$

The first-order autocorrelation for exchanges is defined as

$$\rho_{1,ii} = \frac{-(\omega_i^e + \psi_j - \gamma_j)}{\sigma^2 + 2(\omega_i^e + \psi_i)} \tag{9}$$

The covariance between the new price adjusting information and the idiosyncratic component is ψ_i as defined in (7b) and (7c). The larger the value of ψ_i the stronger the signal of price adjusting information originating from that exchange.

Finally, the information share attributable to a single exchange is defined as

$$IS_i = \frac{(\sigma^2 + \psi_i)\pi_i}{\sigma^2} = \pi_i\left(1 + \frac{\psi_i}{\sigma^2}\right) \tag{10}$$

where π_i is the activity share of an exchange and is defined by the proportion of transactions taking place in the exchange relative to the entire market. The sum of all π_i equals 1. By imposing the rule that $\pi'\psi = 0$ the sum of all information shares across all exchanges sum to 1.

5.2 Independent Variables

This following section lists the series of independent variables used in the study, some of which are key regressors relating to fragmentation and are used to test the hypotheses while the remainder are control variables. The regressions control for the following factors: volatility, bid-ask spread, and total daily volume.

This section discusses methods used to test the impact of fragmentation on the price discovery process. We begin by measuring the level of competition among BTC exchanges. Separate fragmentation figures are calculated for USD and Euro exchanges. Fragmentation is measured using the Herfindahl-Hirschman Index (HHI). It follows previous research (Buti, Rindi, & Werner, 2017; Degryse et al., 2015; Gresse, 2017) and measures the extent to which trading activity concentrates around a single exchange. As a result fragmentation for order books using currency c at time t ($Frag_{c,t}$) is measured as follows:

$$Frag_{c,t} = 1 - \sum_{v=1}^{n} MS_{c,t,v}^{2} \tag{11}$$

where c represents either the USD or Euro order books, t is the observation day, v represents a particular exchange or order book, MS_v^2 is the squared market share of trading venue v, measured by the number of BTC traded in venue v when compared to the market as a whole.

1-HHI is used in order to allow the measure to more obviously measure fragmentation and an increase in *Frag* corresponds to increased fragmentation in the market for any particular stock.

Next, the study focusses on trading activity within a single exchange. Due to the increasing popularity of Bitcoin the market is no longer consolidated around a single exchange. Instead, many exchanges offer order books in which investors can buy and sell BTC. Trading activity is measured for a single exchange using the market share of trading volume attributable to each exchange (*MS*).

$$\mathrm{MS}_{\mathbf{c,i,t}} = \mathrm{Vol}_{\mathbf{c,i,t}} / \mathrm{Vol}_{\mathbf{c,t}} \tag{12}$$

where c represents a particular currency,

t is the observation day,

$Vol_{c,i,t}$ is the daily transaction volume, in currency c, for exchange i at time t,

$Vol_{c,t}$ is the total daily volume for all exchange in currency c at time t.

5.3 Panel Regression

The base for the regression formula is:

$$L_{i,t} = b_0 + b_1 Frag_{i,t} + b_2 MS_{i,t} + b_3 ln\sigma_{i,t} + b_4 lnBASp_{i,t} + b_5 lnVol_{i,t} + b_6 AvgTS_{i,t} + \mu_{i,t} \tag{13}$$

where *Frag and MS* refer to the aforementioned measures of fragmentation and the remainder refer to control variables for volatility (σ), bid-ask spread (*BASp*), and total volume (*Vol*).

The regression model is extended to include the entity and time fixed effects. The extended model is as follows:

$$L_{i,t} = \alpha_i + \gamma_t + b_1 Frag_{i,t} + \ b_2 MS_{i,t} + \ b_3 ln\sigma_{i,t} + b_4 lnBASp_{i,t} + b_5 lnVol_{i,t} + b_6 AvgTS_{i,t} + \mu_{i,t}\ . \tag{14}$$

Quarterly time-dummy variables are used to control for events that affect each exchange over a quarterly time period. Also, exchange dummy variables are used to capture events that are unique to each exchange but remain constant over time.

6.0 Results

This section presents the results of the study. Initially, descriptive statistics are presented to profile the data and measures of the study. Next, the section presents the main result tables testing the hypotheses outlined earlier. The results are discussed before drawing key insights and conclusions from the empirical study of cryptocurrency markets.

6.1 Descriptive Statistics

This section presents the descriptive statistics for Bitcoin markets throughout the study period of January 1 2017 to March 31 2019. Cryptocurrency exchange participants are predominately limited to using their home currency in transactions. As a result, Euro currency traders are largely isolated from trading with USD currency traders. Therefore, the data presented in this section are split into USD trading and Euro trading categories. Separating the order books allows the study to investigate the effects of fragmentation resulting from changes to the structure of order books, that is, the structure of the market, in which an individual investor can participate. This is an important distinction as Euro traders are less influenced by the structure of the USD Bitcoin market. While the geographical location of the change influences the currencies against which its cryptocurrencies transact, exchanges can decide to construct order books for several currencies. For example, of the six cryptocurrency exchanges used in the study only two, Bitfinex and Gemini, restrict trading to a single currency. Many of the sampled exchanges also allow trading in other cryptocurrencies. However, this study focuses on the oldest and most established cryptocurrency, Bitcoin.

Table 1-2 presents descriptive statistics for Bitcoin transactions, with USD and Euro trade data found in Panels A and B, respectively. Daily transactional volume totalled $519 million for USD order book trades and €110 million for Euro order book trades indicating that USD order books are more popular than Euro order book. USD trades are also responsible for trading approximately 82,836 BTC daily while Euro trades account for only 17,260 BTC. This implies that either Bitcoin trading is more popular in the U.S. or that, of these two currency options, the

USD is the preferred currency for Bitcoin transactions. The daily transactional volume for the sampled exchanges accounts for 81% and 74% of all trading activity in the USD and Euro Bitcoin markets, respectively. Therefore, this study encapsulated a significant proportion of the total Bitcoin market and the results reasonably characterise the total market.

Looking toward the size of the transactions the sample encompasses approximately 81.15% and 74.21% of the total trading volume, as measured in BTC, for USD and Euro markets, respectively. While the difference is minimal, it implies that the transactions executed in the sampled exchanges are larger than those that occur in out-of-sample exchanges. This is supported by the data on the total number of daily trades. Total daily trades are listed as 229,060 and 68,614 for USD and Euro markets, respectively. This encapsulates 78% of all USD trades and 83% of all Euro trades. In USD order books, the six sampled exchanges are responsible for 81% of all trading based on daily dollar transactional volume. Given that is only responsible for 78% of all transactions this data provides further support that the sampled USD/BTC order books or typically larger than those of the out-of-sample exchanges.

However, the opposite appears to be true to Euro/BTC order books. With 74% of the Euro volume and 83% of the total number of transactions, the four samples exchanges are responsible for a greater number of smaller transactions. In spite of these differences, the average trade sizes for USD and Euro order book trades are similar at $1,847 and €1,831 respectively. Accounting for exchange rates over the sample period makes the Euro trades slightly more valuable, on average, than USD trades.

Table 1-1 - Descriptive Statistics (Sample)

This table contains the means, standard deviations, and medians as well as the first (P25) and third (P75) quartiles of various measure. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated using all transactions in a single currency over a single trading day. 'Sample – All' contains results over the entire sample period (1 January 2017 to 31 March 2019) while 'Sample – First Half' and 'Sample – Second Half uses data from 1 January 2017 to 14 February 2018 and 15 February 2018 to 31 March 2019, respectively. Volume (USD/Euro) is the total USD/Euro volume (reported in millions) of Bitcoin (BTC) transactions and includes both in and out-of-sample exchanges. Market Share (USD/Euro) is the proportion of USD/Euro volume captured by the sampled exchanges. Volume (BTC) is the total volume, measured in Bitcoin, (reported in thousands) of Bitcoin transactions and consists of data from both in and out-of-sample exchanges. Market Share (BTC) is the proportion of BTC volume captured by the sampled exchanges. Trades Per Day is the total number of BTC transactions (reported in thousands) and consists of both in and out-of-sample exchanges. Market Share (Trades Per Day) is the proportion of trades captured by the sampled exchanges. Average Trade Size (USD/Euro) is the average size of each transaction, measured in its respective currency (USD/Euro).

Panel A: USD ($)

	Mean	Std. Dev.	P25	Median	P75
Sample - All					
Total Volume (USD) (millions)	519.18	627.65	148.93	299.80	644.16
Market Share (Sample - USD)	0.81	0.11	0.73	0.85	0.90
Total Volume (BTC) (thousands)	82.84	54.00	44.30	68.70	104.60
Market Share (Sample - BTC)	0.81	0.10	0.73	0.85	0.90
Total Trades Per Day (thousands)	229.06	167.17	117.10	180.54	278.48
Market Share (Sample - Trades Per Day)	0.78	0.13	0.72	0.83	0.87
Average Trade Size	1,847.29	1,203.33	1,095.57	1,767.84	2,498.39
Sample - First Half					
Total Volume (USD) (millions)	583.80	803.75	96.19	244.03	711.19
Market Share (Sample - USD)	0.81	0.11	0.72	0.86	0.90
Total Volume (BTC) (thousands)	97.39	59.21	59.37	83.26	121.34
Market Share (Sample - BTC)	0.81	0.11	0.73	0.86	0.90
Total Trades Per Day (thousands)	257.52	204.09	124.44	194.58	326.44
Market Share (Sample - Trades Per Day)	0.71	0.14	0.59	0.72	0.85
Average Trade Size	1,661.79	1,570.76	763.09	1,280.49	2,481.31
Sample - Second Half					
Total Volume (USD) (millions)	454.55	365.41	192.22	329.83	606.00
Market Share (Sample - USD)	0.81	0.10	0.74	0.84	0.89
Total Volume (BTC) (thousands)	68.28	43.62	37.55	56.30	86.35
Market Share (Sample - BTC)	0.81	0.10	0.74	0.84	0.89
Total Trades Per Day (thousands)	200.60	112.35	114.08	166.76	259.37
Market Share (Sample - Trades Per Day)	0.86	0.06	0.81	0.85	0.90
Average Trade Size	2,032.80	599.91	1,582.43	2,016.53	2,502.63

Table 1-1 - Descriptive Statistics (Sample) - continued

Panel B: Euro (€)

