Nothing but Noise? Price Discovery between Cryptocurrency Exchanges

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Abstract

We examine the relationship between price discovery contributions of three cryptocurrency exchanges and their noise levels using high frequency data. We document a strong correlation between an exchange's the relative noise level and the standard measures for price discovery. When implementing the information leadership share proposed by Putniņš [2013], which reduces the potential bias caused by noise avoidance, the informational leadership of Bitfinex and Kraken in comparison to those of Poloniex reduce substantially, presumably due to the higher relative noise level on Poloniex. Our results highlight the importance of accounting for different levels of noise, when evaluating price discovery contributions.

Keywords: price discovery, cryptocurrency, Bitcoin, information share, microstructure noise

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1 Introduction

Investors in cryptocurrencies have the choice between a number of trading venues to execute their transactions. Among the factors influencing their decisions are more obvious – and usually measurable – ones, such as transaction cost and available liquidity within a market. There are, however, additional factors which are not directly observable, such as price efficiency and the noisiness of prices. Within the context of several competing exchanges, the most efficient price exists in the market where price discovery is highest. It is this venue that contributes most to the fundamental value and whose prices reflect new information faster than prices reported on other markets. Hence, a market with a high relative price discovery contribution has the potential to attract more clients, which in turn might have a positive impact on liquidity and other aspects of market microstructure.

The latter, however, is also the source of a volatility component in the price, namely market microstructure noise, which is due to, amongst other, price rigidity or tick size effects. This noise constitutes a source of risk as traders might end up with less efficient prices due to uninformative price changes. Consequently, a trader's decision includes a trade-off between choosing a market whose prices reflect new information first, avoiding markets where prices are prone to excessive noise levels, and selecting the market with convenient factors like low transaction fees. Contributions to price discovery and noise avoidance are two aspects of market quality which play a major role when attracting investors. In particular in the context of cryptocurrencies, which are traded online and to the greatest extent without restrictions across markets (and even countries), attracting traders is vital. We therefore analyze price discovery among cryptocurrency markets, while accounting for the relative noise levels of the different exchanges.

The question where prices are set is an old one. Since the seminal papers of Hasbrouck (1995) and Gonzalo and Granger (1995), researchers have two measures at hand which are able to numerically quantify the contribution to price discovery. The measures are readily used, in particular for stock markets (Booth et al., 1999; Grammig et al., 2005; So and Tse, 2004; Comerton-Forde and Putniņš, 2015), but also for commodities like gold (Hauptfleisch et al., 2016) or agricultural products (Dimpfl et al., 2017). Issues related with the standard measures are that Hasbrouck's information share is not unique and that market microstructure frictions have an impact on these measures. The first issue is addressed and resolved by Lien and Shrestha (2012) and Grammig and Peter (2013). Related to our article is the second issue which is addressed by Yan and Zivot (2010) and Putniņš (2013). The authors show how the measures of Hasbrouck (1995) and Gonzalo and Granger (1995) can be combined to obtain a price discovery measure that is robust to potential bias induced by different levels of microstructure noise.

The literature that considers price discovery between cryptocurrency exchanges is still very recent. Brandvold et al. (2015) investigate price discovery between seven Bitcoin exchanges between April 2013 and February 2014. They find the Japanese Mt.Gox and the US BTC-e to be the leaders in price discovery during that period. It should be noted that both exchanges have been closed down after hacker attacks coupled with potential fraud. Pagnottoni and Dimpfl (2019) conduct a similar study, accounting for the effects of fiat currency exchange rates. They find that the Bitcoin price is basically not influenced by fiat currency prices and that price discovery (during the studied period) takes place to the greatest extent on OKCoin, a China based platform. Similar to Brandvold et al. (2015), their identified leading market is not fully operational any longer. Qu (2017) also considers price discovery, albeit not with the methodologies discussed above, and finds that the Chinese markets play an important role for trading in China mainland. Corbet et al. (2018), Baur and Dimpfl (2019), and Kapar and Olmo (2019) consider price discovery between Bitcoin spot and futures. While the first two studies find that the spot price is the leader in price discovery, Kapar and Olmo (2019) find the exact opposite.

The second strand in the cryptocurrency literature which is closely related to our study considers volatility in these markets. Numerous studies find that the volatility of Bitcoin and other cryptocurrencies is much higher than volatility of stocks (cp. Baur et al., 2018; Lahmiri et al., 2018; Symitsi and Chalvatzis, 2018) or commodities, in particular 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 venues.

With the following price discovery analysis of cryptocurrency markets we provide two contributions to the literature. First, we analyze price discovery for three trading venues (Bitfinex, Kraken, Poloniex) and five cryptocurrencies using high frequency transaction data. Second, we examine and explicitly account for the high microstructure noise environment of our analysis by estimating relative noise levels and applying the information shares of Putniņš (2013). While the impact of noise on price discovery contributions has been analyzed theoretically or in terms of simulations by Yan and Zivot (2010) and Putniņš (2013), empirical validation of these ideas are still missing. Thus, we foster the understanding of how noise impacts the measurement of price discovery. To this end, we calculate a measure for market microstructure noise based on Bandi and Russell (2006) to identify the market with the highest relative noise level. Our results indicate that Bitfinex is the leading market for all cryptocurrencies in our sample based on the standard measures. However, the relative contribution seems overestimated as suggested by Putniņš' measure. This is in line with the finding that Poloniex exhibits a considerably higher noise level which overshadows its contribution to price discovery.

The article proceeds as follows. Section 2 introduces the price discovery measures. Section 3 presents some market characteristics and the data along with descriptive statistics. Section 4 compares microstructure noise across the trading venues and provides insights into possible sources. Section 5 holds the results from the price discovery analysis and Section 6 concludes.

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 shares (HIS) proposed by Hasbrouck (1995).[1] Recently, Yan and Zivot (2010) and Putniņš (2013) showed that HIS and CS measure price discovery contributions - in the sense of relative speed of adjustment to new information - correctly only if the markets under consideration exhibit a similar level of microstructure noise. To account for differences in microstructure effects, Putniņš (2013) proposes a new information leadership share (ILS).

