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Nothing but noise? Price discovery across cryptocurrency exchanges☆

Thomas Dimpfl[a], Franziska J. Peter[b,*]

[a] Department of Econometrics, Statistics and Empirical Economics, University of Tübingen, Germany
[b] Department of Empirical Finance and Econometrics, Zeppelin University, Am Seemosser Horn 20, 88045 Friedrichshafen, Germany

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ABSTRACT

We examine the price discovery contributions of cryptocurrency exchanges in the presence of market microstructure noise. Cryptocurrency markets exhibit a decisively higher level of microstructure noise compared with the NYSE or NASDAQ. Therefore, traditional measures of price discovery could be biased. To overcome this concern, we draw on the information leadership share proposed by Putniņš (2013); by leveraging this information, we find that Bitfinex is the leader in the price discovery process. These results highlight the importance of accounting for different levels of noise when evaluating price discovery contributions.

1. Introduction

Cryptocurrencies are traded on more than 300 exchanges worldwide, and across these exchanges, the price discrepancies reach up to 1000 USD for the same cryptocurrency. Defining their fundamental value thus is difficult, because it is unclear which exchange to consider. In a setting in which multiple exchanges trade the same asset, the most informative price exists in the market where price discovery is highest, such that its prices reflect new information faster than prices reported on other markets. In a cryptocurrency context, the situation is more complex, due to considerably greater uncertainty about its fundamental value. That is, cryptocurrencies likely reflect the value of some expected future benefit, but the high volatility inherent in these markets suggests a difficult valuation process. At the extreme, we might even ask if prices on these markets reflect any information at all, or whether they are nothing but noise.

Different levels of microstructure noise distort the traditional price discovery measures of Gonzalo and Granger (1995) and Hasbrouck (1995) in such a way that the measures ultimately indicate noise avoidance rather than a market's true contribution to the fundamental value. Considering these concerns, we provide a detailed description of the noise inherent in our sample

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* Corresponding author.
E-mail addresses: thomas.dimpfl@uni-tuebingen.de (T. Dimpfl), franziska.peter@zu.de (F.J. Peter).

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of cryptocurrency markets compared to well-established U.S. stock markets. We find that cryptocurrency prices are very noisy, exhibiting a signal-to-noise ratio (SNR) of 36% on average; while the average SNR is about 90% on the New York Stock Exchange (NYSE) or NASDAQ. Although some stocks exhibit specific characteristics similar to those that we document for cryptocurrencies, we cannot identify a single stock that would qualify as a "crypto stock." Furthermore, through an analysis of price discovery across cryptocurrency markets, accounting for the relative noise levels of the different exchanges, we establish that Bitfinex is the price discovery leader.

The question of where prices get set is a very old one. Following the publication of seminal papers by Gonzalo and Granger (1995) and Hasbrouck (1995), researchers have had two measures at their disposal, both of which can numerically quantify contributions to price discovery. Accordingly, these measures are used frequently, especially for stock markets (Booth et al., 1999; So and Tse, 2004; Grammig et al., 2005; Comerton-Forde and Putniņš, 2015), though also for commodities like gold (Hauptfleisch et al., 2016) or agricultural products (Dimpfl et al., 2017). However, some issues remain; for example, Hasbrouck (1995) information share is not unique, and both measures potentially are prone to market microstructure frictions. The first issue has been resolved by Lien and Shrestha (2012) and Grammig and Peter (2013). The second issue, which is more relevant for our research, has been addressed by Yan and Zivot (2010) and Putniņš (2013), who suggest combining Gonzalo and Granger (1995) ad Hasbrouck (1995) measures to obtain an information share that is robust to the potential bias induced by different levels of microstructure noise.

Studies of price discovery among cryptocurrency exchanges are relatively rare and recent. Brandvold et al. (2015) investigate price discovery across seven Bitcoin exchanges between April 2013 and February 2014 and identify the Japanese Mt.Gox and the U.S. BTC-e as the price discovery leader in that period. Both of those exchanges have since closed, in response to hacker attacks and allegations of potential fraud. Pagnottoni and Dimpfl (2019) conduct a similar study, accounting for the effects of fiat currency exchange rates, and find that Bitcoin prices are not influenced by fiat currency prices, whereas price discovery mostly takes place on OKCoin, a China-based platform. This identified leading market is not fully operational any longer either. In studying price discovery, Qu (2017) finds that the Chinese markets strongly influence trading in China's mainland. Although Baur and Dimpfl (2019), Corbet et al. (2018), and Kapar and Olmo (2019) all investigate price discovery between Bitcoin spot prices and futures, the first two studies indicate that the spot price leads price discovery, whereas Kapar and Olmo (2019) conclude the opposite.

Another strand of literature that pertains to our research deals with the volatility of cryptocurrencies, which is found to be much higher than the volatility of stocks (Baur et al., 2018; Lahmiri et al., 2018; Symitsi and Chalvatzis, 2018) or commodities, such as gold and silver (Klein et al., 2018). Furthermore, Urquhart (2017) finds that prices cluster at round numbers, which might be related to the microstructure of the trading venue.

With our analysis of cryptocurrency markets, we provide two main contributions. First, we analyze price discovery for three trading venues (Bitfinex, Kraken, Poloniex) and five cryptocurrencies (Bitcoin, Ethereum, Ethereum Classic, Litecoin, and Monero), using high-frequency transaction data. Second, we examine and explicitly account for the microstructure noise environment by estimating relative noise levels and applying the information shares approach suggested by Putniņš (2013). The impact of noise on price discovery contributions has been analyzed theoretically and with simulations by Yan and Zivot (2010) and Putniņš (2013), yet empirical investigations of the associated predictions remain insufficient. By conducting such an analysis, we seek to foster understanding of how noise can affect measures of price discovery. Cryptocurrency markets provide an ideal setting for this analysis, as they are noisier than stock markets, and the noise component itself fluctuates substantially during the day and across days. Our price discovery results indicate that Bitfinex is the leading market for all cryptocurrencies in our sample, if we use standard measures. However, its relative contribution seems overestimated according to Putniņš's measure. This finding aligns with evidence that Poloniex exhibits a considerably higher noise level – according to a measure by Hansen and Lunde (2006) – which overshadows its contribution to price discovery.

The article proceeds as follows: In Section 2, we introduce the price discovery measures and discuss the relevance of microstructure noise. In Section 3, we present some market characteristics and discuss the data and descriptive statistics. Then in Section 4, we compare microstructure noise across trading venues and provide insights on its characteristics and possible sources, along with a comparison to NYSE and NASDAQ. In Section 5, we present the results from the price discovery analysis, and we conclude in Section 6.

2. Price discovery measures and microstructure noise

The two standard approaches commonly applied to measure contributions to price discovery are the component share (CS), based on Gonzalo and Granger (1995), and the information share (HIS), proposed by Hasbrouck (1995).[1] Yan and Zivot (2010) and Putniņš (2013) caution that the CS and HIS can measure price discovery contributions – as the relative speed of adjustment to new information – correctly only if the markets exhibit similar levels of microstructure noise. To account for differences in microstructure effects, Putniņš (2013) also proposes the information leadership share (ILS).

[1] For a comprehensive discussion, details on the derivation, and a comparison of CS and HIS, please refer to the special issue on price discovery, published in 2002 by the *Journal of Financial Markets* (Volume 5, Issue 3).

It is assumed in the models from which the respective information shares are derived that the unobservable efficient price (m_t) of an asset evolves as a random walk,

$$m_t = m_{t-1} + u_t, \tag{1}$$

with white noise innovations u_t. Because the asset itself is traded simultaneously on n markets, the n price series on these markets follow one common stochastic trend. However, the observed prices $p_{i,t}$ on each market i usually are not identical across markets, and they also differ from the fundamental value, due to market microstructure frictions, such that:

$$p_{i,t} = m_t + s_{i,t} \quad \forall i = 1, \ldots, n, \tag{2}$$

where $s_{i,t}$ is a mean zero i.i.d. component that captures information- and non-information-related components, in the sense of Yan and Zivot (2010).