	Mean	Std. Dev.	P25	Median	P75
Sample - All					
Total Volume (Euro) (millions)	110.42	634.49	30.86	56.56	100.66
Market Share (Sample - Euro)	0.74	0.18	0.71	0.80	0.85
Total Volume (BTC) (thousands)	17.26	10.69	9.92	14.65	20.58
Market Share (Sample - BTC)	0.74	0.17	0.71	0.80	0.85
Total Trades Per Day (thousands)	68.61	54.96	38.29	52.84	78.79
Market Share (Sample - Trades Per Day)	0.83	0.10	0.79	0.87	0.90
Average Trade Size	1,831.53	15,625.74	739.19	1,027.45	1,358.66
Sample - First Half					
Total Volume (Euro) (millions)	141.87	894.56	21.18	48.10	107.88
Market Share (Sample - Euro)	0.79	0.09	0.76	0.81	0.85
Total Volume (BTC) (thousands)	19.71	11.11	12.55	17.14	23.04
Market Share (Sample - BTC)	0.80	0.08	0.76	0.81	0.85
Total Trades Per Day (thousands)	78.77	70.46	35.93	57.62	92.83
Market Share (Sample - Trades Per Day)	0.85	0.06	0.82	0.87	0.89
Average Trade Size	2,376.60	22,079.71	590.87	845.77	1,152.16
Sample - Second Half					
Total Volume (Euro) (millions)	78.98	54.23	37.89	69.88	98.40
Market Share (Sample - Euro)	0.69	0.22	0.63	0.77	0.84
Total Volume (BTC) (thousands)	14.81	9.65	8.43	11.65	17.47
Market Share (Sample - BTC)	0.69	0.22	0.63	0.77	0.84
Total Trades Per Day (thousands)	58.45	29.50	38.83	50.13	68.15
Market Share (Sample - Trades Per Day)	0.81	0.12	0.71	0.87	0.91
Average Trade Size	1,286.47	468.98	872.46	1,284.11	1,567.79

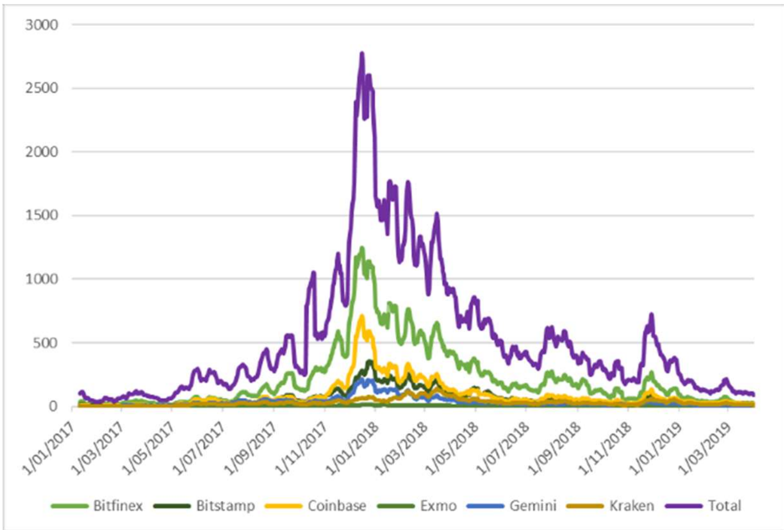
Table 1-2 also differentiates between the first and second half of the sample period. Total dollar transactional volume decreases from \$584 million to \$454 million. Over the same period the USD market share of transactions that the sample captures remain constant at 81% implying that the overall Bitcoin market when traded against the USD, is shrinking. This is to be expected as BTC peaked in price at \$19,783 on December 17 2017. This period corresponds with the height of BTC's popularity in the media and precedes a period of significant devaluation.

Figure 1-2 provides support for the conclusion regarding the size of the USD/BTC market. Panel A in Figure 1-2 shows a significant increase in the size of the USD/BTC market over the study period with a peak in daily trading volume of approximately \$2.75 billion around the time of the peak BTC price. Trading volume decreased quickly after this period. Euro exchanges saw a decrease in daily transactional volume from €142 million to €79 million over the same period. Panel B in Figure 1-2 shows an increase in daily volume similar to that of the USD market. Daily Euro volume peaked at approximately €325 million, however, unlike the USD market, the Euro market is able to sustain the greater level of volume over a roughly three-month period before returning to a more sustainable level. The sample accounts for 79% of the trading volume in the first half of the study but decreases to 69% in the second half. This implies that while the Euro/BTC market shrank over the study period, the investors also looked for opportunities to trade in smaller competing exchanges. According to Figure 1-2 both the USD and Euro market saw a resurgence in activity around September 2018 and the 2018 Christmas season.

While markets shrunk with respect to volume, the average size of transactions increased from \$1,662 to \$2,032. However, the dollar market share remains constant over the period, and that the sample capture 71% of all trades in the first half of the sample and 85.5% in the second half. Therefore, while the remaining USD/BTC transactions were increasing in size for out-of-sample exchanges, the sample exchanges experience a reduction in transaction size. Once again, the Euro market behaves quite oppositely. Average Euro transaction sizes decrease over the sample period from €2,376 to €1,46, as do the market share of trades and volume that are captured by the sample, which decreased from 79% to 68% and €142 million to €79 million, respectively. This implies an overall decrease in the size of the Euro/BTC market over the trading period. Euro traders migrate to out-of-sample exchanges over the sample period while USD traders concentrate on the in-sample exchanges.

These findings are supported by Figure 1-3 which shows the market shares of all USD and Euro transactions that are captured by the sampled exchange. While USD results present some variations the overall sampled market share remains constant, as discussed previously. However, the results evidence significant variability in the Euro market over a five-month period at the start of 2019.

Panel A: USD ($)



Panel B: Euro (€)

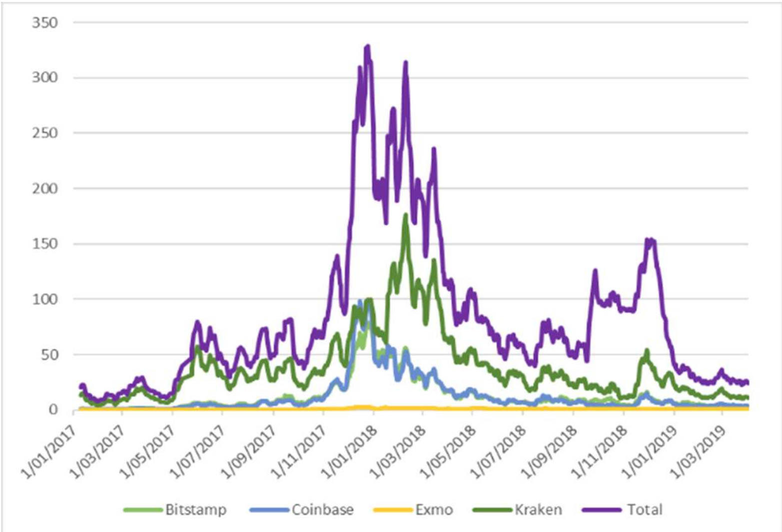


Figure 1-2 – Bitcoin Trading Volume (Exchange)

This graph displays the total transactional volume of Bitcoin. Volume (USD/Euro) is the total USD/Euro volume (reported in millions) of Bitcoin (BTC) transaction. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Individual exchange data is displayed along with the total daily transactional volume which includes out-of-sample exchanges. The displayed results are based on a 10-day moving average.

Over this period sampled Euro market share drops to a minimum of 19% but return to its previous levels shortly after. This five-month period in the Euro market represents a temporary phenomenon and, if removed from the study, would bring the Euro figures more in line with the

USD figures in that a roughly constant market share of transaction volume captured by the sampled exchanges. Future research and further data collection are needed to derive the motivations behind investors' desire to migrate to a less dominant exchanges and why the change was not made permanent.

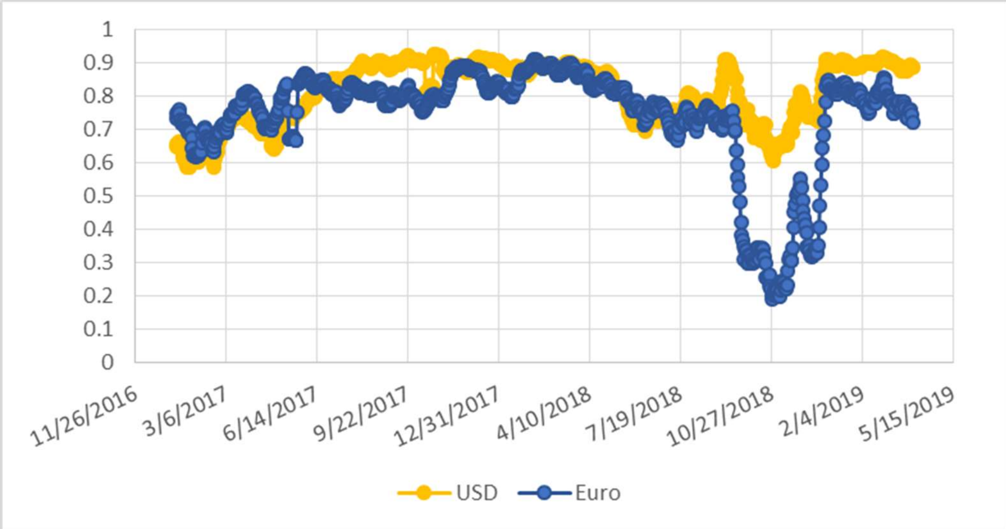


Figure 1-3 – Bitcoin Market Share (Sampled Exchanges)

This figure presents the market share of total daily transactions that are captured by the sampled exchange. Market shares are presented separately for USD and Euro order books. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). The displayed results are based on a 10-day moving average.

Table 1-2 and Table 1-3 presents descriptive statistical data on the sampled exchanges. Data for all USD order books including Bitfinex, Bitstamp, Coinbase, Exmo, Gemini and Kraken are found in Table 1-2 and Table 1-3 contains Euro order book data for Bitstamp, Coinbase, Exmo and Kraken. Only two of the sampled exchanges, Bitfinex and Gemini, exclusively operate USD order books while the remaining exchanges operate in at least two currencies, with the Chinese Yuan being another popular medium of exchange.

Table 1-2: Descriptive Statistics (USD Exchanges)

This table contains the means, standard deviations, and medians as well as the first (P25) and third (P75) quartiles of various measure for each USD cryptocurrency exchange. Panels A - F contain data for the following exchanges: Bitfinex, Bitstamp, Coinbase, Exmo, Gemini and Kraken. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Volume (USD) is the total USD volume (reported in millions) of Bitcoin (BTC) transactions for the exchange. Market Share (USD) is the proportion of USD volume captured by the exchange. Volume (BTC) is the total volume, measured in Bitcoin, (reported in thousands) of Bitcoin transactions for the exchange. Market Share (BTC) is the proportion of BTC volume captured by the exchange. Price (USD) is the average transaction price per BTC on the exchange. σ represents volatility and is the average 5-minute standard deviation in basis points. BASp is the average quoted spread on the exchange. Trades Per Day is the total number of BTC transactions (reported in thousands) for the exchange. Market Share (Trades Per Day) is the proportion of trades captured by the exchange. Average Trade Size (USD) is the average size of each transaction in the exchange, measured in its respective currency (USD).