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

$$m_t = m_{t-1} + u_t, \quad \mathbb{E}[u_t] = \mathbb{E}[u_t u_s] = 0 \ \forall s \neq t, \quad \mathbb{E}[u_t^2] = \sigma_u^2 < \infty. \tag{1}$$

The asset itself is traded simultaneously on n markets. Hence, the n price series on these markets follow one common stochastic trend. However, the observed prices ($p_{i,t}$) on each market i are in general not identical across markets and also differ from the fundamental value due to market microstructure frictions such that

$$p_{i,t} = m_t + s_{i,t} \tag{2}$$

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

Hasbrouck information shares

The Hasbrouck approach relies on a decomposition of the variance of the efficient price innovations into contributions of the different markets. Collect the n (non-stationary)

[1] For a comprehensive discussion and comparison of CS and HIS we refer the interested reader to a special issue on price discovery by the Journal of Financial Markets, Volume 5, Issue 3, 259-390.

prices $p_{n,t}$ 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 the $(n \times n)$ adjustment coefficient matrix, and Γ_j the $(n \times n)$ autoregressive parameter matrices. The $(n \times 1)$ vector of price innovations, ε_t, is serially uncorrelated ($\mathbb{E}[\varepsilon_t \varepsilon_s'] = 0 \ \forall s \neq t$), but potentially contemporaneously correlated ($\mathbb{E}[\varepsilon_t \varepsilon_t] = \Sigma_\varepsilon$, where Σ_ε denotes a positive definite covariance matrix).

Following the law of one price, the theoretical cointegration matrix is given by

$$\beta' = \begin{bmatrix} 1 & -1 & 0 & \dots & 0 \\ 1 & 0 & -1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 0 & 0 & \dots & -1 \end{bmatrix}. \tag{4}$$

HIS are determined from the decomposition of the variance of the efficient price innovation u_t in Equation (1), which relates to the VECM parameters as

$$\sigma_u^2 = \psi' \Sigma_\varepsilon \psi = \psi' B B' \psi, \tag{5}$$

where ψ denotes the vector of long-run impact coefficients of the price innovations in the n markets and is one of the common rows Ξ which in turn can be derived as

$$\Xi = \beta_\perp [\alpha_\perp' (I_n - \sum_{i=1}^{q-1} \Gamma_i) \beta_\perp]^{-1} \alpha_\perp', \tag{6}$$

where $a_\perp$ describes the orthogonal complement of a (Johansen, 1995). Note that Ξ only consists of identical rows if β' has the structure as outlined in Equation (4). The matrix B in Equation (5) measures the contemporaneous effects of the idiosyncratic innovations

u_t and is commonly identified by the lower triangular matrix C derived from a Cholesky decomposition of the covariance matrix $\Sigma_\varepsilon = CC'$. The HIS of market i is then given by

$$IS_i = \frac{([\psi' C]_i)^2}{\psi' CC' \psi}, \tag{7}$$

where the subscript i denotes the i'th element of the row vector $[\psi' C]$. The Cholesky decomposition of the covariance matrix of Σ_ε implies a hierarchical ordering of the information shares in the sense that the first market's information share is maximized and the information share of the market ordered last is minimized. Permuting the ordering of the variables results in upper and lower HIS bounds. The bounds diverge depending on the contemporaneous correlation between the VECM residuals in Equation (3). To obtain a unique measure, commonly the midpoints, i.e. the average of lower and upper HIS bounds, are used.

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 in the increment of a common permanent factor. This representation belongs to the general class of permanent-transitory decompositions for which the permanent component is $I(1)$, but not necessarily a random walk. Following Lehmann (2002) prices (p_t) in n markets are given by

$$p_t = \iota w' p_t + \delta z_t, \tag{8}$$

where ι denotes a vector of ones. $w' p_t$ refers to the price of a weighted portfolio of the same asset traded on n different markets, where the weights $w = (w_1 \dots w_n)'$ are normalized to sum to 1. z_t denotes a stationary component given by $z_t = \beta' p_t$, where β is defined as in Equation (3). The transitory effects are measured by δ and relate to the portfolio weights w by:

$$\imath w' + \delta \beta' = I_n. \tag{9}$$

Gonzalo and Granger (1995) assume that the transitory component does not Granger-cause the common factor, which allows to link the portfolio weight w to the adjustment coefficients matrix α in Equation (3) by

$$w = \alpha_{\perp},$$

that is, w is orthogonal to all $n-1$ vectors of adjustment coefficients in α. The CS of market i is subsequently given by

$$CS_i = \frac{w_i}{\sum_{j=1}^{n} w_j}, \tag{10}$$

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

Putniņš' information leadership shares

As stated above, Yan and Zivot (2010) and Putniņš (2013) argue that in the presence of differing microstructure noise across the exchanges, HIS and CS may not correctly identify the contribution to price discovery. By *noise* Putniņš (2013) refers to microstructure effects caused for instance by tick size or, if transaction data is used, by bid-ask bounces, but also to liquidity effects or noise trading. Putniņš (2013) shows that, if the noise levels of the used price series differ, HIS and CS measure a combination of speed of adjustment and noise avoidance. Consequently, the conclusions drawn from these standard approaches might be misleading, in particular for markets that exhibit different market structures. He further proposes a combination of HIS and CS which under certain restrictions accurately measures contributions to price discovery by canceling out the potential bias due to different noise levels. The resulting price discovery measure termed 'information leadership share' consequently provides an unbiased estimate for price discovery contributions, where price discovery is defined as the relative speed of impounding new information into the price series, i.e. the perception of *who moves first*. The structural model by Yan and Zivot (2010) which leads to the information leadership share proposed by Putniņš (2013) is uniquely identified within a bivariate setting.

Considering an asset traded simultaneously on two markets, the combination of the HIS and CS measures, i.e. the information leadership metric of Yan and Zivot (2010), which results in an elimination of the bias caused by the relative avoidance of noise is given by

$$IL_i = \frac{HIS_i}{HIS_j} \frac{CS_j}{CS_i} \tag{11}$$

where i,j=1,2 denote the two markets, HIS and CS denote the Hasbrouck information share midpoints and component shares given by Equations (7) and (10), where n equals 2. The informational leadership share (ILS) according to Putniņš (2013) is then given by the relative informational leadership metric of each market

$$ILS_i = \frac{IL_i}{IL_i + IL_j}. \tag{12}$$

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

3 Market Details and Data Description

Our sample consists of five cryptocurrencies traded simultaneously on three exchanges. In detail, we use intraday transaction data on Bitcoin (BTC), Ethereum Classic (ETC), Ethereum (ETH), Litecoin (LTC), and Monero (XMR) traded against the US Dollar. Our intraday transaction time series consist of all transactions on the three cryptocurrency exchanges Bitfinex, Kraken, and Poloniex, which are among the most liquid exchanges during the time period considered.

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

The three trading venues differ with respect to a number of features. Table 1 summarizes selected features of each cryptocurrency exchange. The minimum tick size, for instance, differs substantially between the exchanges and is also not stable on the exchanges over time. For Bitcoin, for example, the range is from 0.0001 on Poloniex to 0.1 at Kraken at the end of our sample period. Tick size on Bitfinex was 0.005 until 24 October 2017 when the exchange introduced a flexible minimum tick size to assure that one tick equals a range of 10 to 25 USD[2].