2.1. Hasbrouck information shares

The Hasbrouck (1995) approach relies on a decomposition of the variance of the efficient price innovations u_t in equation (1) into the contributions of the different markets. We can collect the prices $p_{i,t}$ in a single vector p_t. Then the vector of first price differences, Δp_t, can be modeled by a vector error correction model (VECM)

$$\Delta p_t = \alpha\beta' p_{t-1} + \sum_{j=1}^{k} \Gamma_j \Delta p_{t-j} + \varepsilon_t, \tag{3}$$

where β denotes an $(n \times n - 1)$ cointegrating matrix, α is the $(n \times n - 1)$ adjustment coefficient matrix, and Γ_j refers to the $(n \times n)$ autoregressive parameter matrices. The $(n \times 1)$ vector of price innovations, ε_t, is serially uncorrelated but potentially contemporaneously correlated, such that $\mathbb{E}[\varepsilon_t \varepsilon_t'] = \Sigma_\varepsilon$.

In turn, the HIS are determined by the decomposition of the variance of the efficient price innovations u_t in equation (1), which relates to the VECM parameters as $\sigma_u^2 = \psi' \Sigma_\varepsilon \psi$, where ψ denotes the vector of the long-run impact coefficients of the price innovations in the n markets. To identify the contribution of a particular market, it is necessary to isolate the variance contribution of the markets' idiosyncratic innovations, which are assumed to be i.i.d. with unit variance. The variance of composite shocks Σ_ε relates to the idiosyncratic shocks as $\Sigma_\varepsilon = BIB'$, where B measures the contemporaneous effects. Because B is not identified, Hasbrouck (1995) proposes a triangularization of the covariance matrix using Cholesky decomposition $\Sigma_\varepsilon = CC'$. The HIS of market i is then given by:

$$HIS_i = \frac{([\psi' C]_i)^2}{\psi' CC' \psi}, \tag{4}$$

where the subscript i denotes the i-th element of the row vector $[\psi' C]$. Permuting the ordering of the variables in the Cholesky decomposition results in upper and lower HIS bounds. To obtain a unique measure, a common approach is to use the midpoint, calculated as the average of lower and upper HIS bounds.

2.2. Gonzalo and Granger component shares

The CS proposed by Gonzalo and Granger (1995) measures contributions to price discovery as the weight of each market's price innovation, according to the increment of a common permanent factor. It is possible to show that the factor weights w relate to the adjustment coefficients matrix α in equation (3), as $w = \alpha_\perp$, such that w is orthogonal to all $n - 1$ vectors of adjustment coefficients in α. The CS of market i is subsequently given by

$$CS_i = \frac{w_i}{\sum_{j=1}^{n} w_j}, \tag{5}$$

measuring the contribution of market i to the price discovery process.

2.3. Putniņš' information leadership shares

Yan and Zivot (2010) and Putniņš (2013) argue that in the presence of differing microstructure noise across exchanges, neither HIS nor CS correctly identifies the contribution to price discovery. By *noise*, Putniņš (2013) refers to microstructure effects caused, for instance, by the tick size or, if transaction data are used, by bid-ask bounces, as well as to liquidity effects or noise trading. Putniņš (2013) shows that, if the noise levels of the price series differ, HIS and CS measure a combination of the speed of adjustment and noise avoidance. Consequently, the conclusions drawn from these standard approaches might be misleading, especially for venues that exhibit different market structures. He therefore proposes combining HIS and CS, to attain an accurate measure of contributions to price discovery, in that it cancels out potential bias due to varying noise levels. The resulting price discovery measure termed "information leadership share" provides an unbiased estimate of price discovery contributions, where price discovery is defined as the relative speed of impounding new information into the price series,

Table 1
Characteristics of trading venues. The table presents selected market characteristics of Bitfinex, Kraken, and Poloniex (as of July 2018).

	Bitfinex	Kraken	Poloniex
Location	Hong Kong	USA	USA
Fees	Maker fee: 0–0.1%	Maker fee: 0–0.16%	Maker fee: 0–0.1%
	Taker fees: 0.1–0.2%	Taker fees: 0.1–0.26%	Taker fees: 0.1–0.2%
Order Types	Limit	Limit	Limit
	Market	Market	Market
	Stop	Stop Loss	Stop Loss
	Stop-Limit	Take Profit	
	Trailing Stop	Combined Orders	
	Fill or Kill		
	Scaled		
	One Cancels Other		
	Hidden		
	Iceberg		
	Post-Only Limit		
Min. tick	0.005 (BTC)	0.1 to 0.001 (BTC)	0.0001 (BTC)
Margin Trading	YES	YES	YES

reflecting a perception of *who moves first*. The structural model by Yan and Zivot (2010), which leads to the ILS proposed by Putniņš (2013), is uniquely identified within a bivariate setting.

If we consider an asset traded simultaneously on two markets, the information leadership metric suggested by Yan and Zivot (2010) constitutes a particular combination of the HIS and CS measures. It can eliminate the bias caused by the relative avoidance of noise; it is given by:

$$IL_i = \frac{HIS_i}{HIS_j} \cdot \frac{CS_j}{CS_i}, \tag{6}$$

where $i, j = 1, 2, i \neq j$, denote the two markets, and HIS_i and CS_i denote the Hasbrouck information share midpoints and component shares given by equations (4) and (5) for $n = 2$, respectively. According to Putniņš (2013), the ILS then is given by the relative informational leadership metric of each market:

$$ILS_i = \frac{IL_i}{IL_i + IL_j} = \frac{HIS_i^2 \cdot CS_j^2}{HIS_i^2 \cdot CS_j^2 + HIS_j^2 \cdot CS_i^2}. \tag{7}$$

The ILS thus operates within a range that is comparable to the standard measures, i.e., between 0 and 1 or as a percentage share. By replicating the results from different studies and calculating the ILS, Putniņš (2013) shows that this measure can reliably identify which market reacts first to new information. Since cryptocurrency exchanges differ profoundly with respect to market microstructure-related features, such as available order types, tick size, liquidity, and bid-ask spreads, applying the standard measures might lead to incorrect conclusions, but they can be corrected by leveraging the ILS.

3. Market details and data description

Our sample consists of five cryptocurrencies traded simultaneously on three exchanges. We use intraday transaction data of Bitcoin (BTC), Ethereum Classic (ETC), Ethereum (ETH), Litecoin (LTC), and Monero (XMR), traded against the U.S. dollar (USD). The data sets consist of all transactions on three cryptocurrency exchanges, Bitfinex, Kraken, and Poloniex, which are among the most liquid exchanges during the time period considered (March 2017 to November 2017). These three exchanges also account for roughly 30% of Bitcoin trading volume during the sample period, among more than 300 exchanges.[2] The chosen coins rank among the top 10 with respect to traded volume, led by Bitcoin, which attracted up to 80% of the total cryptocurrency market capitalization at the beginning of our sample period.[3]

The three trading venues differ on several features, as detailed in Table 1. The minimum tick size, for example, differs substantially among exchanges and is not stable over time. For Bitcoin, the range is from 0.0001 on Poloniex to 0.1 on Kraken at the end of our sample period. Tick size on Bitfinex was 0.005 until October 24, 2017, when the exchange introduced a flexible minimum tick size to ensure that one tick equals a range of 10–25 USD.[4]

Rounding issues due to tick size and price discreteness arguably may influence the microstructure noise level within a market (Glosten and Harris, 1988; Diebold, 2006; Putniņš, 2013). Differences within the range and the scale of sophistication of the offered order types also have an impact on microstructure noise, both directly, in that they offer various degrees of flexibility

[2] See coinmarketcap.com for a list of exchanges.
[3] According to market data available on bitcoinity.org.
[4] See https://www.bitfinex.com/posts/226.

Table 2
Descriptive statistics for transactions. The table presents descriptive statistics of the transaction data set. Panel A shows the average transaction price (in USD) on Bitfinex, Kraken, and Poloniex for Bitcoin (BTC), Ethereum Classic (ETC), Ethereum (ETH), Litecoin (LTC), and Monero (XMR). Panel B presents the average volume per transaction (in USD) and Panel C provides the average number of trades per day.

	Bitfinex	Kraken	Poloniex
A: Average Prices in USD			
BTC	3,648.43	3,338.75	3,361.35
ETC	12.94	13.84	12.95
ETH	251.75	241.45	231.57
LTC	42.7	45.45	44.21
XMR	80.95	78.19	65.21
B: Volume per Transaction in USD			
BTC	2,391	1,170	839
ETC	461	359	459
ETH	1,302	1,093	855
LTC	596	456	472
XMR	720	341	286
C: Trades per Day			
BTC	46,729	15,108	37,374
ETC	9,961	2,637	5,775
ETH	20,668	14,529	16,364
LTC	16,933	4,073	9,540
XMR	3,079	1,425	4,426

for order submission and trading strategies, and indirectly, by attracting different groups of investors. In particular, order types related to transparency issues, such as iceberg or hidden orders, tend to attract informed traders rather than noise traders and might thereby influence the noise level within a market (Anand and Weaver, 2004; Boulatov and George, 2013). Our a priori assumption that noise levels on Bitfinex, Kraken, and Poloniex differ thus seems justified, though we also acknowledge other relevant factors, as we detail below.