	Panel A: Bitfinex					Panel B: Bitstamp				
	Mean	Std. Dev.	P25	Median	P75	Mean	Std. Dev.	P25	Median	P75
Volume (USD) (millions)	217.42	281.11	42.97	110.85	274.67	66.99	76.77	20.90	39.99	87.26
Market Share (USD)	0.37	0.09	0.29	0.37	0.44	0.14	0.03	0.11	0.13	0.16
Volume (BTC) (thousands)	32.59	25.97	14.45	25.22	44.20	11.25	7.76	5.94	9.49	14.51
Market Share (BTC)	0.37	0.09	0.29	0.37	0.44	0.14	0.03	0.11	0.13	0.16
Price (USD)	5,536.08	3,544.86	2,756.39	4,646.19	7,377.97	5,517.11	3,562.21	2,757.58	4,613.42	7,389.03
σ	5.69	7.55	1.49	3.20	6.13	5.49	7.21	1.47	3.14	6.03
BASp (x100)	0.02	0.02	0.00	0.01	0.03	0.09	0.05	0.05	0.09	0.12
Trades Per Day (thousands)	66.47	61.65	25.63	45.86	84.85	24.45	21.27	9.89	18.05	32.05
Market Share (Trades Per Day)	0.26	0.07	0.21	0.27	0.32	0.10	0.03	0.08	0.10	0.12
Average Trade Size	2,563.89	1,102.07	1,569.45	2,522.86	3,443.87	2,353.76	804.64	1,799.31	2,346.85	2,898.53

	Panel C: Coinbase					Panel D: Exmo				
	Mean	Std. Dev.	P25	Median	P75	Mean	Std. Dev.	P25	Median	P75
Volume (USD) (millions)	88.97	132.87	24.50	43.49	96.17	3.11	3.02	0.67	2.43	4.13
Market Share (USD)	0.16	0.04	0.13	0.16	0.19	0.01	0.01	0.00	0.01	0.01
Volume (BTC) (thousands)	13.55	10.74	6.73	10.49	16.94	0.45	0.21	0.24	0.49	0.58
Market Share (BTC)	0.16	0.04	0.13	0.16	0.19	0.01	0.01	0.00	0.01	0.01
Price (USD)	5,530.16	3,587.31	2,768.13	4,646.37	7,385.02	5,617.35	3,689.41	2,726.06	4,681.75	7,362.97
σ	5.22	7.29	1.29	2.90	5.70	5.51	7.13	1.94	3.33	5.96
BASp (x100)	0.01	0.03	0.00	0.00	0.02	0.29	0.09	0.24	0.28	0.34
Trades Per Day (thousands)	59.01	43.83	34.53	47.63	68.44	8.46	6.92	4.00	6.44	10.28
Market Share (Trades Per Day)	0.27	0.09	0.21	0.24	0.32	0.04	0.01	0.03	0.04	0.04
Average Trade Size	1,152.35	689.01	611.10	957.25	1,589.67	393.71	299.49	124.51	368.90	546.84

Table 1-2: Descriptive Statistics (USD Exchanges) - continued

	Panel E: Coinbase					***Panel F: Exmo***				
	Mean	Std. Dev.	P25	Median	P75	Mean	Std. Dev.	P25	Median	P75
Volume (USD) (millions)	34.76	47.13	8.41	20.02	40.17	31.30	30.45	12.04	21.84	41.37
Market Share (USD)	0.07	0.04	0.05	0.06	0.08	0.07	0.03	0.05	0.07	0.09
Volume (BTC) (thousands)	5.95	5.25	2.43	4.55	7.86	5.57	3.97	2.96	4.50	7.10
Market Share (BTC)	0.07	0.04	0.05	0.06	0.08	0.07	0.03	0.05	0.07	0.09
Price (USD)	5,525.68	3,579.52	2,763.59	4,645.50	7,385.86	5,521.38	3,568.17	2,759.28	4,644.58	7,385.57
σ	5.27	7.28	1.24	2.96	5.86	5.44	7.17	1.45	3.13	6.08
BASp (x100)	0.03	0.04	0.01	0.02	0.04	0.09	0.09	0.03	0.06	0.13
Trades Per Day (thousands)	12.21	12.09	3.85	8.20	15.85	15.86	12.51	6.80	12.87	21.38
Market Share (Trades Per Day)	0.05	0.02	0.03	0.04	0.06	0.07	0.03	0.05	0.07	0.08
Average Trade Size	2,497.04	1,065.28	1,735.52	2,397.24	3,111.59	1,833.50	780.29	1,089.11	1,919.82	2,467.99

The most popular exchange for the USD traders is Bitfinex with an average daily transactional volume of $217 million which represents 36.8% of total USD/BTC volume, including out-of-sample exchanges. Coinbase and Bitstamp are the next more popular USD exchanges with $90 million and $67 million in total daily USD transactional volume, respectively. Coinbase and Bitstamp represent 16% and 13.5% of all USD/BTC market activity. With the exception of Exmo, Gemini and Kraken are the smallest of the sampled exchanges with approximately 6.8% and 7.1% of the total market share, respectively. Exmo is the smallest sampled USD/BTC exchange and accounts for only 0.7% of all USD transactions. Though a minor exchange, Exmo data is included in the study in order to test the robustness of the results with respect to the overall size/popularity of the exchange. Euro markets are noticeably more concentrated over the sample period. Kraken is the dominant exchange for EURO/BTC trading an encompasses 74% of all Euro/BTC trades. Bitstamp and Coinbase maintain similar average market shares of 12.1% and 11.4%, respectively, while Exmo trails with 1.3%. Figure 1-2 displays the exchange specific transactional volume data for both USD and Euro exchanges and shows that while the daily transactional volume fluctuates over time, each exchanges ranking within its respective currency market remains constant.

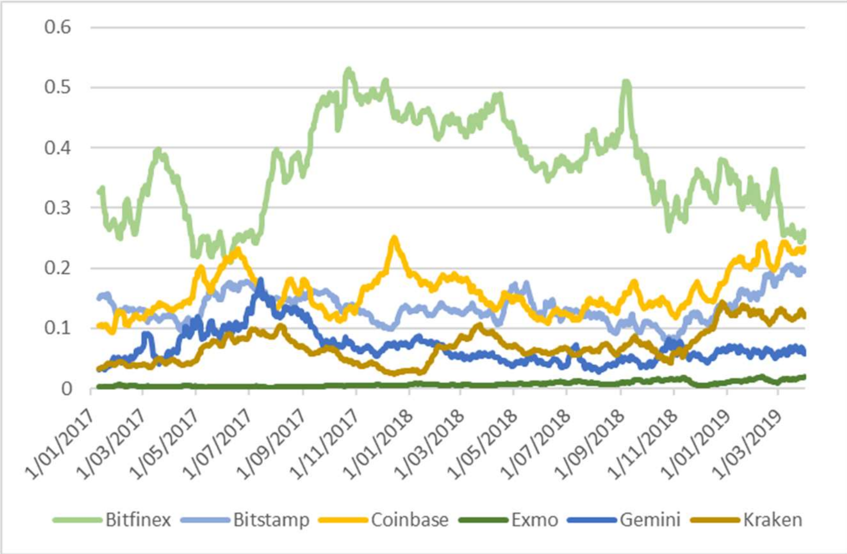
Table 1-3: Descriptive Statistics (Euro Exchanges)

This table contains the means, standard deviations, and medians as well as the first (P25) and third (P75) quartiles of various measure for each Euro cryptocurrency exchange. Panels A - D contain data for the following exchanges: Bitstamp, Coinbase, Exmo, and Kraken. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Volume (Euro) is the total Euro volume (reported in millions) of Bitcoin (BTC) transactions for the exchange. Market Share (Euro) is the proportion of Euro volume captured by the exchange. Volume (BTC) is the total volume, measured in Bitcoin, (reported in thousands) of Bitcoin transactions for the exchange. Market Share (BTC) is the proportion of BTC volume captured by the exchange. Price (Euro) is the average transaction price per BTC on the exchange. σ represents volatility and is the average 5-minute standard deviation in basis points. BASp is the average quoted spread on the exchange. Trades Per Day is the total number of BTC transactions (reported in thousands) for the exchange. Market Share (Trades Per Day) is the proportion of trades captured by the exchange. Average Trade Size (Euro) is the average size of each transaction in the exchange, measured in its respective currency (Euro).

	Panel A: Bitstamp					Panel B: Coinbase				
	Mean	Std. Dev.	P25	Median	P75	Mean	Std. Dev.	P25	Median	P75
Volume (Euro) (millions)	12.05	17.40	2.95	6.34	12.56	12.09	20.73	2.58	5.01	12.12
Market Share (Euro)	0.12	0.06	0.08	0.12	0.16	0.11	0.06	0.06	0.11	0.15
Volume (BTC) (thousands)	2.11	1.84	0.98	1.60	2.66	1.96	1.98	0.86	1.38	2.30
Market Share (BTC)	0.12	0.06	0.08	0.12	0.16	0.11	0.06	0.06	0.11	0.15
Price (Euro)	4,696.00	2,921.67	2,400.80	3,928.86	6,295.65	4,732.10	2,989.10	2,401.74	3,960.50	6,325.04
σ	4.82	6.20	1.48	2.87	5.19	4.36	6.41	1.07	2.48	4.76
BASp (x100)	0.23	0.11	0.14	0.21	0.30	0.04	0.05	0.01	0.02	0.06
Trades Per Day (thousands)	9.06	11.31	3.39	5.55	9.86	20.71	26.04	8.73	12.35	21.14
Market Share (Trades Per Day)	0.11	0.05	0.08	0.10	0.14	0.26	0.08	0.20	0.25	0.31
Average Trade Size	1,137.98	465.67	751.34	1,088.48	1,478.33	444.57	214.21	273.64	420.52	606.47

	Panel C: Exmo					Panel D: Kraken				
	Mean	Std. Dev.	P25	Median	P75	Mean	Std. Dev.	P25	Median	P75
Volume (Euro) (millions)	0.78	0.57	0.26	0.79	1.07	48.37	631.56	6.21	12.10	18.10
Market Share (Euro)	0.01	0.01	0.01	0.01	0.02	0.74	0.18	0.71	0.80	0.85
Volume (BTC) (thousands)	0.16	0.06	0.12	0.16	0.19	4.32	4.73	2.17	2.82	3.86
Market Share (BTC)	0.01	0.01	0.01	0.01	0.02	0.74	0.17	0.71	0.80	0.85
Price (Euro)	4,838.66	3,101.26	2,440.24	4,005.39	6,379.96	16.70	21.49	5.12	9.93	17.98
σ	5.33	6.16	2.14	3.51	5.71	1.07	0.97	0.39	1.05	1.65
BASp (x100)	0.68	0.38	0.50	0.59	0.72	0.00	0.00	0.00	0.00	0.00
Trades Per Day (thousands)	1.71	1.65	0.63	1.24	2.27	68.61	54.96	38.29	52.84	78.79
Market Share (Trades Per Day)	0.03	0.02	0.01	0.02	0.03	0.83	0.10	0.79	0.87	0.90
Average Trade Size	636.08	435.41	343.24	534.33	830.18	1,831.53	15,625.74	739.19	1,027.45	1,358.66

Panel A: USD ($)



Panel B: Euro (€)