Rounding issues due to tick size and price discreteness have been discussed as one factor influencing the microstructure noise level within a market (cp. Glosten and Harris, 1988;

[2]cp. https://www.bitfinex.com/posts/226

Diebold, 2006; Putniņš, 2013, among many others). Differences within the range and scale of sophistication of the offered order types also impact on microstructure noise: directly as they offer various degrees of flexibility in order submission and trading strategies, and indirectly by attracting different groups of investors. In particular, order types which are 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 (cp. Anand and Weaver, 2004; Anand et al., 2005; Boulatov and George, 2013). Hence, our a priori assumption that noise levels on Bitfinex, Kraken, and Poloniex differ seems justified, albeit, as discussed below, there exist other relevant factors, such as volume and trading intensity.

Our intraday data consist of transactions time series stamped at milliseconds (Kraken and Bitfinex) or seconds (Poloniex). All three exchanges offer a free public application programming interface (API) through which its most important live and historic data feeds are accessible via compatible software programs.[3] For the price discovery analysis we align Bitfinex, Kraken, and Poloniex transaction prices on a one second frequency. As the average number of transactions per minute ranges from 1 to 32 higher frequencies do not seem necessary. The data range from 8th of March 2017 to 8th of November 2017. All three exchanges operate seven days a week on a 24 hour basis.

Table 2 presents descriptive statistics of daily trading volume, the average number of transactions, as well as buys and sells of the five cryptocurrencies across the three exchanges. The first three columns show statistics on the trading volume. For all five currencies the transacted volume (over the whole sample period) on Bitfinex exceeds those of the other two exchanges. For BTC, ETC, LTC, and XMR Kraken constitutes the least liquid trading venue. The average volume per transaction does not differ substantially between the three exchanges.

[3]For further information, see the 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 R-packages *httr* (Wickham, 2018) and *jsonlite* (Ooms, 2014).

Table 2: Descriptive Statistics

The table presents descriptive statistics (minimum, maximum, mean, and the sum over the whole sample period) on the volume, number of transactions, and number of buys and sells of Bitfinex, Kraken, and Poloniex for Bitcoin (BTC), Ethereum (ETH), Ethereum Classic (ETC), Litecoin (LTC), and Monero (XMR).

		Bitfinex	Kraken	Poloniex	Bitfinex			Kraken			Poloniex		
		Volume per transaction			Trades per day			Trades per day			Trades per day		
					Buys	Sells	All	Buys	Sells	All	Buys	Sells	All
BTC	MIN	<0.01	<0.01	<0.01	3,986	2,163	6,149	641	712	1,367	5,720	4,453	10,173
	MAX	997.39	400.00	645.04	98,931	96,507	195,438	19,420	22,549	41,969	51,905	99,981	128,411
	MEAN	0.69	0.39	0.31	22,956	23,774	46,729	7,127	7,981	15,108	18,543	18,831	37,374
	SUM	7,915,140	1,426,009	2,811,111	5,624,099	5,824,582	11,448,681	1,746,107	1,955,281	3,701,388	4,543,029	4,613,697	9,156,726
ETC	MIN	<0.01	<0.01	<0.01	289	377	691	67	81	157	337	315	652
	MAX	80994.61	20000.00	30073.13	15,467	14,986	29,499	5,879	5,721	11,600	17,234	18,649	29,448
	MEAN	45.01	29.28	41.09	5,309	4,652	9,961	1,318	1,319	2,637	2,844	2,932	5,775
	SUM	109,834,247	18,999,009	58,144,484	1,300,689	1,139,789	2,440,478	324,349	324,437	648,786	696,682	718,226	1,414,908
ETH	MIN	<0.01	<0.01	<0.01	519	963	1,487	430	363	902	1,101	1,296	2,469
	MAX	4,996.15	5,852.80	7,847.18	18,544	17,523	33,018	25,440	24,170	46,235	36,512	35,212	69,920
	MEAN	6.99	5.47	4.65	10,962	9,706	20,668	7,455	7,074	14,529	8,127	8,237	16,364
	SUM	35,410,773	19,482,885	18,651,184	2,685,782	2,377,877	5,063,659	1,826,581	1,733,090	3,559,671	1,991,144	2,018,155	4,009,299
LTC	MIN	<0.01	<0.01	<0.01	109	124	373	23	28	51	228	259	492
	MAX	5,000.00	4,885.01	6,900.00	19,480	16,915	31,828	8,644	8,393	16,848	25,157	19,805	39,789
	MEAN	16.18	10.97	13.34	8,831	8,103	16,933	2,081	1,992	4,073	5,020	4,519	9,540
	SUM	67,114,433	10,988,498	31,186,945	2,163,501	1,985,124	4,148,625	511,906	489,985	1,001,891	1,229,964	1,107,264	2,337,228
XMR	MIN	<0.01	<0.01	<0.01	108	92	327	18	25	45	234	531	768
	MAX	3,000.00	2,177.73	3,054.95	13,996	13,984	27,980	7,090	8,258	15,348	29,323	12,692	30,289
	MEAN	10.03	5.32	5.20	1,493	1,586	3,079	669	756	1,425	2,346	2,081	4,426
	SUM	7,565,092	1,865,762	5,643,377	365,776	388,468	754,244	164,574	185,962	350,536	574,691	509,791	1,084,482

Descriptive statistics on the transaction prices (minimum, maximum, mean and standard deviation) can be found in Table 3. We observe a slightly higher standard deviation on Poloniex for all five currencies. The range of prices, i.e. minimum and maximum, however do not deviate substantially across the trading venues.

Table 3: Descriptive Statistics On Transaction Prices
The table presents descriptive statistics on the transaction prices on Bitfinex, Kraken, and Poloniex for Bitcoin, Ethereum, Ethereum Classic, Litecoin, and Monero.

		Bitfinex	Kraken Price	Poloniex
BTC	MIN	888.20	881.89	888.99
	MAX	7899.90	7788.00	7771.00
	MEAN	3648.43	3338.75	3361.35
	STD	1687.56	1463.72	1773.30
ETC	MIN	1.22	1.21	1.18
	MAX	23.30	24.00	24.00
	MEAN	12.94	13.84	12.95
	STD	4.88	5.02	5.22
ETH	MIN	16.25	15.56	16.22
	MAX	395.03	404.99	408.13
	MEAN	251.75	241.45	231.57
	STD	86.22	88.82	95.74
LTC	MIN	3.74	3.62	3.55
	MAX	90.91	95.00	93.67
	MEAN	42.70	45.45	44.21
	STD	17.64	16.94	18.72
XMR	MIN	12.25	12.15	12.10
	MAX	154.99	159.90	153.43
	MEAN	80.95	78.19	65.21
	STD	37.12	38.07	38.86

In order to pre-test whether the data are suitable for our analysis, we conduct unit root tests which clearly indicate that the transaction prices of all cryptocurrencies on all three exchanges are non-stationary. Cointegration tests reveal that the prices of the same cryptocurrency which is observed on three different platforms follow the same stochastic trend.