The intraday data consist of transaction time series, stamped at milliseconds (Kraken and Bitfinex) or seconds (Poloniex), from March 8, 2017 to November 8, 2017. All three exchanges regularly operate seven days a week, on a 24-h basis, with the expectation of maintenance or other unforeseen downtimes. They also offer free public application programming interfaces (API), through which their live and historic data feeds are accessible via compatible software programs.[5] For the price discovery analysis, we align Bitfinex, Kraken, and Poloniex transaction prices at a 1-s frequency. The average number of transactions per minute ranges from 1 to 32, so higher frequencies do not seem necessary. If, within a 1-s interval, no transaction has been recorded, the previous price remains as valid, which is standard in the literature. Returns are calculated as log-returns.

Descriptive statistics for the transaction prices that form the basis for the subsequent noise calculation and the price discovery analysis are in Panel A of Table 2. Arbitrage considerations imply that the prices should not deviate too strongly across exchanges. But this prediction does not seem to hold true in cryptocurrency markets. For example, the average transaction price of Bitcoin on Bitfinex is roughly 300 USD higher than on Kraken or Poloniex. The minimum prices (not reported) match better, but the maximum prices still deviate by 100 USD. As has been documented frequently, cryptocurrency prices deviate substantially across exchanges (Pieters and Vivanco, 2017). The deviations are less pronounced for Ethereum Classic and Litecoin. For Ethereum and Monero, the difference in average prices covers a range of 15–20 USD, which means a price discrepancy of up to 20% among Bitfinex, Kraken, and Poloniex.

To ensure the available data are suitable for our analysis, we conduct unit root tests. They show that the transaction prices of all cryptocurrencies on all three exchanges are non-stationary. Cointegration tests reveal that the prices of the same cryptocurrency on the three considered platforms follow the same stochastic trend. Finally, all markets exhibit microstructure noise, according to the test proposed by Aït-Sahalia and Xiu (2019).

Table 2 contains the average daily trading volume (Panel B, in USD) and the average number of transactions (Panel C) of the five cryptocurrencies across the three exchanges. For all five currencies, the transacted volume (over the whole sample period) on Bitfinex substantially exceeds the volume of the other two exchanges. In the case of Bitcoin, the total volume on Bitfinex is almost seven times higher than on Kraken and almost four times as high as on Poloniex. In terms of the volume per transaction, Bitfinex also emerges as the dominant exchange, though these differences are less pronounced. Similarly, the number of Bitcoin trades per day is three times higher on Bitfinex than on Kraken and 2.5 times higher on Poloniex than on Kraken. For the

[5] See detailed documentations of Bitfinex' API at http://docs.bitfinex.com/docs, Kraken's API at https://www.kraken.com/help/api, and Poloniex's API at https://poloniex.com/support/api. We retrieved the data using the R-packages *httr* (Wickham, 2018) and *jsonlite* (Ooms, 2014).

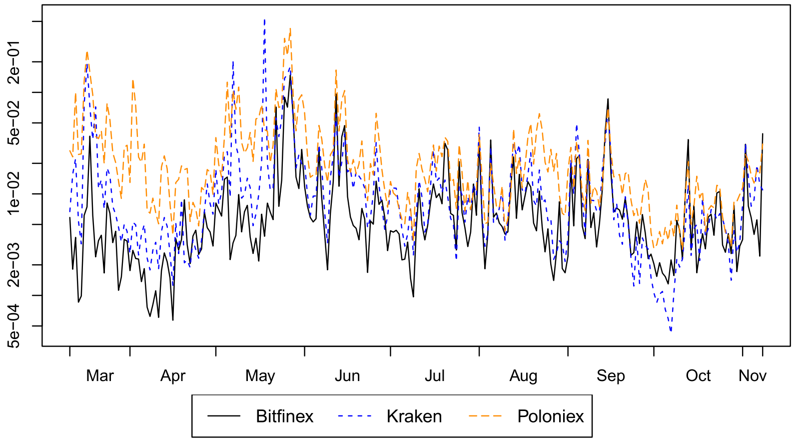


Fig. 1. Time series of daily noise evolution. The figure presents the time series of market microstructure noise of Bitcoin on the three exchanges: Bitfinex (black solid line), Kraken (blue dashes), and Poloniex (yellow long dashes). The y-axis is in logs. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

remaining cryptocurrencies, Bitfinex is also the most active trading venue, in terms of the daily number of transactions. In total, the descriptive statistics in Table 2 suggest that Kraken is the least active trading venue for all cryptocurrencies in our sample. With respect to the differences among the cryptocurrencies, Bitcoin is by far the most traded one, followed by Ethereum and Litecoin. The least actively traded cryptocurrency in our sample is Monero, in terms of both USD trading volume and the number of transactions.

4. Market microstructure noise: level and sources

Cryptocurrency markets, in particular those for Bitcoin, exhibit a very high level of volatility (Symitsi and Chalvatzis, 2018). Prior to analyzing price discovery, we therefore consider the noise levels across cryptocurrency markets and their sources. As an empirical measure for microstructure noise, we rely on research into realized volatility (RV; Andersen et al., 2003; Aït-Sahalia et al., 2011; Andersen et al., 2011), which documents the bias of realized volatility due to microstructure noise at high frequencies. Using results provided by Bandi and Russell (2006), Hansen and Lunde (2006) show that for a model similar to our equation (2), the variance of the noise component, denoted $mn_{i,t}$, can be estimated consistently as the difference between the sum of the squared intraday returns at the highest available frequency m (denoted $RV^{(m)}$) and a consistent estimator of the integrated variance (IV) of the price process. For the latter measure, we use realized variance calculated at 5-min intervals. The estimator of daily market microstructure noise then is given as:

$$mn_{i,t} = \frac{1}{2m}\left(RV^{(m)} - \widehat{IV}\right), \tag{8}$$

which converges in probability to $\mathbb{E}[s_t^2]$ as $m \to \infty$. Subsequently, we rescale the measure to a daily level. Our choice of the estimate of IV still might be affected by some remaining microstructure noise though, so our estimate of the noise is potentially downward biased. In turn, the results for microstructure noise that we present below constitute the lower bound of the noise.

4.1. Noise and information

Fig. 1 illustrates the evolution of market microstructure noise over time. This time series plot of Bitcoin noise highlights that the noise component changes substantially over time. We observe particularly high noise levels in the first four months of our sample, with a peak in May 2017. The pattern is similar for the other cryptocurrencies.

To compare the level of microstructure noise across exchanges over time, we calculate the relative noise level (in percent) as $\widetilde{mn}_{i,t} = \left(mn_{i,t}/\sum_i mn_{i,t}\right) \cdot 100$ across exchanges. The result is depicted in Fig. 2 for Bitcoin; the respective graphs for the remaining cryptocurrencies are in Fig. A.1 in the Appendix. When we compare the shaded areas, we note that Poloniex (light gray) exhibits the highest relative noise level. Bitfinex, in contrast, has a relatively low noise level, especially at the beginning of the sample period. Toward the end, we find episodes when Kraken exhibits the lowest level (e.g., end of September, early October). Even if this overall tendency is stable, the relative noise levels fluctuate widely from day to day.

Table 3 provides the average and (due to potential outliers and the pronounced fluctuations observed in Figs. 1 and 2) the median of the absolute daily noise level across the entire sample for the three considered trading venues and all cryptocurrencies. The median values reveal that the noise level on Poloniex is substantially higher than on Bitfinex and Kraken for all five

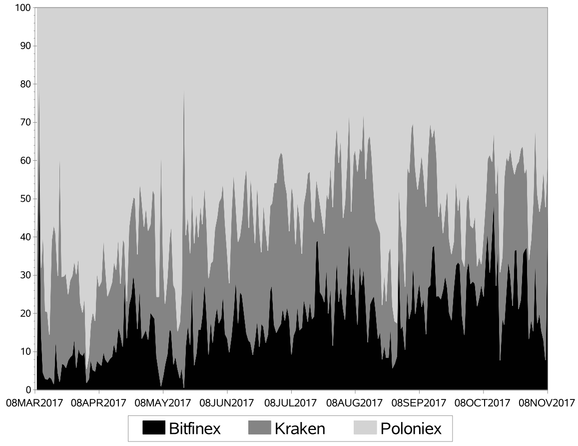


Fig. 2. Time series of daily relative noise level. The figure presents the evolution of the daily relative level of market microstructure noise of the three exchanges, Bitfinex (black), Kraken (dark gray), and Poloniex (light gray), for Bitcoin over the sample period.