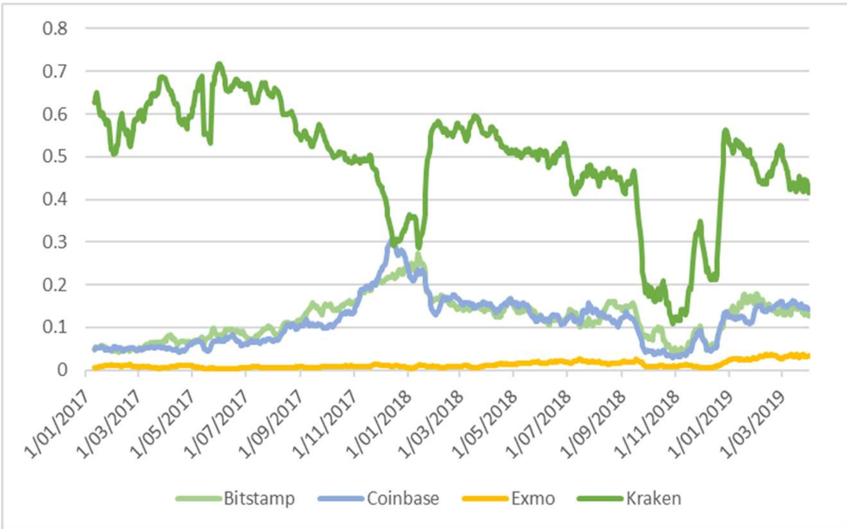


Figure 1-4 - Market Share (Exchange)

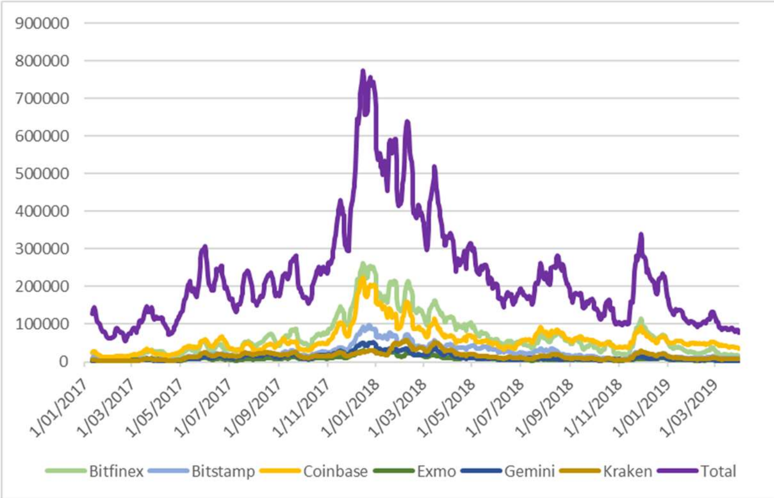
This graph displays exchange market share data. Market Share (MS) is the exchange-specific market share, measured as a proportion of total volume. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Individual exchange data is displayed. Displayed results are based on a 10-day moving average.

In both Panels A and B of Figure 4, the dominant exchange maintains dominance over the sample period. Within the USD market the dominant exchange, Bitfinex, experiences some significant loss in market share during the middle of 2017 but begins to recover and reassert its dominance towards the end of July 2017. During this mid-2017 period, all non-dominant sampled exchanges attract additional liquidity and build market share. Figure 4 provides support for the notion that competing exchanges in the USD market can entice customers to migrate from the dominant exchange, Bitfinex, to their order books. This pattern repeats itself over the 2019 period where Bitfinex begins to lose market share while competing exchanges increase their market share of the trading volume. Towards March of 2019, the market shares for both Bitfinex and Coinbase converge indicating an increase in fragmentation as traders move away from a single dominant exchange.

A similar pattern is seen in the Euro market. While the dominant exchange, Kraken, maintains its dominance over the sample period, it does temporarily lose significant market share to Bitstamp and Coinbase around the end of 2017/start of 2018. However, as previously mentioned, Kraken loses significant market share toward the end of 2018. But traders preferred to move to out-of-sample exchanges during this period as indicated in Figure 4 where we see a decrease in market share for Kraken, while the market shares for Bitstamp and Coinbase remain fairly constant. In summary, the USD market is converging with competing exchanges able to attract liquidity way from the dominant exchange, Bitfinex, while the Kraken is able to sustain its dominance over the Euro market.

While Bitfinex and Kraken dominate their respective market in terms of daily trading volume, data on the number of daily transactions illustrates a more competitive landscape. In the USD market Coinbase is competing with Bitfinex regarding the number of daily transactions. On average, Bitfinex executes 25.9% daily transactions while Coinbase executes 27.2%. However, given that the average transaction size of $1,152 is significantly smaller for Coinbase when compared to $2,563 for Bitfinex, Bitfinex is able to maintain its position as the top USD/BTC exchange by volume (Table 1-3).

Panel A: USD ($)



Panel B: Euro (€)

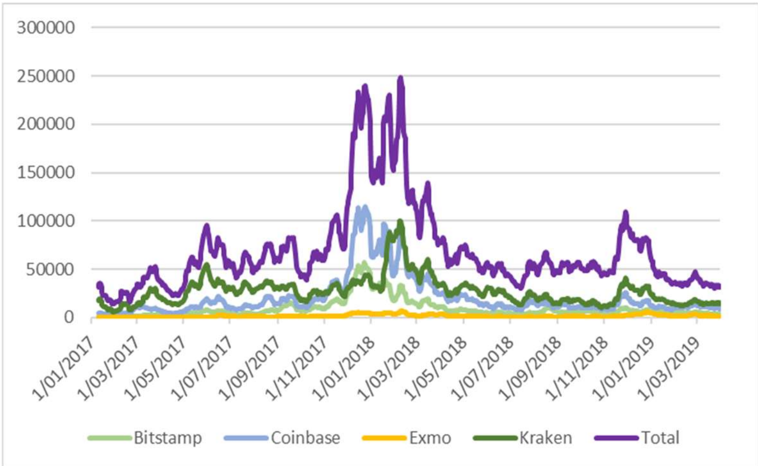


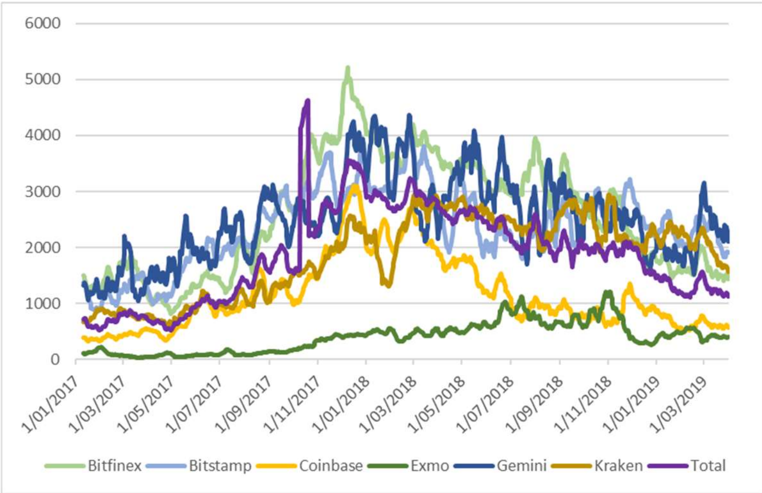
Figure 1-5 - Number of Daily Trades by Exchange

This graph displays information on the number of daily Bitcoin (BTC) transactions. The total number of BTC transactions and consists of both in and out-of-sample exchanges. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Individual exchange data is displayed along with the total volume which includes out-of-sample exchanges. The displayed results are based on a 10-day moving average.

Once again, the analysis shows a more dominant relationship in the Euro market. Kraken dominates by daily transactional volume and is also able to transact 83% of all Euro/BTC trades over the sample period. The next best result comes from Coinbase who transact roughly 26.3% of all transactions, according to Table 1-3. However, while Coinbase executes the second largest number of transactions, it also executes the smallest transaction, on average, of €444. Even

Exmo, who is only responsible for 2.5% of all trades, has an average trade size of €636. In the Euro market Bitstamp and Coinbase both attract roughly 12% of all Euro volume. However, Bitstamp attracts fewer larger transactions while Coinbase is responsible for executing a greater number of smaller transactions. These results are further supported by Figure 6.

Panel A: USD ($)



Panel B: Euro (€)

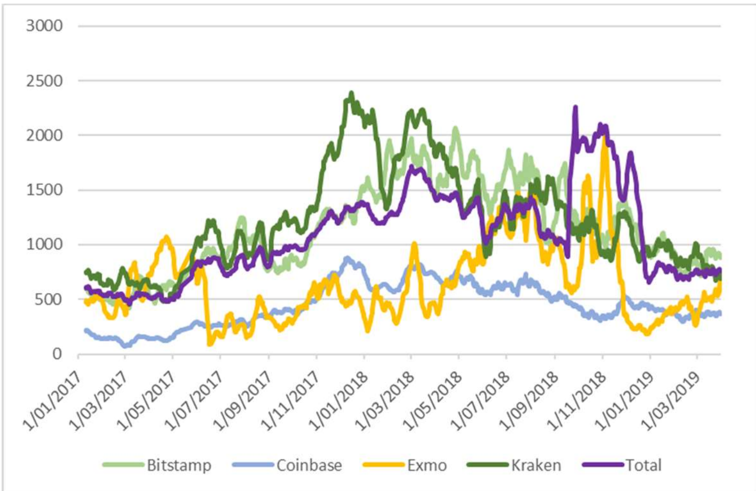


Figure 1-6 - Average Trade Size by Exchange

This graph displays information on the average sizes of transactions. Average Trade Size (USD/Euro) is the average size of each transaction, measured in its respective currency (USD/Euro). Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Individual exchange data is displayed along with the total market which includes out-of-sample exchanges. The displayed results are based on a 10-day moving average.

Table 1-4 and Table 1-5 report results regarding the correlations amongst the independent variables in the study for USD and Euro markets, respectively. When looking at the key fragmentation measures, Frag and Frag (Others), it is evident that the exchanges in the study have a significant impact on the microstructure of the Bitcoin market within their respective currency's order book. Correlation coefficients closer to zero identify order books that are less dominant by a single exchange. Table 1-4 Panel A reports a correlation coefficient of 0.68 while Table 1-6 Panel A reports a result of 0.59. The exchange specific correlation coefficients report that the USD and Euro order books are dominated by the Bitfinex and Kraken respectively. Correlation coefficients of -0.02 for Bitfinex and -0.05 for Kraken indicate that the overall market microstructure relies heavily on this inclusion of these exchanges within their order books. Other exchanges, if removed from the fragmentation measure, have a negligible impact on the structure of the market as indicated by their near-perfect positive correlations between Frag and Frag (Others). This is further supported by the correlation coefficients between Frag and the remaining independent variables. Table 1-4 Panel B and Table 1-5 Panel D, representing the dominant USD and Euro exchanges of Bitfinex and Kraken, respectively, display larger variations between coefficients for the two Frag measures. Less influential markets displayed in the remaining panels report only minimal differences. Additional findings pertaining to the correlation coefficients are discussed in the regression results below.