4 Market Microstructure Noise – Level and Sources

Cryptocurrency markets, and in particular Bitcoin, have been documented to be highly volatile. Prior to analyzing price discovery in the presence of microstructure noise, we shed some light on the noise levels across the cryptocurrency markets and discuss its sources. As an empirical measure for microstructure noise we rely on the literature on realized volatility (cp. Andersen et al., 2003; Aït-Sahalia et al., 2011; Andersen et al., 2011) which documents a bias of realized volatility due to microstructure noise at high frequencies. The common solution is to resort to lower, e.g. 5 minute intervals. Bandi and Russell (2006) show that for a model as in Equation (2), the daily variance of the noise component $s_{i,t}$ (denoted by $mn_{i,t}$) is consistently estimated from the squared intraday returns at the highest available frequency as

$$mn_{i,t} = \frac{1}{2M} \sum_{j=1}^{M} r_{k,t}^2 \underset{\mathrm{M} \to \infty}{\overset{\mathrm{p}}{\to}} \mathbb{E}\left[s_t^2\right], \tag{13}$$

where $r_{k,t}$ is the kth intradaily return on day t and M is the number of intervals during the day. In order to compare the level of microstructure noise mn across the exchanges, we calculate the relative noise level as $\widetilde{mn}_{i,t} = ms_{i,t}/\sum_i mn_{i,t}$ across the exchanges i.

Figure 1 illustrates the daily relative noise level $\tilde{m}s_t$ across the sample period for Bitcoin. The respective graphs for the remaining cryptocurrencies can be found in the Appendix in Figure A.1. The first observation is that the noise levels are not static, but vary substantially across the sample period. Furthermore, while there are some spikes in the relative noise levels, Figure 1 indicates that Poloniex exhibits the largest relative noise level. This observation holds for the remaining cryptocurrencies as well.

In order to get an overall impression of the relative noise level, Table 4 provides the average and – due to the spikes observed in the previous graph – the median of the absolute daily noise level mn across the entire sample for the three considered trading venues and all cryptocurrencies. The median values confirm that on average the noise level on Poloniex is substantially larger compared to Bitfinex and Kraken for all five

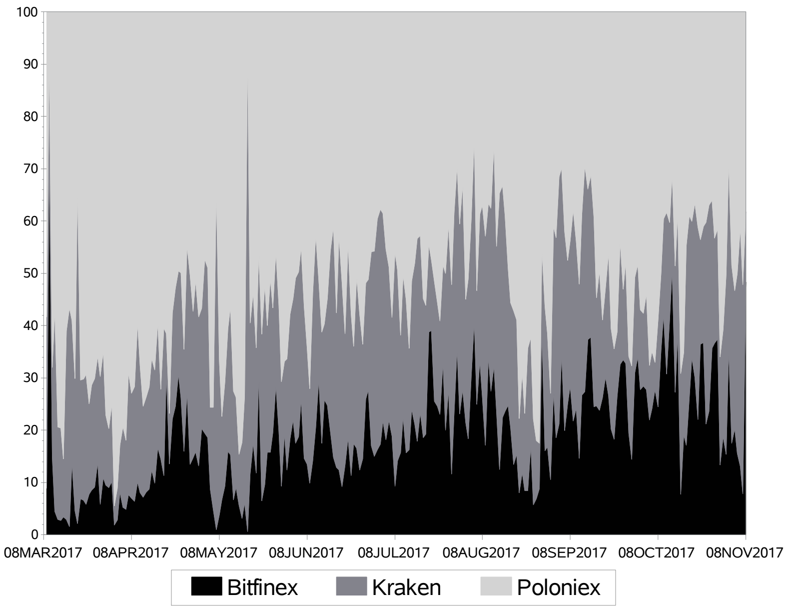

Figure 1: Time series of daily relative noise level.
The figure presents the evolution of the daily relative level of market microstructure noise of the three exchanges Bitfinex (black), Kraken (dark gray), and Poloniex (light gray) for Bitcoin.

currencies. The same holds for the average noise except for ETH. For ETH we observe the largest average noise level on Kraken.

The higher noise level on Poloniex is also visible from the volatility signature plot for Bitcoin in Figure 2. However, it is only present when considering a frequency higher than 10 seconds, while at lower frequencies the noise level on Kraken slightly exceeds the one on Poloniex. We observe a similar pattern for ETC and LTC. For all five currencies Bitfinex exhibits the lowest realized volatility estimates at any frequency. Volatility signature plots have first been used by Andersen et al. (1999) to illustrate the effect of the sampling frequency on the estimation of realized volatility. If we compare our Bitcoin signature plot to their Figure 6 it turns out that Bitcoin resembles an illiquid asset in the stock market, even though Bitcoin is the most liquid amongst our considered cryptocurrencies.

Table 4: Average noise level
The table shows the mean and median of daily noise levels mn ($\times 100$) calculated according to Equation (13) for Bitcoin (BTC), Ethereum Classic (ETC), Ethereum (ETH), Litecoin (LTC), and Monero (XMR) on Bitfinex, Kraken, and Poloniex.

	Mean			Median		
	Bitfinex	Kraken	Poloniex	Bitfinex	Kraken	Poloniex
BTC	1.71	1.93	3.10	0.48	0.76	1.64
ETC	2.63	1.89	3.18	1.23	0.67	1.55
ETH	2.36	3.81	3.25	0.93	1.33	1.61
LTC	2.04	2.06	3.10	1.02	0.99	1.25
XMR	2.33	1.66	2.06	0.63	0.41	0.89

The sources of microstructure noise are manyfold, but do not display a consistent character across the exchanges. As we have already discussed in Section 3, the tick size (and in particular the change of 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 this was the only one. In contrast, we find lower noise levels on these two markets. An additional source might be trading volume and intensity (proxied by the number of trades) as presented in Table 2. Considering traded volume as a measure for liquidity, we would expect the most liquid markets to be less prone to microstructure noise. This conjecture is supported by the data in so far as relative higher liquidity seems to be related to a lower noise level. However, trading volume and trading intensity are not sufficient to uniquely determine the ordering of the markets with respect to their relative noise levels: If we consider Bitcoin, the most liquid market is Bitfinex which also exhibits the lowest noise level. However, Kraken is the least liquid market, but still shows a noise level which is lower than the one on Poloniex. For Monero, we find that Poloniex is the most active market and also shows on average a lower noise level than Bitfinex. However, the noise level on Kraken is substantially lower albeit trading of XMR is very thin there.