Table 3
Average noise level. The table shows the mean and median of daily noise levels *mn* (×100) calculated according to equation (8) for Bitcoin (BTC), Ethereum Classic (ETC), Ethereum (ETH), Litecoin (LTC), and Monero (XMR) on Bitfinex, Kraken, and Poloniex.

	Bitfinex	Kraken	Poloniex
A: Mean			
BTC	1.71	1.93	3.10
	(0.77)	(0.34)	(0.31)
ETC	2.63	1.89	3.18
	(0.31)	(0.26)	(0.42)
ETH	2.36	3.81	3.25
	(0.30)	(34.35)	(0.33)
LTC	2.04	2.06	3.10
	(0.24)	(0.21)	(0.36)
XMR	2.33	1.66	2.06
	(0.80)	(0.26)	(0.26)
B: Median			
BTC	0.48	0.76	1.64
ETC	1.23	0.67	1.55
ETH	0.93	1.33	1.61
LTC	1.02	0.99	1.25
XMR	0.63	0.41	0.89

currencies. The same finding holds for the average noise level, with the exception of Ethereum, for which we observe the largest average noise level on Kraken.

These findings also emerge from the volatility signature plots in Fig. 3, which illustrate the dependence of the volatility estimation on the sampling frequency. To this end, realized volatility is calculated using transaction data sampled at 1- to 300-s sampling intervals, then plotted against the sampling frequency. With this approach, we can identify the bias of the realized volatility estimation at high frequencies. If observed returns were free of microstructure noise, the volatility signature plot would be a straight line. In the presence of noise, the noise component becomes more dominant with increasing sampling frequency (decreasing sampling intervals), such that it commonly results in the L-shaped behavior depicted by the signature plot. Considering the volatility signature plot for Bitcoin, the high noise level on Poloniex is only present at sampling frequencies higher than 10 s, whereas at lower frequencies (e.g., 30 s), the noise level on Kraken is most pronounced. We observe a similar pattern for ETC and LTC. For all five cryptocurrencies, Bitfinex exhibits the lowest realized volatility estimates at any frequency. Andersen et al. (1999) used volatility signature plots to illustrate the effect of sampling frequency on estimates of realized volatility. If we compare our Bitcoin signature plot to their Figure 6, we note that Bitcoin resembles an illiquid asset in the stock market, even though Bitcoin is the most liquid of our sample cryptocurrencies.

Because microstructure noise is an inherent feature of the high-frequency nature of the data, we also examine its intraday behavior. To this end, we calculate the noise measure in equation (8) on an hourly basis and subsequently average across days. Fig. 4 presents a smoothed time series of intraday noise levels for Bitcoin, where the vertical lines mark the opening and closing times of the most important stock exchanges around the world. We used a cubic smoothing spline function to highlight the

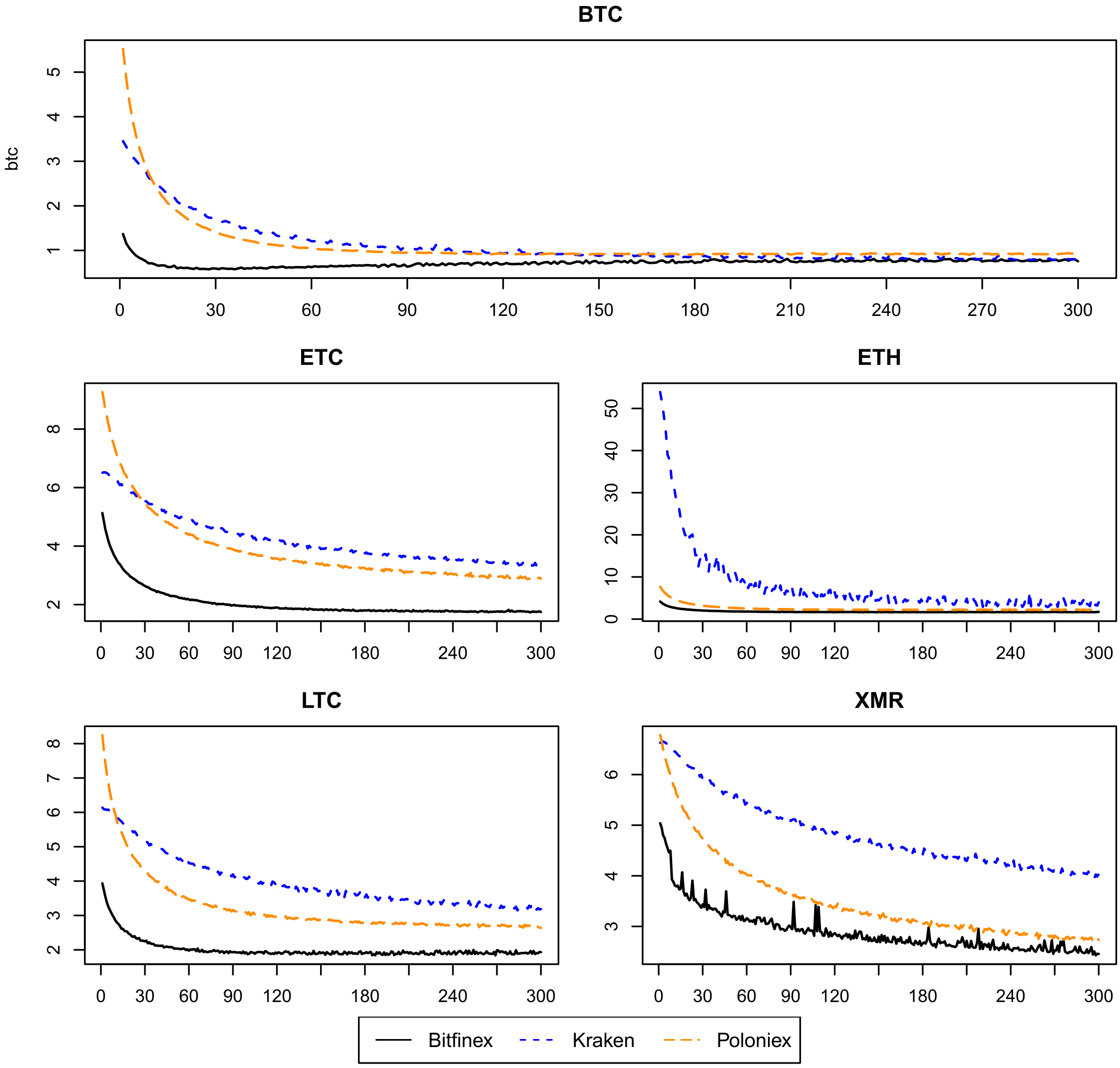


Fig. 3. Volatility signature plots. The graphs presents signature plots of realized volatility for Bitcoin (BTC), Ethereum Classic (ETC), Ethereum (ETH), Litecoin (LTC), and Monero (XMR), at sampling frequencies from 1 to 300 s. The solid line represents calculations for Bitfinex prices, the dashed line indicates Kraken, and the long dashes indicate Poloniex.

different periods of the day, instead of relying on raw, intraday noise data. As Fig. 4 illustrates, the noise component does not change substantially during the day. On the Hong Kong-based exchange Bitfinex, it is rather stable; the U.S.-based trading platforms Kraken and Poloniex instead exhibit an increase in the noise component during the afternoon hours. The pattern is similar for the remaining cryptocurrencies. Overall, the highest noise level occurs in the period between the opening of the NYSE and the close of the European stock markets.