Table 1-4: Correlations (USD Exchanges)

This table contains the correlation coefficients between various measure for each USD exchange in the sample. Panel A contains correlation measures based on all USD exchanges while the remaining figures in Panels B - G contain exchange specific data. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Frag is the result of calculating 1 minus the Herfindahl-Hirschman using exchange volume data. Frag (Other) is similar to Frag except it excludes market share data for the current exchange. MS is the exchange-specific market share, measured as a proportion of total volume. σ is the average 5-minute standard deviation in basis points. BASp is the average quoted spread on the exchange. Vol is the total USD volume (reported in millions) of Bitcoin (BTC) transactions and includes both in and out-of-sample exchanges. AvgTS is the average size of each transaction in the exchange, measured in its respective currency (USD).

Panel A: All

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.68	1					
(3)	MS (USD)	-0.11	0.62	1				
(4)	σ	-0.68	-0.45	0.08	1			
(5)	BASp	0.05	-0.19	-0.46	0.02	1		
(6)	Vol	-0.67	-0.46	0.07	0.95	-0.07	1	
(7)	AvgTS	-0.26	0.05	0.45	0.34	-0.38	0.39	1

Panel B: Bitfinex

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	-0.02	1					
(3)	MS (USD)	-0.91	0.40	1				
(4)	σ	-0.69	0.01	0.65	1			
(5)	BASp	0.01	-0.13	-0.08	-0.02	1		
(6)	Vol	-0.67	0.05	0.65	0.97	-0.11	1	
(7)	AvgTS	-0.69	0.31	0.76	0.79	-0.35	0.84	1

Panel C: Bitstamp

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.99	1					
(3)	MS (USD)	0.03	0.18	1				
(4)	σ	-0.69	-0.69	-0.05	1			
(5)	BASp	-0.15	-0.15	0.01	0.28	1		
(6)	Vol	-0.67	-0.68	-0.11	0.96	0.15	1	
(7)	AvgTS	-0.59	-0.56	0.13	0.76	-0.07	0.80	1

Panel D: Coinbase

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.97	1					
(3)	MS (USD)	-0.13	0.10	1				
(4)	σ	-0.69	-0.66	0.17	1			
(5)	BASp	0.21	0.23	0.06	-0.22	1		
(6)	Vol	-0.67	-0.65	0.12	0.96	-0.33	1	
(7)	AvgTS	-0.67	-0.62	0.21	0.89	-0.29	0.92	1

Panel E: Gemini

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.99	1					
(3)	MS (USD)	0.09	0.19	1				
(4)	σ	-0.67	-0.66	-0.02	1			
(5)	BASp	0.09	0.05	-0.43	0.10	1		
(6)	Vol	-0.67	-0.67	-0.03	0.93	0.06	1	
(7)	AvgTS	-0.36	-0.34	0.23	0.57	-0.04	0.65	1

Panel F: Exmo

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	1.00	1					
(3)	MS (USD)	0.15	0.15	1				
(4)	σ	-0.67	-0.67	-0.07	1			
(5)	BASp	0.17	0.17	-0.45	-0.22	1		
(6)	Vol	-0.67	-0.67	-0.20	0.96	-0.28	1	
(7)	AvgTS	-0.21	-0.21	0.66	0.46	-0.58	0.41	1

Panel G: Kraken

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.99	1					
(3)	MS (USD)	0.05	0.13	1				
(4)	σ	-0.66	-0.66	-0.14	1			
(5)	BASp	0.06	0.02	-0.47	0.01	1		
(6)	Vol	-0.67	-0.68	-0.12	0.93	-0.14	1	
(7)	AvgTS	-0.37	-0.35	0.30	0.46	-0.67	0.58	1

Table 1-5: Correlations (Euro Exchanges)

This table contains the correlation coefficients between various measure for each USD exchange in the sample. Panel A contains correlation measures based on all Euro exchanges while the remaining figures in Panels B - E contain exchange specific data. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Frag is the result of calculating the Herfindahl-Hirschman using exchange volume data and subtracting this value from 1. Frag (Other) is similar to Frag except it excludes market share data for the current exchange. MS is the exchange-specific market share, measured as a proportion of total volume. σ is the average 5-minute standard deviation in basis points. BASp is the average quoted spread on the exchange. Vol is the total Euro volume (reported in millions) of Bitcoin (BTC) transactions and includes both in and out-of-sample exchanges. AvgTS is the average size of each transaction in the exchange, measured in its respective currency (Euro).

Panel A: All

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.59	1					
(3)	MS (Euro)	-0.18	0.66	1				
(4)	σ	-0.02	-0.05	0.01	1			
(5)	BASp	-0.24	-0.38	-0.36	0.12	1		
(6)	Vol	0.18	0.11	0.01	0.84	-0.07	1	
(7)	AvgTS	0.15	0.41	0.44	0.39	-0.02	0.36	1

Panel B: Bitstamp

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.99	1					
(3)	MS (Euro)	-0.02	0.10	1				
(4)	σ	0.00	0.08	0.67	1			
(5)	BASp	-0.52	-0.53	-0.23	-0.07	1		
(6)	Vol	0.18	0.24	0.48	0.86	-0.17	1	
(7)	AvgTS	0.17	0.23	0.57	0.71	-0.47	0.70	1

Panel C: Coinbase

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.99	1					
(3)	MS (Euro)	-0.01	0.13	1				
(4)	σ	-0.08	0.02	0.69	1			
(5)	BASp	-0.56	-0.57	-0.27	-0.13	1		
(6)	Vol	0.18	0.26	0.49	0.84	-0.26	1	
(7)	AvgTS	0.21	0.30	0.72	0.79	-0.51	0.73	1

Panel D: Exmo

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	1.00	1					
(3)	MS (Euro)	0.32	0.33	1				
(4)	σ	0.06	0.06	-0.18	1			
(5)	BASp	-0.53	-0.53	-0.46	0.02	1		
(6)	Vol	0.18	0.18	-0.36	0.85	-0.09	1	
(7)	AvgTS	0.33	0.33	0.26	-0.11	-0.02	-0.08	1

Panel E: Kraken

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	-0.05	1					
(3)	MS (Euro)	-0.96	0.21	1				
(4)	σ	-0.04	-0.68	-0.07	1			
(5)	BASp	-0.50	-0.13	0.41	0.18	1		
(6)	Vol	0.18	-0.51	-0.32	0.85	0.04	1	
(7)	AvgTS	0.01	-0.63	-0.11	0.85	0.01	0.79	1

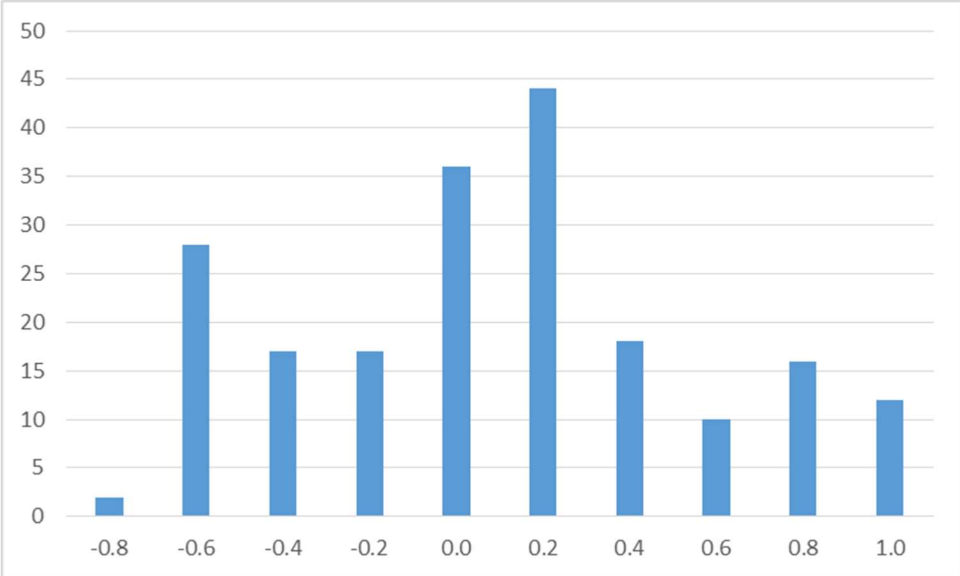


Figure 1-7 - Correlation Coefficient Distribution

This figure contains a histogram of correlation coefficients found in Table 1-4 and Table 1-5. Correlation coefficients are grouped into categories that are 0.2 wide. The x-axis label indicates the maximum allowable value for each category. Note that correlations = 1 where parameters are compared against themselves are removed from this figure.

Figure 7 groups all the correlation coefficients in the study. It ignores any correlations between *Frag* and *Frag (Others)* as the measures are constructed in a similar fashion and often result in (nearly) perfect positive correlations. Note that the majority of variable pairs are not highly correlated with each other. However, there is a subset of variables with higher correlations.

6.2 Fragmentation and Price Discovery

This section reports on the results of the fragmentation and price discovery measures that form the basis for this study. Panel A in Table 1-5 indicates that the microstructure of the USD Bitcoin market has remained consistent over the study period. Frag is reported as 0.8 across the entire sample period while the first and second half Frag measures are reported to be 0.79 and 0.8, respectively. This is evidence that the overall level of competition is constant across the sample period and that no major fragmenting events occurred caused by one exchange growing in popularity relative to its competitors. This is further supported by the Market Share (MS) measures in Table 1-5 Panel A which also remain stable at 0.13 and 0.14.

However, the Euro Bitcoin markets, whose fragmentation measures are presented in Panel B of Table 1-5**Error! Reference source not found.**, show that microstructure of the market is not constant over the sample period. Fragmentation (*Frag*) across the sample period is reported to be 0.7 while the same measure is reported to be 0.64 and 0.76 over the first and second half of the sample period, respectively. The increase in Frag over time is representative of an increase in fragmentation throughout the sample period. The *MS* further supports this finding results in Table 1-6 Panel B which show that, on average, each exchange captures 18% of the total transactional volume while first and second half measures again support an increase in fragmentation with *MS* results of 0.2 and 0.17, respectively. This is further proof that transactional volume moved away from the dominant exchange, Kraken. Over time, European investors begin to favour satellite exchanges and the market becomes less centralised around a single dominant exchange.

Table 1-6: Market Fragmentation Measures

This table reports the means, standard deviations, and medians as well as the first (P25) and third (P75) quartiles of the fragmentation measures used in the study. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated using all transactions in a single currency over a single trading day. 'Sample – All' contains results over the entire sample period (1 January 2017 to 31 March 2019) while 'Sample – First Half' and 'Sample – Second Half uses data from 1 January 2017 to 14 February 2018 and 15 February 2018 to 31 March 2019, respectively. Frag is the result of calculating the Herfindahl-Hirschman using exchange volume data and subtracting this value from 1. All exchanges reference the same 'Frag' figure for a given transaction day. MS is the exchange-specific market share, measured as a proportion of total volume.