A second measure for liquidity and, thus, a potential driver of market microstructure noise, is the spread. Descriptive statistics on daily spread estimates based on 30 second

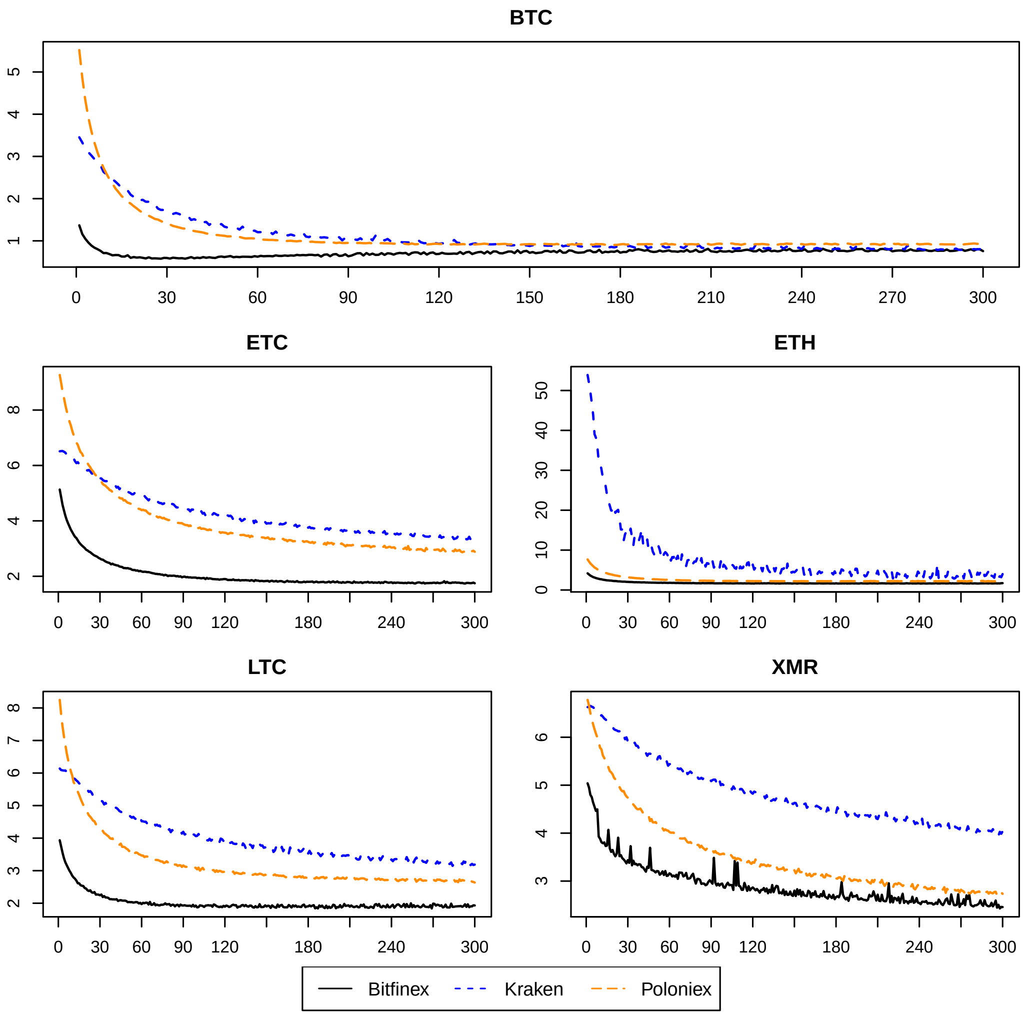

Figure 2: Volatility signature plots
The graphic presents signature plots of realized volatility of Bitcoin (BTC), Ethereum Classic (ETC), Ethereum (ETH), Litcoin (LTC), and Monero (XMR) for sampling frequencies from 1 to 300 seconds. The black solid line represents calculations for Bitfinex prices, the blue dashed line is Kraken, and the orange long dashes are Poloniex.

quote data are presented in Table 5. On average, we find the spread to be smallest on Bitfinex and highest on Kraken for all considered cryptocurrencies. As Poloniex has the smallest possible tick size, we would have expected a smaller spread on average than on the two other exchanges, but that does not seem to be the case. The relation to our microstructure noise estimate is therefore, again, not such that a narrower spread guarantees a lower noise level. While this holds for Bitfinex, it does not hold for Kraken and Poloniex. If we consider again the example of Bitcoin, the average spread is roughly 1 USD on Bitfinex while it is 3.22 USD on Poloniex and 5.88 USD on Kraken. Hence, the noise component should be lowest on Bitfinex which is what we find and document in Table 4. However, Kraken should then have a higher noise level than Poloniex which is not in line with our results.

Table 5: Descriptive Statistics on Spreads
The table presents descriptive statistics on the quoted and relative spread calculated from 30s bid/ask quotes 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

One potential factor causing the higher noise level on Poloniex compared to the other two platforms might lie within the way trading occurs on Poloniex as opposed to Kraken or Bitfinex. The latter provide a wallet for the user where she can store fiat currency which is then used to buy and sell any cryptocurrency. On Poloniex, traders use USDC, a stable coin that is worth 1 USD. In theory, the price of 1 USDC should always exactly equal 1 USD. However, it seems that this is not the case. Between March and December 2017, USDC varied between 0.91 and 1.06 USD[4], hence presenting an additional source of noise on Poloniex which is not an issue on any of the two other markets. This special feature on Poloniex might be the driver for the generally higher noise level on Poloniex.

[4]Daily data on USDC are available from coinmarketcap.com.

While a comparison of the noise level across the cryptocurrency exchanges provides useful insights for the subsequent price discovery analysis, it does not yet reveal how much noise versus fundamental information there is in cryptocurrency prices. If we argue that prices reflect information, then the conclusion by Cheah and Fry (2015), that the fundamental value of Bitcoin is zero, would suggest that there is no information and cryptocurrency prices reflect only noise. Given that there are some useful applications of cryptocurrencies (even though some of these may not always be regarded as useful by society or may even be illegal), the fundamental value should not be zero. At least costs for power and computer resources should be reflected in the price of Bitcoin as initially miners generated income only from mining and only in the last years moved to collecting fees (Easley et al., 2019).

Volatility signature plots present another possibility to examine the information versus noise relationship in financial assets. Calculating realized volatility at the highest available frequency provides an estimate for the variance of the microstructure noise component. In addition, when calculated at a lower frequency (commonly 5 minutes), the realized variance is a good estimate for the variance of the stochastic process in question (cp. Bandi and Russell, 2006). Consequently, a comparison of the two components gives a hint as to how much information versus noise is contained in the price. Indeed, the plots presented in Figure 2 imply an average signal-to-noise ratio between 13% for Bitcoin and almost 40% for Monero. The fact that for Bitcoin the ratio is lowest is in line with the conclusions drawn from the PIN estimates.