Although this comparison of noise levels across cryptocurrency exchanges provides useful insights for the subsequent price discovery analysis, it cannot reveal how much noise versus fundamental information exists in cryptocurrency prices. If we accept that prices reflect information, then Cheah and Fry (2015) assertion that the fundamental value of Bitcoin is zero would suggest there is no information, and cryptocurrency prices reflect only noise. Given some useful applications of cryptocurrencies though, such as for storing and transacting money outside the fiat money system (regardless of whether wider society views such activities as useful or even makes them illegal), the fundamental value should not be zero. At the very least, costs for power and computer resources should be reflected in the price of Bitcoin, because initially miners generated income from mining and only in recent years moved to collecting fees (Easley et al., 2019). In addition, the price could reflect some convenience yield for potential usage. All of these aspects together suggest that cryptocurrency prices reflect some pricing-relevant information.

The volatility signature plots in Fig. 3 provide a means to examine the information versus noise relationship in financial assets. In the absence of noise, the graph would be flat, because the calculation of realized volatility is not contaminated by

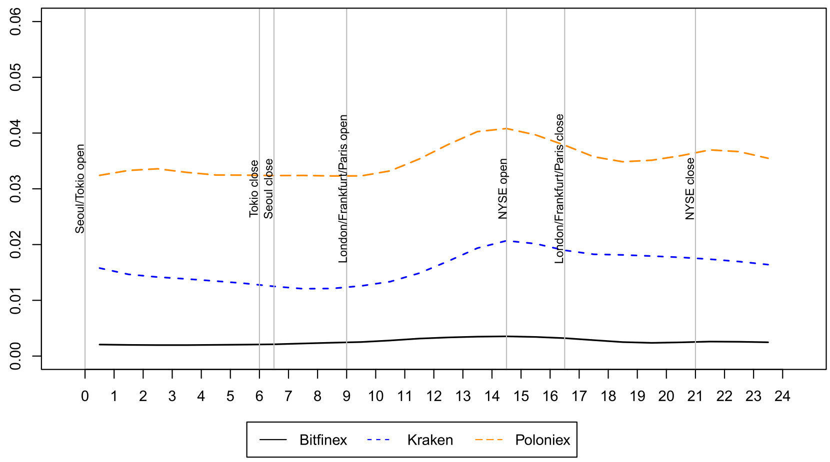


Fig. 4. Bitcoin intraday noise pattern. The figure depicts the development of Bitcoin's noise component across the trading day (according to UTC) for Bitfinex (solid line), Kraken (dashed line), and Poloniex (long dashes).

Table 4
Cryptocurrency Signal-to-Noise ratio. The table presents the average daily SNR for the five cryptocurrencies on each exchange, along with averages by cryptocurrency and exchange.

	Bitfinex	Kraken	Poloniex	Average
BTC	0.27	0.21	0.13	0.20
ETC	0.26	0.55	0.34	0.39
ETH	0.30	0.37	0.31	0.33
LTC	0.33	0.38	0.29	0.33
XMR	0.49	0.66	0.44	0.53
Average	0.33	0.43	0.30	0.36

microstructure noise. In contrast, when the noise component (Bandi and Russell, 2006) grows more important, the deviation between the calculations obtained with high and low (commonly, 5 min) frequencies increases. That is, a comparison of the components indicates how much information versus noise is contained in the price. Considering any of the graphs in Fig. 3, the difference between the calculation on 1-s versus 5-min intervals appears substantial.

We also calculate the signal-to-noise ratios (SNRs) and report the results in Table 4, for all cryptocurrencies and markets. In total, we find a SNR ratio of 36% across all markets and cryptocurrencies. On average, this ratio is lowest for Bitcoin and highest for Monero. That is, a cryptocurrency with a lower absolute noise level like Bitcoin does not necessarily have a higher SNR. In other words, the price of Bitcoin is no more informative than the other prices, just because its average noise level (Table 3) is lower. In the markets, the highest noise level on average appears on Poloniex, which also exhibits the lowest SNR. Kraken has a higher SNR than Bitfinex, even though the noise levels do not differ substantially. For the individual cryptocurrencies on single exchanges though, we find a clearer pattern, in which noisier prices lead to lower SNRs, with the exception of Bitcoin.

4.2. Drivers of market microstructure noise

The sources of microstructure noise are diverse. As we discussed in Section 3, the tick size (and in particular, changes in the tick size across time) might be one source of microstructure noise. However, we would have expected a higher noise level on Bitfinex and Kraken than on Poloniex if it were the only source. In contrast, we find lower noise levels on these two markets. An additional source might be trading volume and the number of trades, as presented in Table 2. Considering traded volume as a measure for liquidity, we expect the most liquid markets to be less prone to microstructure noise. This conjecture is supported by the data in so far, as the relatively higher liquidity seems related to a lower noise level. However, trading volume and the number of trades are not sufficient to determine the ordering of the markets with respect to their relative noise levels. For Bitcoin, the most liquid market is Bitfinex, which also exhibits the lowest noise level. Although Kraken is the least liquid market, it still shows a noise level that is lower than that on Poloniex. For Monero, we find that Poloniex is the most active market, and it also shows a lower average noise level than Bitfinex. Yet the noise level on Kraken is substantially lower, despite its trading activity of Monero being very low (Table 2).

Another variable that might relate to market microstructure is the bid-ask spread, which could affect the noise level in the transaction data directly through the bid-ask bounce, or indirectly, if used as a measure of liquidity. Table 5 contains the descriptive statistics for daily spread estimates (in USD) based on 30-s quote data are presented in. On average, the spread is

Table 5

Descriptive statistics on spreads. The table presents descriptive statistics on the quoted and relative spread (in USD) calculated from bid-ask quotes sampled at 30 s intervals on Bitfinex, Kraken, and Poloniex for Bitcoin (BTC), Ethereum Classic (ETC), Ethereum (ETH), Litecoin (LTC), and Monero (XMR).

		Quoted Spread			Relative Spread in %		
		Bitfinex	Kraken	Poloniex	Bitfinex	Kraken	Poloniex
BTC	MEAN	0.924	5.875	3.215	0.036	0.157	0.124
	STD	0.432	36.525	1.313	0.021	0.112	0.056
ETC	MEAN	0.032	0.139	0.056	0.304	0.905	0.519
	STD	0.022	0.809	0.032	0.136	0.499	0.162
ETH	MEAN	0.228	0.416	0.462	0.163	0.301	0.244
	STD	0.194	0.217	0.235	0.138	0.255	0.082
LTC	MEAN	0.050	0.179	0.104	0.217	0.765	0.363
	STD	0.023	0.086	0.046	0.203	0.698	0.220
XMR	MEAN	0.288	6.453	0.270	0.631	1.406	0.523
	STD	0.121	91.986	0.142	0.306	0.968	0.190

Table 6

Stock market noise. The table presents average daily noise levels mn (×100; Mean), the median of daily average noise levels (Median), and the signal-to-noise ratio (SNR) of the NYSE and NASDAQ stocks, sorted by average daily trading volume (Volume). N is the number of stocks per bin on which the calculation is based.

	Volume	Mean	Median	SNR	N
NYSE	315	0.1351	0.0587	0.83	16
	1,046	0.0160	0.0076	0.90	162
	3,235	0.0037	0.0008	0.91	1,074
	7,113	0.0026	0.0007	0.94	754
	12,177	0.0014	0.0008	0.95	346
NASDAQ	368	0.1404	0.0648	0.87	274
	920	0.0446	0.0206	0.89	656
	2,986	0.0193	0.0079	0.88	1,154
	7,069	0.0064	0.0030	0.90	576
	12,108	0.0029	0.0010	0.91	176

smallest on Bitfinex and highest on Kraken for all considered cryptocurrencies. Because Poloniex has the smallest possible tick size, we might expect a smaller spread on average than on the two other exchanges, but that is not the case. The relation to our microstructure noise estimate again rejects the notion that a narrower spread guarantees a lower noise level. That is, this prediction holds for Bitfinex, but not for Kraken and Poloniex. Using the example of Bitcoin, the average spread is roughly 1 USD on Bitfinex, 3.22 USD on Poloniex, and 5.88 USD on Kraken. These values imply the noise component should be lowest on Bitfinex, which is what we find and document in Table 3, but also that Kraken should have a higher noise level than Poloniex, which is not evident in our results.

4.3. Comparison with stock market noise levels

To evaluate the amount of noise inherent to the three cryptocurrency markets, we draw on a comparison with the stock market. To this end, we compute market microstructure noise, realized variance, and the SNR for NYSE and NASDAQ stocks from January 3, to June 30, 2017. The sample consists of transaction prices of 2728 stocks traded on the NYSE and 2982 stocks traded on NASDAQ. These transactions take place during regular trading hours, between 9:30 a.m. EST and 4:00 p.m. EST. Overnight returns are excluded from the analysis.