Panel A: USD ($)

	Mean	Std. Dev.	P25	Median	P75
1-HHI					
Sample - All	0.797	0.063	0.748	0.806	0.843
Sample - First Half	0.795	0.071	0.733	0.806	0.850
Sample - Second Half	0.800	0.053	0.765	0.806	0.833
Market Share (USD)					
Sample - All	0.135	0.125	0.046	0.107	0.172
Sample - First Half	0.135	0.127	0.044	0.109	0.171
Sample - Second Half	0.135	0.123	0.048	0.106	0.173

Table 1-6: Market Fragmentation Measures - continued

Panel B: Euro (€)

	Mean	Std. Dev.	P25	Median	P75
1-HHI					
Sample - All	0.701	0.122	0.624	0.693	0.756
Sample - First Half	0.639	0.093	0.566	0.642	0.711
Sample - Second Half	0.763	0.116	0.682	0.733	0.828
Market Share (Euro)					
Sample - All	0.185	0.202	0.031	0.115	0.226
Sample - First Half	0.198	0.226	0.017	0.090	0.297
Sample - Second Half	0.172	0.173	0.034	0.126	0.179

The consistency in the USD Bitcoin market can partly be explained by the fact that there is no single dominant USD exchange. Table 1-2, Panel A reports Bitfinex as being the dominant USD Bitcoin exchange with a market share of 37% while Table 1-3 Panel D reports Kraken as the dominant Euro exchange with an average market share of 74%. As a result, there is more room for the evolution of the Euro market where competing exchanges can attract investors from the dominant exchange. Competition amongst USD exchanges is more realised upon the opening dates in the sample periods. This is further supported by the *Frag* measures in Table 1-6 which indicate more competition amongst USD exchanges compared to Euro exchanges, as indicated by the higher *Frag* value.

Upon initial analysis the information shares (IS) results contained in support the previous notion that the USD Bitcoin market is less centralised than the Euro Bitcoin market. Table 1-7, Panel A reports that on average USD exchanges individually contain 17% of all price adjusting information while Panel B reports that individual Euro exchanges contribute 25% of all price adjusting information. This is further supported by the individual exchange IS measures. Three of the six USD exchanges contain informational content in the double figures, ranging from 0.15 to 0.52. Coinbase is a US-based exchange and is the leading informational source of US/BTC price information. The majority of price adjusting information in the Euro Bitcoin market, however, originates from the Kraken exchange which boasts an IS of 0.85. Kraken, which is headquartered in Europe, is also the only Euro exchange whose informational content reaches double figures. The remaining exchange, Bitstamp, Coinbase and Exmo represent only 7%, 6%, and 2% of the informational content, respectively, in the Euro Bitcoin market.

This provides support for H1-1 and indicated that no single exchange is responsible for advertising all price-relevant information. It also provides support for H1-4 in that the leading source of price adjusting information for a particular fiat currency/BTC pair are exchanges that are headquartered in the country where that fiat currency originates.

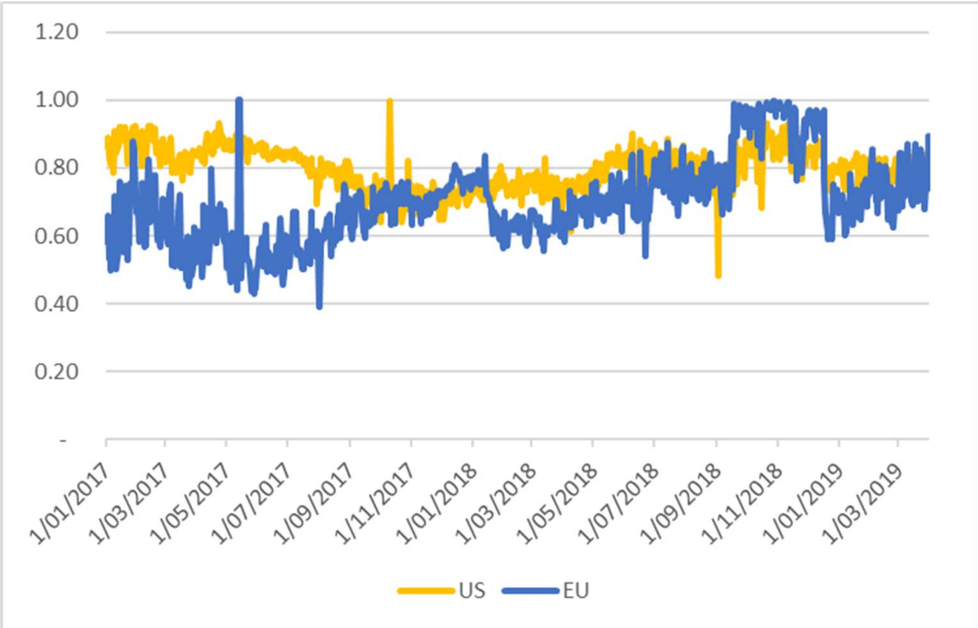


Figure 1-8 – Intra-Market Fragmentation (Bitcoin)

This graph displays the fragmentation levels of both USD and Euro markets. Fragmentation (Frag) is the result of calculating the Herfindahl-Hirschman using exchange volume data and subtracting this value from 1Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019).

Figure 8 provides a visual representation of the change in market microstructure across USD and Euro order books. While both USD and Euro markets show inter-day variability in the level of fragmentation within their respective order books, the USD market shows greater consistency in the level of fragmentation while the overall upward trend in the Euro market measure of fragmentation indicated greater fragmentation over time as Kraken loses some of its dominance over the sample period.

Table 1-7: Information Share

This table reports values for Hasbrouck's (1995) information share (IS) for each exchange (Bitfinex, Bitstamp, Coinbase, Exmo, Gemini and Kraken). It reports means, standard deviations, and medians as well as the first (P25) and third (P75) quartile value. Results are calculated for each exchange over a single trading day over the sample period (1 January 2017 to 31 March 2019). Panels A and B contain IS data based on order books and transactions conducted in USD ($) and Euro (€), respectively. All consists of data from each exchange operating under its respective currency.

Panel A: USD ($)

	Mean	Std. Dev.	P25	Median	P75
All	0.167	0.178	0.034	0.080	0.233
Bitfinex	0.518	0.058	0.486	0.523	0.558
Bitstamp	0.153	0.030	0.133	0.150	0.171
Coinbase	0.236	0.041	0.211	0.233	0.257
Exmo	0.011	0.002	0.010	0.011	0.013
Gemini	0.039	0.009	0.034	0.038	0.044
Kraken	0.041	0.010	0.035	0.041	0.047

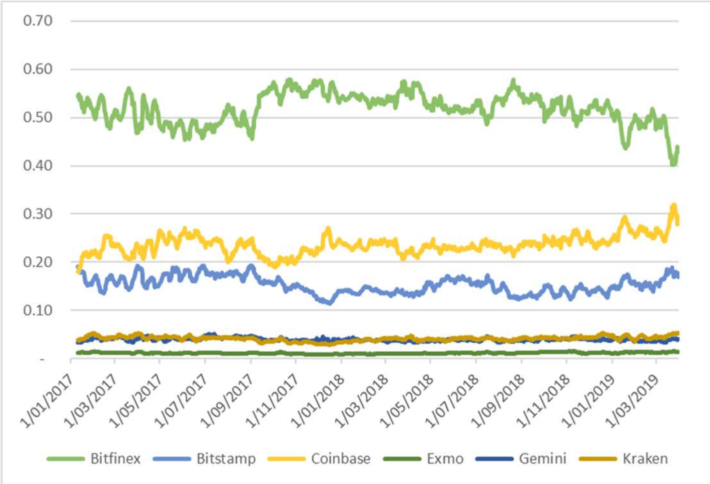
Panel B: Euro (€)

	Mean	Std. Dev.	P25	Median	P75
All	0.250	0.349	0.034	0.061	0.367
Bitstamp	0.068	0.027	0.052	0.063	0.077
Coinbase	0.061	0.021	0.047	0.058	0.070
Exmo	0.021	0.008	0.015	0.018	0.023
Kraken	0.851	0.050	0.833	0.861	0.880

Figure

provides further support for the centralisation of information in the Euro Bitcoin market. USD IS data contained in Panel A shows a greater dispersion of price adjusting information while Panel B shows that this information is more concentrated around a single exchange, Kraken.

Panel A: USD ($)



Panel B: Euro (€)

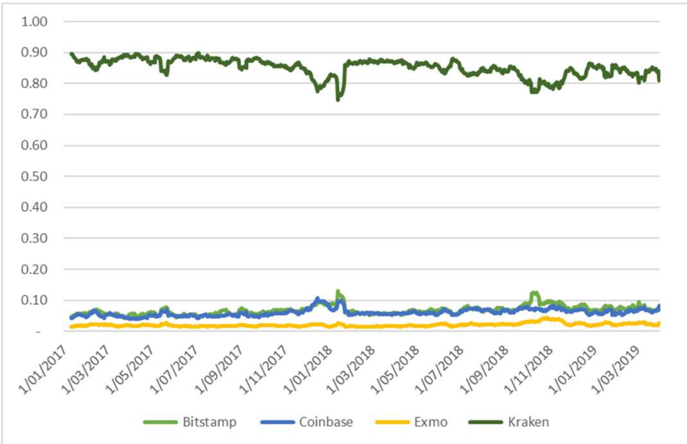


Figure 1-9 - Information Share by Exchange

This graph displays the values for Hasbrouck's (1995) information share (IS) for each exchange (Bitfinex, Bitstamp, Coinbase, Exmo, Gemini and Kraken). Results are calculated for each exchange over a single trading day over the sample period (1 January 2017 to 31 March 2019). Panels A and B contain IS data based on order books and transactions conducted in USD ($) and Euro (€), respectively. The displayed results are based on a 10-day moving average.

6.3 Regression Results

This section reports on the results of the regression analysis conducted in this study. Regression results are found in Table 1-8 to Table 1-10 with Panels A and B containing results for USD and Euro order books, respectively. Beginning with the market share (MS) measure, the results support H1-2 in that increased market share for an exchange is positively related with an increase in the informational contents of the respective exchange's trades. Coefficients range from 0.05 to 0.685 in Panels A and B of Table 1-8.