5 Price Discovery between Cryptocurrency Exchanges

5.1 Results from Traditional Measures

We examine the price discovery contributions of Bitfinex, Kraken, and Poloniex starting with a trivariate setting and estimate the standard price discovery measures given by Equations (7) and (10). Table 6 shows CS and HIS estimates for the three markets and five cryptocurrencies based on averages over daily estimation of the VECM in Equation (3). Considering the CS, Bitfinex is the dominant market in terms of price discovery for all five cryptocurrencies, except for Monero (XMR). With the exception of Bitcoins, Kraken shows the smallest price discovery contribution ranging between 13.4% for Litecoin (LTC) and 21,7 % for Monero (XMR). The Hasbrouck information share midpoints (HIS) emphasize the leadership of Bitfinex for all currencies but Monero (XMR) even more with HIS midpoint estimates ranging from 61.6% for Ethereum Classic (ETC) to 89.7% for Bitcoin (BTC). The increased price discovery contribution based on the Hasbrouck approach (compared to the CS results) of Bitfinex is predominantly due to a smaller price discovery contribution of Kraken when relying on Hasbrouck midpoints rather than the component share.

The HIS bounds have been estimated as the average of all possible permutations with the market of interest ordered first for the upper and ordered last for the lower bound. The estimated HIS lower and upper bounds are very tight for all currencies and exchanges, indicating that there is almost no contemporaneous correlation present at a one second sampling frequency. Consequently, the midpoints can be used as a valid proxy for the information share based on the Hasbrouck methodology.[5]

5.2 Price Discovery in the Presence of Noise

Table 7 shows the correlation of daily HIS and CS of all exchanges with the relative daily noise level for Bitcoin.[6] We find that 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. This

[5]Figure 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. A possible explanation might be found within several announcements of Bitfinex via their internet page and social media that the exchange is experiencing delays in the processing of outbound USD wires to customers. Additionally, Bitfinex reported to be under Distributed-Denial-of-Service (DDoS) attacks in mid June.

[6]Correlations for the remaining four currencies can be found in Table A.1 in the Appendix.

Table 6: Price discovery measures in a trivariate system.
The table shows average components shares (CS) and Hasbrouck information shares (HIS) based on a daily VECM estimates including 1 second transactions from Bitfinex, Kraken, and Poloniex.

	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)

corresponds to the idea put forth in Yan and Zivot (2010) and Putniņš (2013) that conventional price discovery methodologies quantify a mix of speed of adjustment and noise avoidance and are potentially biased. Consequently, as an example, the daily CS of Bitfinex might be biased downwards whenever its daily noise level relative to Kraken and Poloniex increases, resulting in a negative correlation as observed in Table 7.

Interestingly we do not observe significant correlations between daily HIS and the relative daily noise level for Bitcoin. For the remaining currencies, Table A.1 in the appendix shows significant correlations of noise and HIS in several cases, however, overall the correlations between CS and the relative noise level are stronger compared to 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, while HIS measures a mixture of relative noise avoidance and informational leadership. It is also consistent with the simulation study by Putniņš (2013), who reports that compared to CS, HIS puts more emphasis on measuring who moves first relative to avoidance of noise.

Consequently, we estimate the ILS for all three bivariate combinations of cryptocurrency exchanges for each of the five cryptocurrencies. The results are presented in Table 8. Considering the bivariate setting including Bitfinex and Kraken, we observe only small

Table 7: Correlation between CS, HIS and relative noise level

The table reports the Pearson correlation coefficients between HIS, CS and the relative noise level $\tilde{ms}$ on Bitfinex, Kraken, and Poloniex. p-values associated with a test whether the correlation is statistically significant are in parentheses.

	BTC		
	Bitfinex Noise	Kraken Noise	Poloniex Noise
Bitfinex CS	-0.304	0.028	0.201
	(0.000)	(0.662)	(0.002)
Bitfinex HIS	0.031	-0.040	0.007
	(0.632)	(0.529)	(0.907)
Kraken CS	0.298	-0.191	-0.075
	(0.000)	(0.003)	(0.239)
Kraken HIS	0.039	-0.045	0.005
	(0.545)	(0.488)	(0.943)
Poloniex CS	0.144	0.187	-0.244
	(0.024)	(0.003)	(0.000)
Poloniex HIS	-0.079	0.098	-0.015
	(0.216)	(0.124)	(0.815)

differences between CS, HIS, and ILS as all of them identify Bitfinex as the leading exchange with a contribution to price discovery of more than 85%. The differences in the noise level on Bitfinex and Kraken are therefore not pronounced enough to severely bias the standard measures. Turning to the bivariate setting including Bitfinex and Poloniex, CS and HIS clearly indicate Bitfinex' leadership in price discovery for Bitcoin (BTC), Ethereum (ETH), Ethereum Classic (ETC) and Litecoins (LTC). However, the ILS estimates reveal an upward bias of the standard measures and report contribution for Bitfinex, which are 10 to 15 percentage points lower. Keeping in mind the considerably higher noise level on Poloniex (as documented in Figure 2 and Table 4) this result matches the conclusions 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 (XMR) we even observe a switch of the leading exchange from Bitfinex to Kraken, when using the potentially unbiased ILS estimate. Analysing price discovery between Kraken and Poloniex, the average noise levels given in Table (4) 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 expectations, as the ILS estimates are clearly below the standard measures for all five currencies and the Poloniex' leadership over Kraken with respect to price discovery is more pronounced compared to the results presented in Tables 6.

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

6 Conclusion

We investigate the microstructure noise component on and price discovery between three trading platforms for five cryptocurrencies. We find that the levels of microstructure noise are substantially different across the exchanges. While the tick size, the bid/ask spread, or trading intensity seem to play a role in explaining these differences, their impact on the noise component is not clear-cut. A special case is Poloniex as trading occurs against a stable coin (USDC) instead of fiat currencies like the euro or the US dollar which most likely poses an additional source of volatility such that Poloniex turns out to be prone the most to market microstructure noise.

Our price discovery analysis reveals that overall Bitfinex is the leading exchange, followed by Poloniex and Kraken. Recently, Yan and Zivot (2010) and Putniņš (2013) argue that the presence of microstructure noise, in particular if it is not harmonic across different exchanges, prevents the traditional information share measures of Gonzalo and Granger (1995) and Hasbrouck (1995) to correctly identify the contribution to price discovery. We show that for Poloniex (which is the market which has on average the highest level of microstructure noise) the 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 which is understated by the Hasbrouck information share and the Gonzalo/Granger component share.