Table 6 presents the averages across stocks for the mean and median microstructure noise, calculated according to equation (8). The results are grouped by average daily trading volume (in USD) using bin boundaries $\{500, 1500, 5000, 10000, 15000\}$. With this fixed grid we can compare the lower volume bins with the cryptocurrencies whose average transaction volume is comparatively lower than that of a single transaction in the stock market. The results suggest that the cryptocurrency markets are decisively more noisy than the stock markets. The average noise is at least 12 times higher in the cryptocurrency market when we compare the Bitfinex BTC with the lowest bin of the NASDAQ, i.e. the two values that represent the lowest noise market in the cryptocurrency sample and the highest noise bin of our stock sample. As this example indicates, the noise component inherent in the cryptocurrency market can only be labeled huge relative to the market microstructure noise prevailing on the NYSE and on NASDAQ on average.

When it comes to single stocks, we find that four stocks on NASDAQ (PIXY, DCTH, UNIS, and FNBC) exhibit an average noise that is higher than the lowest average Bitcoin noise level on Bitfinex. The PIXY average noise ($mn \times 100$) is 3.61, even higher than the average of any of the documented cryptocurrencies. For DCTH, UNIS, and FNB, $mn \times 100$ results in values of 2.35, 2.18, and 1.92. On the NYSE, in contrast, we do not find any stock that would exhibit a higher average noise level than Bitcoin on

Table 7
Price discovery measures in a trivariate system. The table shows average components shares and Hasbrouck information shares, based on daily VECM estimates, including 1-s transactions from Bitfinex, Kraken, and Poloniex. Standard deviations of the daily estimates are in parentheses.

	Component Share			Hasbrouck Information Share								
	Bitfinex	Kraken	Poloniex	Bitfinex			Kraken			Poloniex		
				Mid	Low	Up	Mid	Low	Up	Mid	Low	Up
BTC	82.2	10.0	7.8	89.7	89.4	90.0	4.7	4.7	4.8	5.5	5.3	5.8
	(10.0)	(7.3)	(6.0)	(10.4)	(10.6)	(10.3)	(6.3)	(6.2)	(6.3)	(7.1)	(7.0)	(7.2)
ETC	54.4	20.5	25.2	61.6	60.8	62.5	12.7	12.6	12.8	25.7	24.8	26.5
	(10.2)	(10.7)	(7.8)	(11.4)	(11.6)	(11.4)	(9.9)	(9.9)	(10.0)	(9.6)	(9.6)	(9.8)
ETH	57.8	17.7	24.5	62.3	61.6	62.9	11.2	11.1	11.3	26.5	25.9	27.1
	(16.6)	(10.9)	(13.9)	(21.5)	(21.7)	(21.3)	(10.2)	(10.1)	(10.2)	(19.6)	(19.4)	(19.7)
LTC	61.5	13.4	25.1	68.5	67.8	69.2	6.9	6.8	7.0	24.6	23.9	25.2
	(13.9)	(9.8)	(10.6)	(17.0)	(17.2)	(16.9)	(8.2)	(8.2)	(8.2)	(15.0)	(14.9)	(15.2)
XMR	46.2	21.7	32.0	48.8	48.0	49.6	15.7	15.6	15.9	35.5	34.6	36.3
	(12.1)	(13.1)	(8.8)	(14.8)	(14.7)	(14.9)	(13.6)	(13.6)	(13.6)	(12.2)	(12.1)	(12.3)

Bitfinex. Its highest individual average refers to EMG, with $mn \times 100 = 0.74$, which is less than half of the Bitfinex average.

Furthermore, relative to the SNR of roughly 36% for the cryptocurrency markets, stock markets reveal for all markets and bins, an average ratio above 80%. This evidence reaffirms our findings that cryptocurrency prices are tremendously noisy, and it highlights the need to account for microstructure noise in a price discovery analysis of these markets.

Zooming in on the four NASDAQ stocks with noise levels higher than Bitcoin, we find that they still exhibit a higher SNR than Bitcoin. The lowest, observed for UNIS, is 34% and thus is substantially higher than the Bitcoin average of 20%. Then PIXY, DCTH, and FNBC show even higher ratios of 39%, 52%, and 57%, respectively. The smallest SNR on NASDAQ (NYSE) refers to FIXD, equal to 17% (CBX, 12%), lower than the ratios documented for any cryptocurrency in Table 4. In summary, we do not find any stock that would combine all the properties (average noise level, signal-to-noise ratio) that we observe for Bitcoin (or any other cryptocurrency).

5. Price discovery across cryptocurrency exchanges

5.1. Results from traditional measures

We examine the price discovery contributions of Bitfinex, Kraken, and Poloniex, starting with a trivariate setting, then estimate the standard price discovery measures given by equations (4) and (5) based on transaction data sampled at 1-s intervals using log-returns. Table 7 contains the CS and HIS estimates for the three markets and five cryptocurrencies, based on averages over the daily estimation of the VECM in equation (3). Daily estimates are illustrated in Fig. A.2. According to the CS, Bitfinex is the dominant market in terms of price discovery for the cryptocurrencies, except for Monero. With the exception of Bitcoin, Kraken shows the smallest price discovery contribution, ranging between 13.4% for Litecoin and 21.7% for Monero. The HIS midpoints emphasize the leadership of Bitfinex for all currencies but Monero; these midpoint estimates range from 61.6% for Ethereum Classic to 89.7% for Bitcoin. The increased price discovery contribution based on the Hasbrouck approach (cf. CS results) of Bitfinex is predominantly due to the smaller price discovery contribution of Kraken when we use the Hasbrouck midpoints rather than the component share.

The HIS bounds were estimated as the average of all possible permutations, with the market of interest ordered first for the upper and last for the lower bound. The estimated HIS lower and upper bounds are very tight for all currencies and exchanges, indicating almost no contemporaneous correlation present at a 1-s sampling frequency. Consequently, the midpoints can be used as valid proxies for the information share, based on the Hasbrouck methodology.[6]

5.2. Price discovery in the presence of noise

The component shares exhibit statistically significant negative correlation with the own market's noise level. The correlations with the other exchanges' noise level are either positive or not statistically significant. Yet we do not observe significant correlations between daily HIS and the relative daily noise level for Bitcoin. For the remaining currencies, we find significant correlations between noise and HIS in several cases. Overall, the correlations between CS and the relative noise level are stronger than the correlations between relative noise and HIS. This observation is consistent with the analytical results of Yan and Zivot (2010), who show that CS is more closely related to the relative avoidance of noise, whereas HIS measures a mixture of relative

[6] Fig. A.2 illustrates the daily HIS midpoints and CS over the sample period. Corresponding to the findings of Mizrach and Neely (2008), the daily information shares exhibit a rather high degree of variation. Considering the HIS and CS of Bitcoin as an example, the Bitfinex price discovery measures exhibit particularly high volatility during April and June. As a possible explanation, we note the potential effect of several announcements by Bitfinex, on its webpage and social media, that the exchange was experiencing delays in processing of outbound USD wires to customers. Bitfinex also acknowledged it was experiencing distributed-denial-of-service (DDoS) attacks in mid-June.

Table 8
Bivariate information leadership Analysis. The table reports the component share (CS) of Gonzalo and Granger (1995), the Hasbrouck (1995) information share (HIS), and the information leadership share (ILS) of Putniņš (2013). The shares are averages of daily estimates, with standard deviations in parentheses.