Table 1-8: Regression Results (No Fixed Effects)

*This table contains the results of the panel regression analysis with no fixed effects. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated for each exchange using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Frag is the result of calculating the Herfindahl-Hirschman using exchange volume data and subtracting this value from 1. MS is the exchange-specific market share, measured as a proportion of total volume. σ is the average 5-minute standard deviation in basis points. BASp is the average quoted spread on the exchange. Vol is the total USD/Euro volume (reported in millions) of Bitcoin (BTC) transactions and includes both in and out-of-sample exchanges. AvgTS is the average size of each transaction in the exchange, measured in its respective currency (USD/Euro). σ, BASp, Vol and AvgTS have been transformed using the natural logarithm (ln). T-statistics can be found in parentheses below each regression coefficient. *,** and *** identify results of 90%, 95%, and 99% statistical significance, respectively. Information on the relevant fixed effects, adjusted R^2 and number of observations are also reported.*

Panel A: USD ($)

	Bitfinex	Bitstamp	Coinbase	Exmo	Gemini	Kraken
Constant	-0.158	-0.027	-0.155	-0.007	0.112	0.136
	(-1.15)	(-0.41)	(-1.7) *	(-1.06)	(7.06) ***	(7.52) ***
Frag	0.445	0.115	0.178	0.009	0.051	0.047
	(6.43) ***	(6.31) ***	(6.41) ***	(5.98) ***	(7.66) ***	(7.6) ***
MS	0.610	0.372	0.460	0.205	0.050	0.059
	(11.86) ***	(13.35) ***	(14.5) ***	(6.99) ***	(5.12) ***	(5.36) ***
σ	-0.004	-0.005	-0.005	-0.001	0.008	0.007
	(-0.66)	(-1.37)	(-1.09)	(-1.96) **	(10.67) ***	(8.47) ***
BASp	0.006	0.015	-0.001	0.002	-0.001	0.000
	(3.19) ***	(8.3) ***	(-1.57)	(4.41) ***	(-3.67) ***	(-0.38)
Vol	0.002	-0.001	0.015	0.000	-0.007	-0.008
	(0.29)	(-0.22)	(2.73) ***	(0.75)	(-9.06) ***	(-9.18) ***
AvgTS	0.008	0.004	-0.016	0.000	0.003	0.002
	(0.81)	(0.91)	(-2.76) ***	(0.31)	(3.45) ***	(1.99) **
Fixed Effects	None	None	None	None	None	None
Adjusted R^2	0.340	0.364	0.236	0.327	0.244	0.272
N	820	820	820	820	820	820

Table 1-8: Regression Results (No Fixed Effects) - continued

Panel B: Euro (€)

	Bitstamp		Coinbase		Exmo		Kraken	
Constant	-0.164		-0.038		-0.105		-0.325	
	(-2.52)	**	(-0.68)		(-1.56)		(-1.92)	*
Frag	0.176		0.092		0.168		0.495	
	(12.92)	***	(6.67)	***	(12.02)	***	(5.68)	***
MS	0.356		0.314		0.552		0.685	
	(10.04)	***	(9.61)	***	(2.66)	***	(9.35)	***
σ	-0.016		-0.003		-0.011		0.006	
	(-4.42)	***	(-0.82)		(-3.55)	***	(1.18)	
BASp	0.026		0.008		0.021		0.013	
	(5.84)	***	(5.56)	***	(4.27)	***	(3.73)	***
Vol	0.005		0.009		0.004		0.003	
	(1.63)		(2.87)	***	(1.19)		(0.5)	
AvgTS	0.011		-0.001		0.001		-0.007	
	(2.01)	**	(-0.22)		(0.65)		(-0.75)	
Fixed Effects	None		None		None		None	
Adjusted R^2	0.255		0.255		0.239		0.411	
N	820		820		820		820	

The results are also robust for time fixed effects as shown in Panels A and B of Table 1-9, where coefficients range from 0.081 to 0.619. The results with time fixed effects in Table 1-9 are significant at the 1% level across all exchanges in both the USD and Euro markets, except for the Exmo Euro exchange. USD markets show greater consistency in the reported MS coefficients. More dominant USD exchanges with a greater market share of the transactional volume, such as Bitfinex and Bitstamp, are more likely to attract informed trades than less dominant exchanges. These results can be supported by the works of (Chowdhry & Nanda, 1991) who find that informed traders find greater difficulty participating in exchanges with less transactional volume.

These results are consistent with informed investors transacting in a dark pool experience a lower probability of execution and must return to the displayed order book to locate a counterparty to the transaction in a timely fashion. Informed investors are more likely to transact on the same side of the order book and therefore require a greater pool of uninformed traders with whom they can trade. Exchanges with lower levels of trading volume will have lower levels of uninformed trading activity. This results in less informational content to their trades as informed investors migrate to more liquid exchanges where the risk of finding a counterparty to the transaction is reduced. However, some informed trading will always follow the uninformed investors. Therefore, the results support hypothesis 1-2 and are consistent with the notion that greater market share is positively correlated with greater informational content in trades as there are more uninformed traders with whom the informed can transact. The results are also consistent with the idea that the informational content of transactions on more liquid exchange, that is those who capture a greater market share of transaction, is more sensitive to increases in market share. Increased sensitivity occurs as their large pool of uninformed investors is more likely to attract additional informed trade given the already greater probability of execution on these exchange.

Overall market microstructure, as measured by Frag, has a positive relationship with the informational content of an exchange's transactions. This result is indicated by the positive regression coefficients for Frag across all sampled exchanges in both USD and Euro Bitcoin markets. Regression coefficients range from 0.01 to 0.495 in Table 1-8 and Table 1-9 and are consistently significant at the 1% level. These findings support H1-3 in that the increased fragmentation of order books is positively related to increases in the informational content of an exchange's trades. The results can be explained by the theory presented by Mendelson (1987) who propose that smaller exchanges have difficulty in attracting informed activity without a sufficient pool of uninformed trades with which the informed can interact. Therefore, greater fragmentation leads to the migration of uninformed traders to the new exchanges. While some informed activity can follow the uninformed to the new exchanges, once again the level of uninformed activity is not enough to support these trades. The lack of support is due to an insufficient number of counterparties to the informed trades at the desired price level. This is consistent with the previous findings for MS which report that while increased market share does lead to more informed activity on an exchange, the increase in informational content in lower for less liquid exchanges due to their lower levels of uninformed trading compared to more dominant exchanges.

The lower *Frag* coefficients for less liquid exchanges such as Exmo also supports the notion that these exchanges find it more difficult to locate a counterparty for the informed traders when compared to more liquid exchanges (Mendelson, 1987). So when markets fragment and smaller exchanges entice some investors to transact in their order books, the increases in fragmentation they cause can support some level of informed trading activity, though not as must as more liquid exchanges. But once again, these smaller exchanges largely attract uninformed traders.

Table 1-9: Regression Results (Time Fixed Effects)

*This table contains the results of the panel regression analysis with time fixed effects. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated for each exchange using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Frag is the result of calculating the Herfindahl-Hirschman using exchange volume data and subtracting this value from 1. MS is the exchange-specific market share, measured as a proportion of total volume. σ is the average 5-minute standard deviation in basis points. BASp is the average quoted spread on the exchange. Vol is the total USD/Euro volume (reported in millions) of Bitcoin (BTC) transactions and includes both in and out-of-sample exchanges. AvgTS is the average size of each transaction in the exchange, measured in its respective currency (USD/Euro). σ, BASp, Vol and AvgTS have been transformed using the natural logarithm (ln). T-statistics can be found in parentheses below each regression coefficient. *,** and *** identify results of 90%, 95%, and 99% statistical significance, respectively. Information on the relevant fixed effects, adjusted R^2 and number of observations are also reported.*

Panel A: USD ($)

	Bitfinex	Bitstamp	Coinbase	Exmo	Gemini	Kraken
Constant	-0.237	-0.079	-0.151	-0.002	0.133	0.148
	(-1.32)	(-1.08)	(-1.54)	(-0.29)	(7.44) ***	(7.59) ***
Frag	0.439	0.132	0.180	0.011	0.050	0.045
	(4.31) ***	(6.08) ***	(5.43) ***	(5.59) ***	(6.57) ***	(6.04) ***
MS	0.619	0.399	0.430	0.185	0.081	0.083
	(9.2) ***	(11.34) ***	(8.64) ***	(5.59) ***	(6.04) ***	(5.42) ***
σ	-0.009	-0.011	-0.009	0.000	0.008	0.007
	(-1.23)	(-2.66) ***	(-1.81) *	(-1.15)	(10.88) ***	(7.4) ***
BASp	0.019	0.023	0.005	0.002	-0.002	-0.001
	(3.39) ***	(6.83) ***	(3.09) ***	(4.06) ***	(-4.35) ***	(-0.52)
Vol	-0.002	0.000	0.010	0.000	-0.008	-0.008
	(-0.25)	(0.004)	(1.708) *	(-0.045)	(-9.38) ***	(-8.882) ***
AvgTS	0.025	0.003	-0.005	0.000	0.002	0.001
	(2.21) **	(0.58)	(-0.64)	(-1.45)	(2.44) **	(1.01)
Fixed Effects	Time	Time	Time	Time	Time	Time
Adjusted R^2	0.347	0.382	0.249	0.334	0.265	0.277
N	820	820	820	820	820	820

Table 1-9: Regression Results (Time Fixed Effects) - continued

Panel B: Euro (€)

	Bitstamp	Coinbase	Exmo	Kraken
Constant	-0.159	-0.002	0.001	-0.145
	(-2.2) **	(-0.04)	(0.02)	(-0.79)
Frag	0.161	0.093	0.140	0.404
	(8.47) ***	(4.85) ***	(7.74) ***	(4.22) ***
MS	0.347	0.342	0.012	0.604
	(7.58) ***	(7.54) ***	(0.04)	(7.72) ***
σ	-0.017	0.000	0.002	0.010
	(-3.46) ***	(-0.05)	(0.44)	(1.34)
BASp	0.032	0.008	0.019	0.010
	(4.88) ***	(4.31) ***	(3.31) ***	(1.28)
Vol	0.004	0.005	-0.003	-0.001
	(1.02)	(1.617)	(-0.91)	(-0.159)
AvgTS	0.011	0.002	0.007	-0.006
	(1.71) *	(0.3)	(2.72) ***	(-0.61)
Fixed Effects	Time	Time	Time	Time
Adjusted R^2	0.255	0.260	0.286	0.418
N	820	820	820	820

Since these less liquid order books attract more uninformed traders and informed ones from other displayed order book, the concentration of informed to uninformed investors increases in the dominant exchange, supporting both H1-2 and H1-3. This dilution in informed trading means that major exchanges like Bitfinex in the U.S. and Kraken in Europe lose more uninformed than informed order flow. As a result of the increased concentration of informed traders, the informational content of trading activity in the dominant exchange increases by a greater amount than their less liquid competitors. This, again, supports the findings in this study which reports consistently higher Frag regression coefficients for exchanges with higher market shares than those with smaller market shares. Even with a loss in market share, more liquid exchanges are still able to support larger degrees of informed trading due to their significant uninformed trading pool.

However, the increase in the informational content of exchanges resulting from increased fragmentation does not come without a cost. Greater informed trading on an exchange is consistent with greater levels of information asymmetry (Chowdhry & Nanda, 1991; Madhavan, 1995).