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)

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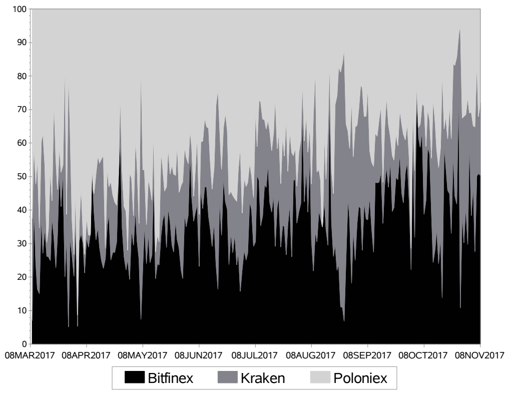
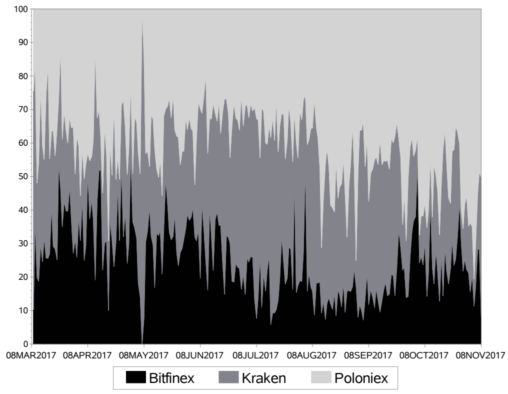
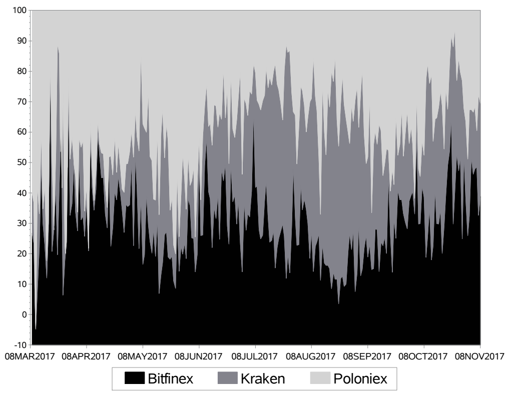
Appendix



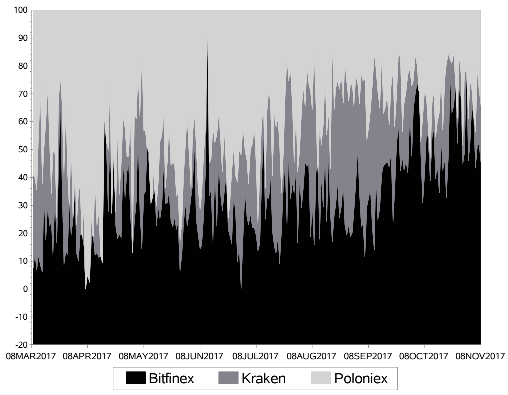
(a) Daily Relative Noise Level ETC



(b) Daily Relative Noise Level ETH

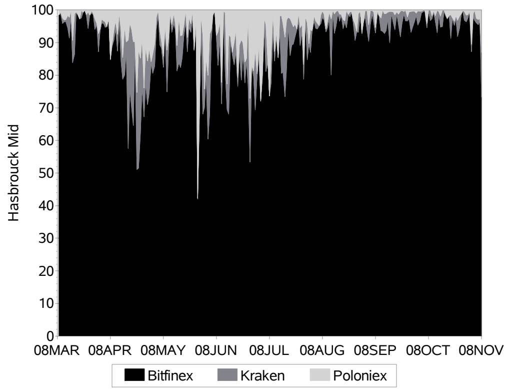


(c) Daily Relative Noise Level LTC

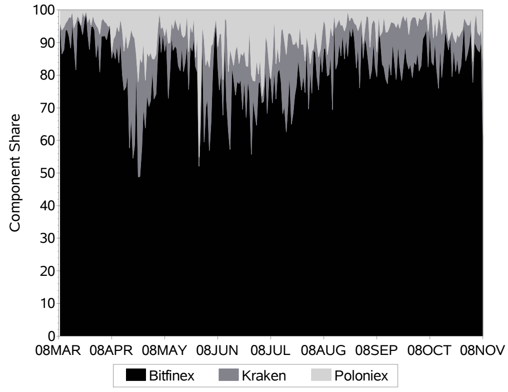


(d) Daily Relative Noise Level XMR

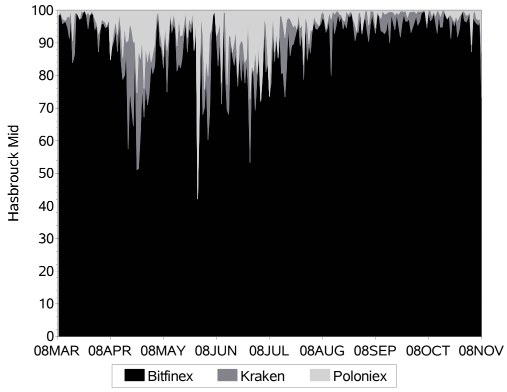
Figure A.1: Time series of daily relative noise level on Bitfinex, Kraken, and Poloniex.
The figure presents the evolution of the daily relative level of market microstructure noise of the three exchanges Bitfinex (black), Kraken (dark gray), and Poloniex (light gray) for Ethereum (ETH), Ethereum Classic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



