Liquidity co-movements and volatility regimes in cryptocurrencies

Hubert Anciaux* Christophe Desagre† Nicolas Nicaise‡ Mikael Petitjean§

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Abstract

We find significant evidence of liquidity commonalities among cryptos, in particular when liquidity is estimated by relying on order-book-based proxies. Both the magnitude and pervasiveness of these comovements are very similar to those estimated for US stocks 10 and 20 years ago. When we introduce volatility regimes based on the VCRIX volatility index on cryptocurrencies, we identify stronger liquidity co-movements in high volatility regimes across all cryptocurrencies and for all liquidity proxies. The magnitude and pervasiveness of commonalities are weaker in the low volatility regime when liquidity is arguably more idiosyncratic, affecting cryptos differently and leading to more disconnected movements relative to market liquidity. We conclude that the liquidity co-movements are not orthogonal to what was observed in the past for more centralized markets.

Keywords: Liquidity, co-movements, bitcoin, volatility, cryptos.

JEL codes: G10, G12.

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*Louvain School of Management, Email: hubert.anciaux@protonmail.ch

†Louvain School of Management (LFIN-IMMAQ, UCLouvain), 151 Chaussée de Binche, 7000 Mons, Belgium, Email: christophe.desagre@uclouvain.be. *Corresponding author.*

‡Louvain School of Management, Email: nicolas.nicaise@outlook.fr

§IESEG School of Management (LEM UMR 9221 CNRS) and Louvain School of Management (LFIN-IMMAQ, UCLouvain). E-mail: m.petitjean@ieseg.fr.

1. Introduction

According to Corbet et al. (2019, p. 3), cryptocurrencies *'are peer-to-peer electronic cash systems which allow online payments to be sent directly from one party to another without going through a financial institution.'* Over the last ten years, cryptocurrencies have become increasingly popular among financial assets. In just a single year, the market capitalization of the first decentralized digital currency, i.e. the Bitcoin, went up from $10.1 billion in October 2016 to $79.7 billion in October 2017 (Corbet et al., 2019). In 2017, the price of Bitcoin increased from $1,103 to $16,792, representing a 1422% year-on-year return on investment. In November 2020, the price of Bitcoin was again close to the $16,000 threshold that it first broke up in December 2017.

While there are more than a thousand cryptocurrencies, Bitcoin still remains the main cryptocurrency in terms of market capitalization today. According to Corbet et al. (2019), the growth in the demand for cryptocurrencies can be explained in particular by the facts that they have low transaction costs, rely on a peer-to-peer system and do not include government intervention in their design. Nevertheless, Sockin and Xiong (2018) highlight that we still need to improve our understanding of this technology to better assess its benefits and risks in order to build an adapted regulatory framework. This has become even more relevant since the introduction of Bitcoin futures in December 2017.

In the meantime, the rising popularity of cryptos has also spread to the academic world where cryptocurrencies have become an important research topic. Most academic papers on cryptocurrencies investigate traditional research questions such as volatility clustering, asset pricing bubbles, market efficiency, and portfolio diversification. There are much fewer papers on liquidity and its dependence on volatility.

Liquidity measures the degree to which transactions of an asset can happen at short notice and at a fair price (Dick-Nielsen and Rossi, 2018). Higher liquidity is important for market participants since it is typically associated with lower investment risk and favorable market conditions.

From a macro perspective, the successful management of liquidity on financial markets require policymakers and financial regulators to pay close attention to the presence of a common factor in the movements of liquidity across assets. Stronger co-variations between assets would indeed increase the propagation of liquidity shocks, including to other markets, and could have a significant impact on the stability of financial markets (Klein and Song, 2017).

From a micro standpoint, the existence of a common factor in liquidity has strong implications for investment decisions (Koch et al., 2016) since the likelihood of facing systematic liquidity risk and non-diversifiable transaction costs increases with common liquidity movements (Anagnostidis and Fontaine, 2018).

In the past 20 years, researchers have studied co-movements in several financial dimensions (Heston and Rouwenhorst, 1994, 1995; Brockman and Chung, 2002; Chordia et al., 2000; Domowitz et al., 2005; Hasbrouck and Seppi, 2001; Karolyi et al., 2012). Among them, co-movements in liquidity have attracted a lot of attention (Chordia et al., 2000; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001; Brockman and Chung, 2002; Domowitz et al., 2005; Brunnermeier and Pedersen, 2009).

Despite the profusion of academic research on liquidity, there are much fewer papers which investigate the liquidity of cryptos, so that it is still not clear whether the covariance risk of individual crypto liquidity with the aggregate is positively linked to required returns. There is still no clear indication that systematic liquidity risk is related to the returns of cryptos.