Table 1-10: Regression Results (Time Fixed Effects & Frag (Other))

*This table contains the results of the panel regression analysis with time fixed effects and using an alternative measure of intra-market fragmentation, Frag (Other). Frag (Other) is the result of calculating the Herfindahl-Hirschman using exchange volume data and subtracting this value from 1. Frag (Other) is similar to Frag except it excludes market share data for the current exchange. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated for each exchange using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). MS is the exchange-specific market share, measured as a proportion of total volume. σ is the average 5-minute standard deviation in basis points. BASp is the average quoted spread on the exchange. Vol is the total USD/Euro volume (reported in millions) of Bitcoin (BTC) transactions and includes both in and out-of-sample exchanges. AvgTS is the average size of each transaction in the exchange, measured in its respective currency (USD/Euro). σ, BASp, Vol and AvgTS have been transformed using the natural logarithm (ln). T-statistics can be found in parentheses below each regression coefficient. *,** and *** identify results of 90%, 95%, and 99% statistical significance, respectively. Information on the relevant fixed effects, adjusted R^2 and number of observations are also reported.*

Panel A: USD ($)

	Bitfinex	Bitstamp	Coinbase	Exmo	Gemini	Kraken
Constant	-0.284	-0.074	-0.139	-0.002	0.133	0.148
	(-1.6)	(-1.02)	(-1.43)	(-0.28)	(7.44) ***	(7.61) ***
Frag (Other)	0.608	0.132	0.179	0.011	0.050	0.045
	(4.76) ***	(6.13) ***	(5.43) ***	(5.59) ***	(6.52) ***	(6.07) ***
MS	0.279	0.362	0.367	0.184	0.071	0.076
	(7.93) ***	(9.87) ***	(6.94) ***	(5.58) ***	(5.13) ***	(4.97) ***
σ	-0.003	-0.010	-0.009	0.000	0.008	0.007
	(-0.41)	(-2.61) ***	(-1.76) *	(-1.14)	(10.87) ***	(7.41) ***
BASp	0.018	0.023	0.005	0.002	-0.002	-0.001
	(3.22) ***	(6.82) ***	(3.07) ***	(4.06) ***	(-4.37) ***	(-0.55)
Vol	-0.004	0.000	0.010	0.000	-0.008	-0.008
	(-0.55)	(-0.036)	(1.635)	(-0.047)	(-9.354) ***	(-8.89) ***
AvgTS	0.024	0.003	-0.004	0.000	0.002	0.001
	(2.09) **	(0.6)	(-0.58)	(-1.44)	(2.49) **	(1.03)
Fixed Effects	Time	Time	Time	Time	Time	Time
Adjusted R^2	0.351	0.382	0.249	0.334	0.265	0.277
N	820	820	820	820	820	820

Table 1-10: Regression Results (Time Fixed Effects & Frag (Other)) - continued

Panel B: Euro (€)

	Bitstamp	Coinbase	Exmo	Kraken
Constant	-0.151	0.003	0.002	-0.093
	(-2.1) **	(0.05)	(0.03)	(-0.58)
Frag (Other)	0.160	0.095	0.140	0.616
	(8.57) ***	(5.06) ***	(7.74) ***	(4.82) ***
MS	0.295	0.307	0.005	0.238
	(6.36) ***	(6.53) ***	(0.02)	(8.87) ***
σ	-0.017	0.000	0.002	0.021
	(-3.38) ***	(0.05)	(0.44)	(2.79) ***
BASp	0.032	0.008	0.019	0.011
	(4.82) ***	(4.29) ***	(3.31) ***	(1.47)
Vol	0.003	0.005	-0.003	-0.016
	(0.91)	(1.446)	(-0.914)	(-2.696) ***
AvgTS	0.012	0.003	0.007	0.002
	(1.81) *	(0.43)	(2.72) ***	(0.22)
Fixed Effects	Time	Time	Time	Time
Adjusted R^2	0.256	0.262	0.286	0.422
N	820	820	820	820

As a result, fragmentation negatively impacts the uninformed investors as the informed take advantage of satellite exchanges to cream-skim the most profitable orders, leaving behind trades executing at less favourable prices. This notion of cream-skimming is consistent with results reported Easley et al. (1996) and Bessembinder and Kaufman (1997). Regression results show that an exchange's information share is positively related to its bid-ask spread. The concentration of informed activity, and the resulting increase in information asymmetry, lead to wider bid-ask spreads as investors attempt to protect themselves against increased risk resulting from exposure to more investors with superior information.

Table 1-11 provides additional support for the H1-2 and H1-3. It contains a variant of the *Frag* measure, *Frag (Other),* which measures fragmentation in the market using only competing BTC exchanges. Therefore, it excludes the impact that the current exchange has on the structure of the market. Once again, *MS* coefficients are positive and range from 0.071 to 0.367 across USD and Euro exchanges. All coefficients are significant at the 1% level except for the European Exmo order book. Due to this, the European Exmo coefficient is excluded from the reported *MS* coefficients above. *Frag(Other)* coefficients are all positive and range from 0.011 to 0.616. Once again, the coefficients for *MS* and *Frag (Other)* are larger for more active exchanges.

The results of the hypothesis testing are summarised in Table 11. In summary, increased market fragmentation either leads to an increase in the concentration of informed investors on the dominant exchange or the introduction of informed investors on smaller satellite exchanges. As a result, investors can no longer look towards a single exchange to gather all relevant price adjusting information. Further, the process of price discovery which entails forming an accurate opinion of price levels becomes more difficult as a market becomes more fragmented. Investors protect themselves against the risk of information asymmetry and adverse selection by widening bid-ask spreads, leading to a degeneration of market quality factors such as bid-ask spreads. The widening of bid-ask spreads is seen as a negative outcome to fragmentation as it increased the cost of a round-trip transaction for investors.

Table 1-11: Summary of Hypothesis Testing and Results

Hypothesis	Result Table	Conclusion
H1-1: When multiple exchanges offer the ability to transact in the same asset, price adjusting information is spread across multiple exchanges and does not originate from a single source.	1-8**Error! Reference source not found.**	Accept
H1-2: Market share is positively related to the informational content of prices on an exchange.	1-9 1-10 1-11	Accept
H1-3: Market fragmentation is positively related to the informational content of prices on an exchange.	1-9 1-10 1-11	Accept
H1-4: USD (Euro) exchanges contribute more information to USD (Euro) transactions than Euro (USD) transactions.	1-8**Error! Reference source not found.**	Accept

7.0 Discussion and Future Research

This research implies that increased competitive market fragmentation results in the degradation of an investor's ability to formulate accurate prices. With price-adjusting information spread across multiple exchanges, gathering all the information necessary to construct accurate prices becomes more difficult and costly. This means that investors trading in consolidated markets, where the number of exchanges in which they can transact is kept to a minimum, will find it easier to identify and incorporate information contained within transaction prices.

Since consolidated markets are more efficient and more accurately convey prices that resemble the true value of the assets, they are more supportive of uninformed trading. This means that less sophisticated investors will find it easier to trade in consolidated markets since the advertised prices in these markets are more accurate. However, more sophisticated and informed investors will find it more profitable to trade in fragmented markets. Fragmented markets make it easier for informed investors to conceal the intentions behind their trades. Protecting private information is important to informed investors as it provides them with compensation for taking on the responsibility of gathering costly information. Since it is more difficult to distinguish between superior information and noise in fragmented markets, informed investors can use these markets to better leverage their superior information.

The results surrounding market fragmentation are also important from a regulatory standpoint. Recent regulatory changes in Europe, such as the Markets in Financial Instruments Directive (MiFID), have a significant influence on the level of competitive market fragmentation. European equity market investors are increasingly relying on alternatives to the primary exchange, such as multilateral trading facilities (MTFs), to conduct transactions. Many of these venues report the results of successful transactions independently. Very few exchanges, most notably dark pools, report their transactions to a central consolidated tape. This makes collecting permanent price-adjusting information more difficult as investors must have access to, and consolidate transaction results across many exchanges to help markets maintain accurate prices levels. The lack of a published consolidated order book also means that incorporating relevant quote data into transactions prices is also more difficult. As a result, there is a greater margin of error in advertised and historical trade prices. This opens regulatory agencies to a debate about whether policies must be put in place to provide investors with a more centralised source for trade and order book information.

Policies regarding more centralised access to trade and order book information are also relevant with regards to levelling the playing field between retail and institutional investors. Institutional investors are viewed as more sophisticated with regards to their ability to gather superior private information as well as access multiple exchanges simultaneously with the aid of computer software. While little can and should be done surrounding the generation of private information, the results in this thesis open the floor to a debate about whether retail investors should have more access to tools which source liquidity from multiple exchanges. Compensation for costly information gathering is a reward to informed investors for their contribution to market efficiency. However, informed investors receive additional benefits because they afford to invest in told that allow them greater access to liquidity. The question remains as to whether institutional investors are deserving of greater access to liquidity, compared to retail investors, simply because they are more likely to be able to afford it. If regulators do not intend to provide retail investors with the same accessibility to liquidity that institutional investors can afford, then this leads to the question of whether governments should play a role in restricting the number of exchanges.

Finally, there are currently no government-mandated reporting policies for cryptocurrency exchanges. The results of this thesis show that cryptocurrency markets are similar to equity markets in the way they react to fragmenting events. As investment in cryptocurrencies continues to grow, the results imply that regulatory bodies should include cryptocurrency exchanges in their discussion of trade reporting and investor protection policies.

Corbet, Lucey, Peat, and Vigne (2018) study the direction and intensity of informational spillovers across assets, including various cryptocurrencies. Future research would benefit from testing whether a particular cryptocurrency's market microstructure influences the value of substitute cryptocurrencies. These results would allow researchers to gain insight into whether cryptocurrencies uniquely establish their prices of if their prices are influenced by competing cryptocurrencies. If the research resulted in a single cryptocurrency as the information leader, it would imply that investors need only monitor one cryptocurrency market to gain an accurate representation of the value of all competing cryptocurrencies.

While Corbet et al. (2018) study the spillover across different cryptocurrencies, they do not isolate for the effects of the different fiat currencies used in the transactions. Further research could help identify which fiat currency, if any, leads the market as a source of permanent price-adjusting information. This would have significant implicants regarding the breadth and scope of information investors must observe to determine efficient price levels.

Finally, both of the empirical studies presented in this thesis can be improved by allowing for directional testing within their hypotheses. As it stands, the study can only identify the presence of positive and negative relationships between fragmentation and price discovery. By improving upon the model, future research can prove that fragmentation leads to changes in the informativeness of prices in exchanges or vice versa.

In conclusion, a broader question to consider is can the lessons from this study of fragmented financial asset markets be applied to the price formation and information content in other assets markets. For instance, are fragmented commodity markets, like gold or other resources, optimal or suboptimal in terms of information asymmetry and price determination. There is a potential for a program of research into different market fragmentation stemming from the current thesis.

8.0 Conclusion

This study investigates the applicability of equity-based principles to instances of competitive market fragmentation in a relatively new asset class, cryptocurrencies. Using transaction and order-book data on the most dominant cryptocurrency, Bitcoin, it follows de Jong et al. (2001) and calculates a multivariate version of Hasbrouck's (1995) information share. The results confirm that an exchange's market share and the level of competitive fragmentation are positively related to the informativeness of exchange prices (Madhavan, 1995).

The result is explained by the migration of informed investors to competing exchanges. This, in turn, increases events of information asymmetry as individual exchange transaction prices become more informative. However, as permanent price-adjusting information is dispersed across an increasing number of exchanges, gathering all relevant information surrounding asset prices becomes more difficult and the price discovery process deteriorates. Innovations that leads markets to fragment are altruistically motivated in their desire to reduce information asymmetry among investors. However, the reality is quite the opposite. Much like the fragmenting events in equity market, fragmentation in cryptocurrency markets increases levels of information asymmetry in the market. Benefits experienced by informed investors are a direct result of the increases in information asymmetry uninformed investors are subject to.

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