	Bitfinex			Kraken		
	CS	HIS	ILS	CS	HIS	ILS
BTC	88.6	94.6	88.0	11.4	5.4	12.0
	(8.3)	(6.8)	(14.1)	(14.1)	(14.4)	(13.7)
ETC	71.4	81.6	78.6	28.6	18.4	21.4
	(12.4)	(11.7)	(12.4)	(12.4)	(11.7)	(12.4)
ETH	73.4	80.2	74.3	26.6	19.8	25.7
	(14.6)	(16.4)	(17.7)	(14.6)	(16.4)	(17.7)
LTC	79.6	88.1	84.5	20.4	11.9	15.5
	(13.9)	(12.5)	(13.1)	(13.9)	(12.5)	(13.1)
XMR	66.0	73.2	70.8	34.0	26.8	29.2
	(16.2)	(17.2)	(14.9)	(16.2)	(17.2)	(14.9)
	Bitfinex			Poloniex		
	CS	HIS	ILS	CS	HIS	ILS
BTC	91.1	93.8	78.9	8.9	6.2	21.1
	(7.0)	(8.1)	(21.2)	(7.0)	(8.1)	(21.2)
ETC	69.0	71.9	57.9	31.0	28.1	42.1
	(8.3)	(10.0)	(11.9)	(8.3)	(10.0)	(11.9)
ETH	70.1	70.0	55.6	29.9	30.0	44.4
	(15.7)	(20.9)	(20.8)	(15.7)	(20.9)	(20.8)
LTC	71.2	73.9	61.0	28.8	26.1	39.0
	(12.1)	(15.9)	(18.2)	(12.1)	(15.9)	(18.2)
XMR	58.9	58.1	48.6	41.1	41.9	51.4
	(9.6)	(12.6)	(13.8)	(9.6)	(12.6)	(13.8)
	Kraken			Poloniex		
	CS	HIS	ILS	CS	HIS	ILS
BTC	41.5	27.4	16.9	58.5	72.6	83.1
	(20.0)	(21.0)	(13.6)	(20.0)	(21.0)	(13.6)
ETC	49.8	40.9	31.7	50.2	59.1	68.3
	(14.5)	(16.2)	(11.4)	(14.5)	(16.2)	(11.4)
ETH	44.9	35.6	27.4	55.1	64.4	72.6
	(18.4)	(20.7)	(14.2)	(18.4)	(20.7)	(14.2)
LTC	39.0	28.4	23.9	61.0	71.6	76.1
	(17.0)	(18.0)	(13.7)	(17.0)	(18.0)	(13.7)
XMR	44.6	36.8	32.4	55.4	63.2	67.6
	(15.2)	(17.5)	(12.4)	(15.2)	(17.5)	(12.4)

noise avoidance and informational leadership. It is also consistent with the simulation study by Putniņš (2013), who reports that compared with CS, HIS puts more emphasis on measuring who moves first, relative to the avoidance of noise.

We estimate the ILS for all three bivariate combinations of cryptocurrency exchanges for each of the five cryptocurrencies.[7] Considering the bivariate setting including Bitfinex and Kraken, we observe only small differences among CS, HIS, and ILS in Table 8; all of them identify Bitfinex as the leading exchange, with a contribution to price discovery that exceeds 85%. The differences in the noise level on Bitfinex and Kraken are not pronounced enough to severely bias the standard measures. Turning to the bivariate setting with Bitfinex and Poloniex, we note that CS and HIS clearly indicate Bitfinex's leadership in price discovery for Bitcoin, Ethereum, Ethereum Classic, and Litecoin. However, the ILS estimates reveal an upward bias of the standard measures and report contributions for Bitfinex, which are 10–15 percentage points lower. Keeping in mind the considerably higher noise level on Poloniex (as documented in Fig. 3 and Table 3), this result matches the conclusions issued by Yan and Zivot (2010) and Putniņš (2013), that the ILS can alleviate the bias in the standard measures due to noise avoidance. In the case of Monero, we even observe a switch of the leading exchange, from Bitfinex to Kraken, when we adopt the potentially unbiased ILS estimate. Analyzing price discovery between Kraken and Poloniex, the average noise levels in Table 3 indicate an upward bias of the CS and HIS measures of Kraken due to the considerably higher noise level on Poloniex. The results support our expectation: ILS estimates are clearly below the standard measures for all five currencies, and Poloniex's leadership over Kraken with respect to price discovery is more pronounced than it appears in the results in Table 7.

Overall, our results emphasize the caveats related to standard measures for price discovery and support the conclusions of Putniņš (2013). Accounting for different levels of noise when measuring the contributions to price discovery of different trading venues is essential.

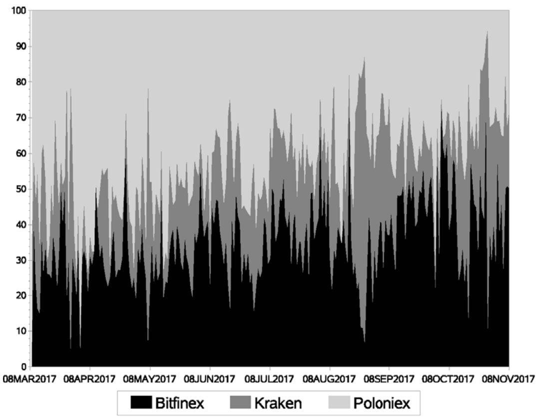
[7] Patel et al. (2020) recently have proposed a methodology to estimate the ILS for trivariate systems.

6. Conclusion

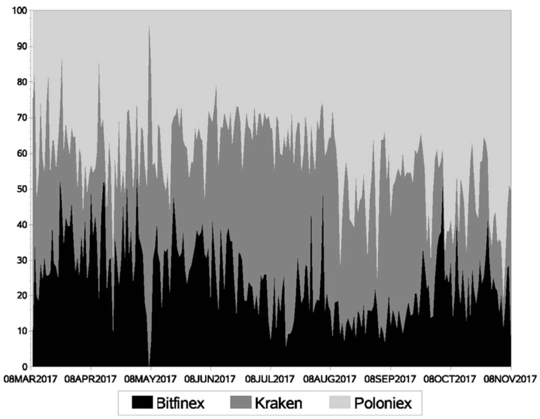
We examine the microstructure noise component and its impact on price discovery among three trading platforms for five cryptocurrencies. The levels of microstructure noise differ substantially across exchanges. Although the tick size, bid-ask spread, and the number of transactions may have some role in explaining these differences, their impact on the noise component is not clear-cut. A special case is Poloniex, which only offers trading against a stable coin rather than against fiat currencies, so it likely creates an additional source of noise. Our results show that cryptocurrency traders face the highest noise level on Poloniex. Overall, prices on any of the cryptocurrency exchanges are not as informative as those on the NYSE or NASDAQ, resulting in SNRs that are about half the magnitude as those resulting from the NYSE or NASDAQ. That is, cryptocurrency prices reflect more than just noise, but they have not yet reach the level of informativeness of stock prices.

Our price discovery analysis reveals that overall, Bitfinex is the leading cryptocurrency exchange, followed by Poloniex and Kraken. Yan and Zivot (2010) and Putniņš (2013) argue that different levels of microstructure noise prevent traditional information share measures, such as those proposed by Gonzalo and Granger (1995) and Hasbrouck (1995), from offering correct identification of contributions to price discovery. We show that for Poloniex – the market with the highest noise level – traditional measures suggest a lower information share compared to the information leadership share proposed by Putniņš (2013), which accounts for the noise component in the price series. In other words, the higher level of microstructure noise on Poloniex overshadows its contribution to price discovery, such that traditional measures cannot reliably detect the true contribution.