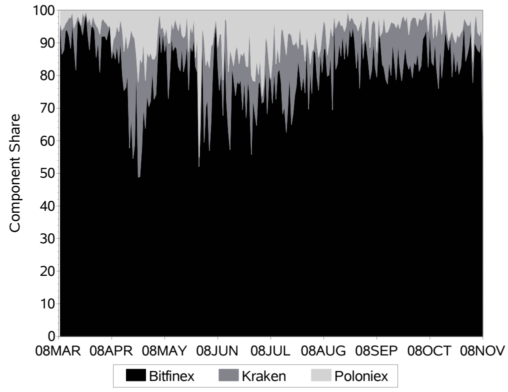
(a) Daily HIS BTC



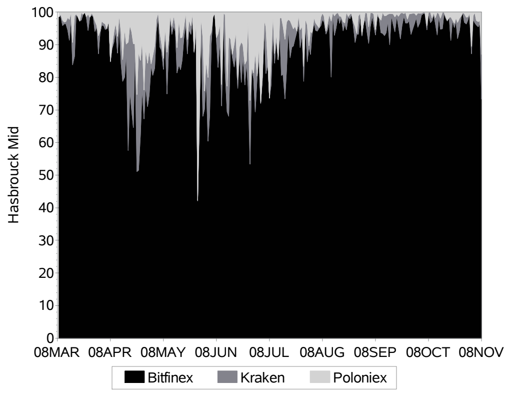
(b) Daily CS BTC



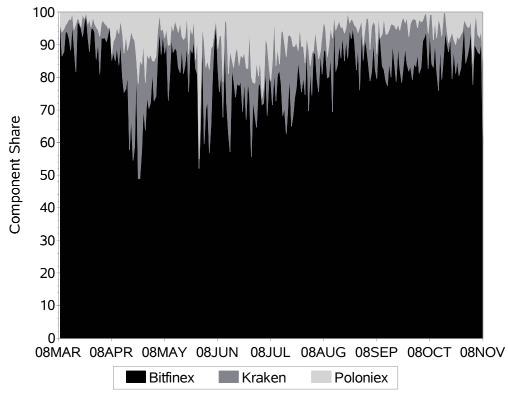
(c) Daily HIS ETC



(d) Daily GG ETC

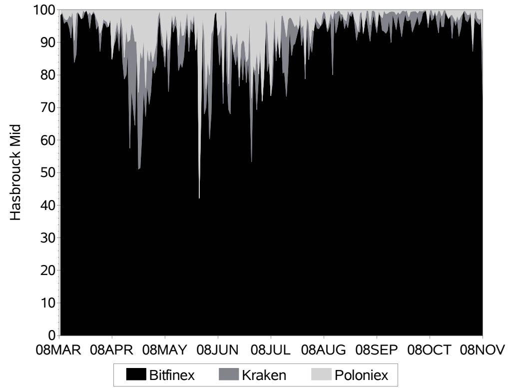


(e) Daily HIS ETH

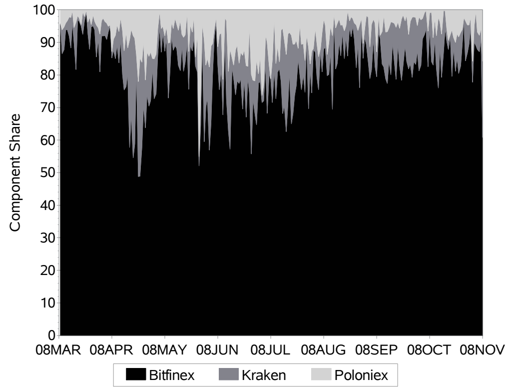


(f) Daily GG ETH

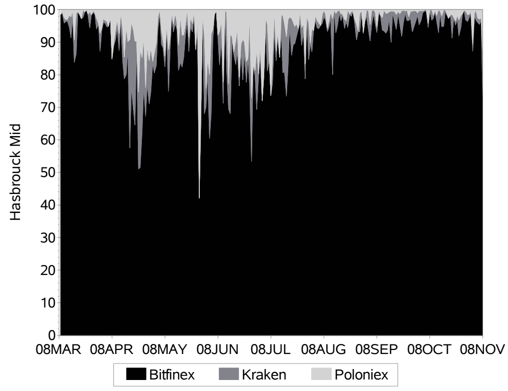
Figure A.2: Daily HIS and CS estimates.
The figure reports daily estimates for HIS and GG for Bitcoin (BTC), Ethereum (ETH), Ethereum Classic (ETC), Litecoin (LTC) and Monero (XMR).



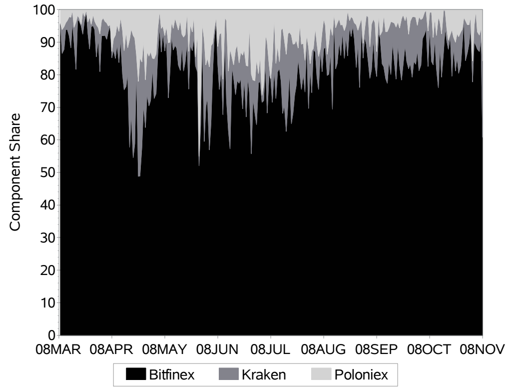
(g) Daily HIS LTC



(h) Daily GG LTC



(i) Daily HIS XMR



(j) Daily GG XMR

Figure A.2: Daily HIS and CS estimates (continued).

Table A.1: Correlation between HIS, CS and relative noise level.
The table reports the Pearson correlation coefficients between HIS, CS, and the relative noise level $\widetilde{ms}$ on Bitfinex, Kraken, and Poloniex for ETC, ETH, LTC, and XMR. p-values associated with a test whether the correlation is statistically significant are in parentheses.

ETC			
	Bitfinex Noise	Kraken Noise	Poloniex Noise
Bitfinex CS	-0.529	0.343	0.107
	(0.000)	(0.000)	(0.095)
Bitfinex HIS	-0.249	0.191	0.018
	(0.000)	(0.003)	(0.777)
Kraken CS	0.312	-0.510	0.270
	(0.000)	(0.000)	(0.000)
Kraken HIS	0.188	-0.309	0.164
	(0.003)	(0.000)	(0.010)
Poloniex CS	0.275	0.244	-0.513
	(0.000)	(0.000)	(0.000)
Poloniex HIS	0.103	0.089	-0.190
	(0.108)	(0.165)	(0.003)

ETH			
	Bitfinex Noise	Kraken Noise	Poloniex Noise
Bitfinex CS	-0.495	0.102	0.335
	(0.000)	(0.112)	(0.000)
Bitfinex HIS	-0.242	-0.094	0.330
	(0.000)	(0.143)	(0.000)
Kraken CS	0.580	-0.637	0.204
	(0.000)	(0.000)	(0.001)
Kraken HIS	0.498	-0.463	0.078
	(0.000)	(0.000)	(0.226)
Poloniex CS	0.137	0.379	-0.562
	(0.032)	(0.000)	(0.000)
Poloniex HIS	0.007	0.344	-0.403
	(0.914)	(0.000)	(0.000)

Table A.1: Correlation between HIS, CS and relative noise level (continued).

LTC			
	Bitfinex Noise	Kraken Noise	Poloniex Noise
Bitfinex CS	-0.501	0.300	0.072
	(0.000)	(0.000)	(0.262)
Bitfinex HIS	-0.252	0.180	0.003
	(0.000)	(0.005)	(0.960)
Kraken CS	0.408	-0.545	0.281
	(0.000)	(0.000)	(0.000)
Kraken HIS	0.269	-0.402	0.233
	(0.000)	(0.000)	(0.000)
Poloniex CS	0.276	0.105	-0.345
	(0.000)	(0.101)	(0.000)
Poloniex HIS	0.147	0.001	-0.121
	(0.022)	(0.988)	(0.058)

XMR			
	Bitfinex Noise	Kraken Noise	Poloniex Noise
Bitfinex CS	-0.459	0.284	0.150
	(0.000)	(0.000)	(0.019)
Bitfinex HIS	-0.074	0.210	-0.121
	(0.248)	(0.001)	(0.060)
Kraken CS	0.323	-0.467	0.131
	(0.000)	(0.000)	(0.041)
Kraken HIS	0.200	-0.368	0.151
	(0.002)	(0.000)	(0.018)
Poloniex CS	0.133	0.323	-0.402
	(0.037)	(0.000)	(0.000)
Poloniex HIS	-0.137	0.164	-0.026
	(0.033)	(0.010)	(0.688)