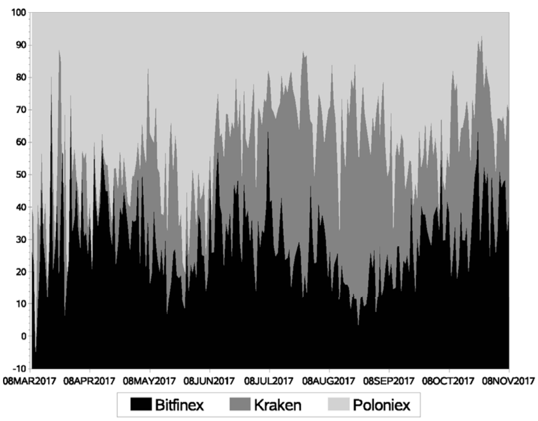
Appendix



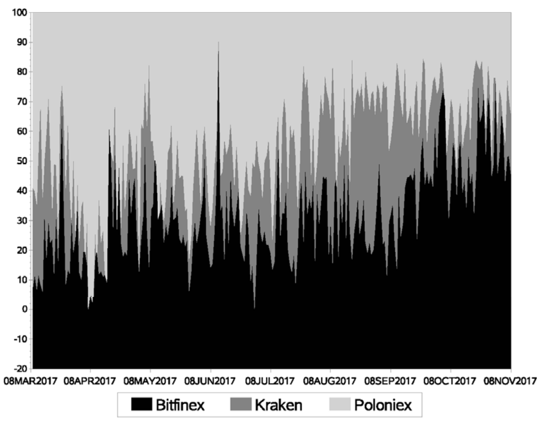
(a) Daily relative noise level ETC



(b) Daily relative noise level ETH

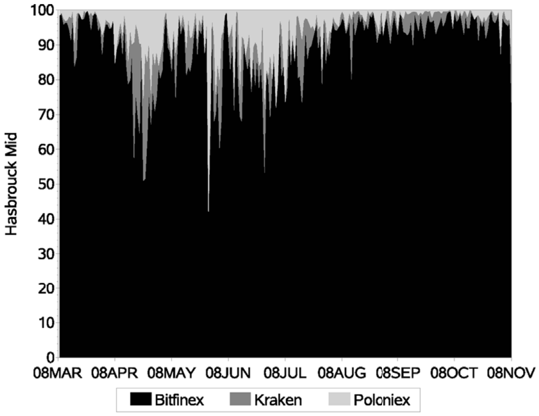


(c) Daily relative noise level LTC

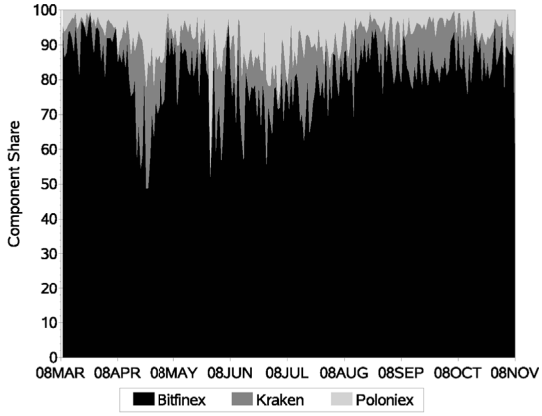


(d) Daily relative noise level XMR

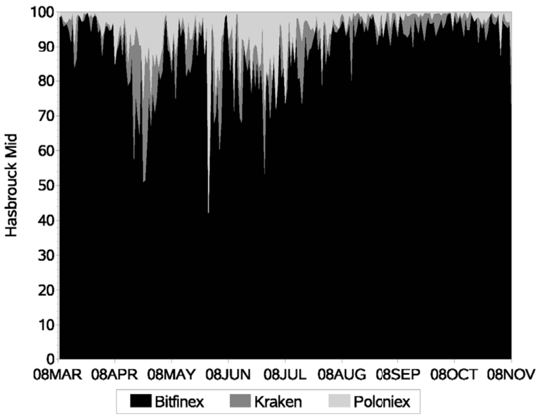
Fig. A.1 Evolution of daily relative noise level. The figure presents the evolution of the daily relative level of market microstructure noise of the three exchanges: Bitfinex (black), Kraken (dark gray), and Poloniex (light gray) for Ethereum Classic (ETC), Ethereum (ETH), Litecoin (LTC), and Monero (XMR).



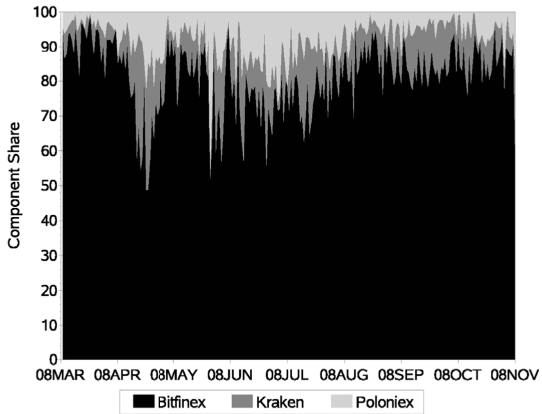
(a) Daily HIS BTC



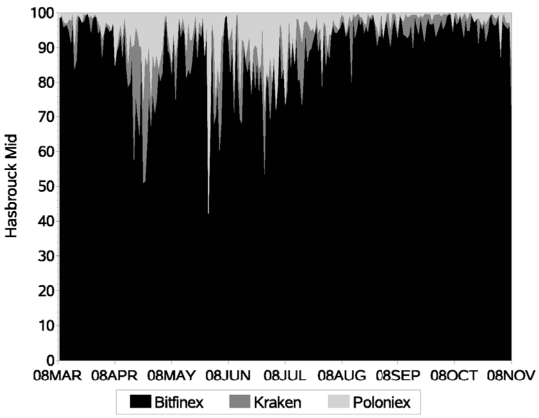
(b) Daily CS BTC



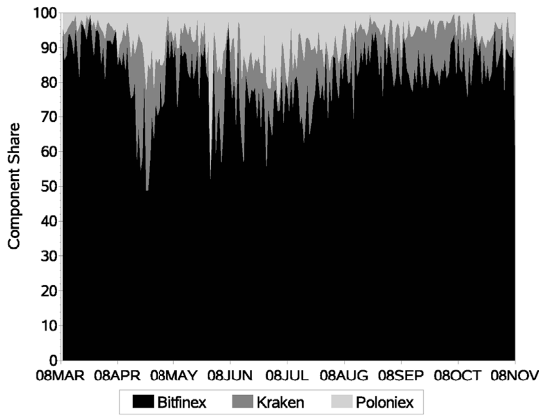
(c) Daily HIS ETC



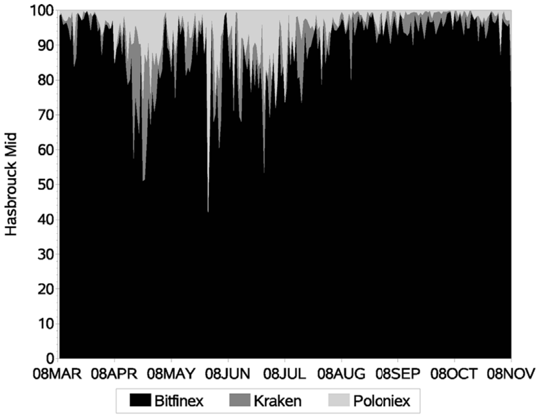
(d) Daily CS ETC



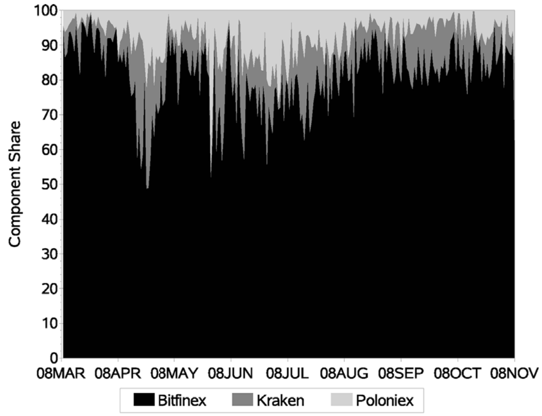
(e) Daily HIS ETH



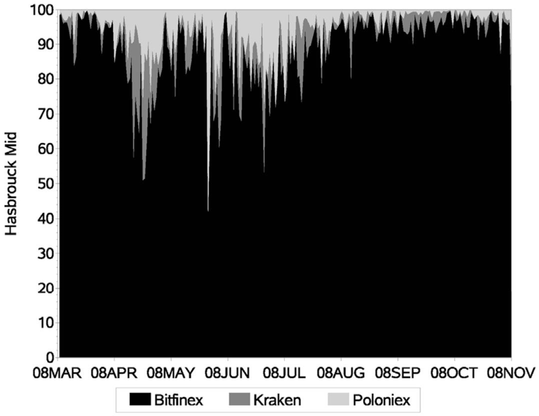
(f) Daily CS ETH



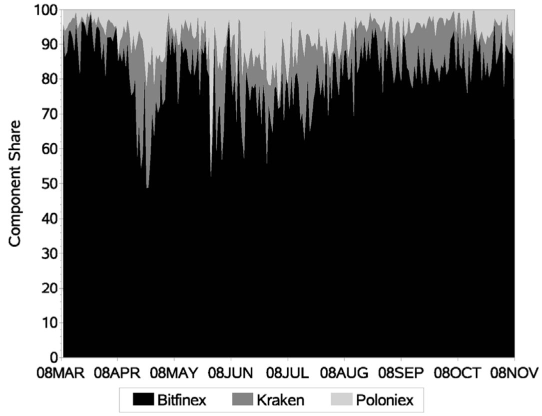
(g) Daily HIS LTC



(h) Daily CS LTC



(i) Daily HIS XMR



(j) Daily CS XMR

Fig. A.2 Daily HIS and CS estimates. The figure reports daily estimates for HIS and CS for Bitcoin (BTC), Ethereum (ETH), Ethereum Classic (ETC), Litecoin (LTC), and Monero (XMR).

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