Marshall et al. (2018) do study liquidity and Liu et al. (2019) do investigate the factor structure in returns and volatility, but they only focus on the Bitcoin which is just one cryptocurrency among many others. There is also no analysis of the impact of volatility on the magnitude and pervasiveness of liquidity co-movements among cryptos in the literature yet.

The motivation of this paper is precisely to fill that gap and extend the literature on cryptos by estimating commonalities in liquidity on the most active Bitfinex platform for the five most popular cryptocurrencies, i.e., Bitcoin, Ethereum, Bitcoin Cash, EOS and Ripple, while introducing volatility regimes based on the VCRIX volatility index on cryptocurrencies.

The remainder of this paper is as follows. Section 2 contains a description of our data and of our sample, the variables under scrutiny, some descriptive statistics, and the methodology. In Section 3, we report our empirical findings. Section 4 concludes.

2. Empirical part

2.1. Data and sample

We obtain intraday order book data and trades from Kaiko, an independent data provider, for the five most popular cryptocurrencies in terms of market capitalization as of January 2020 (namely Bitcoin, Ethereum, Bitcoin Cash, EOS and Ripple) paired with US dollar on the Bitfinex exchange.[1]

In the trade dataset, we have information on date and time, price, number of cryptocurrencies exchanged, and a dummy variable that indicates whether the trade is buyer- or seller-initiated.

[1] Bitfinex is a trading platform headquartered in Hong-Kong and dedicated to digital assets and cryptocurrencies like Bitcoin, EOS, Ripple, etc. (`https://www.bitfinex.com/`).

The order book dataset contains minute-by-minute snapshots[2] with bid/ask prices and quantities up to the 5^{th} limit.

We tun the same the cleaning algorithm described in Liu et al. (2019) who use the same dataset. This implies the removal of negative prices and negative bid-ask spreads from the dataset, among others.

Table 1 summarises the number of observations and the average number of observations per day in the trade and order book datasets respectively, for each cryptocurrency.

Table 1: Descriptive statistics

Cryptocurrency	Symbol	NT	DANT	NO	DANO
Bitcoin	BTC	35,913,013	104,096	630,580	1,833
Bitcoin Cash	BCH	9,976,566	28,918	614,857	1,787
Eos	EOS	12,749,502	36,955	636,329	1,855
Ripple	XRP	13,482,419	39,080	615,906	1,796
Ethereum	ETH	19,866,751	57,585	582,566	1,703

This Table reports the number of trades (NT), the daily average of trades (DANT), the number of observations (NO), and the daily average number of observations (DANO) for each cryptocurrency.

2.2. Variables

We compute two ex-ante and two ex-post liquidity measures for every trade. The ex-ante measures are the Proportional Quoted Spread (PQS) and the Quoted Depth (DEPTH), defined as follows:

$$PQS_t = \frac{p_t^A - p_t^B}{p_t^M} \tag{1}$$

$$DEPTH_t = \frac{q_t^A + q_t^B}{2} \tag{2}$$

[2]We observe a change in the frequency of quotes in the middle of April 2018. At the beginning of our period, Bitfinex provided a quote every minute. The frequency of observations nearly doubled after April 2018.

where at time t, p_t^A and p_t^B are the best quoted ask and bid prices respectively and p_t^M is the midquote. Similarly, q_t^A and q_t^B are the quantities of a given cryptocurrency available for the best ask and bid respectively.

The ex-post liquidity measures are the Proportional Effective Spread (PES) and the Proportional Traded Spread (PTS), defined as :

$$PES_t = 2D_t \frac{p_t^{trade} - p_t^M}{p_t^M} \tag{3}$$

$$PTS_t = \frac{PES_t}{2} \tag{4}$$

where D_t is the direction of the trade at time t (+1 for buy orders and -1 for sell orders) and p_t^{trade} is the trade price. Next, we compute the quote duration as being equal to the time during which the quote remains unchanged in the order book.[3]

We aggregate the proxies over five-minute intervals and only keep the intervals containing at least three observations.[4] In accordance with Beaupain et al. (2010), we use three different weighting methods: equal weights, size weights, and time weights. We use equal weights to compute the Equally-Weighted PQS (EWPQS) and the Equally-Weighted Depth (EWDEPTH). We then use size-weighted averages to compute additional ex ante liquidity proxies. More specifically, PQS_t is weighted by the depth available at the best quotes ($DEPTH_t$) to give the Size-Weighted PQS (SWPQS); PES_t and PTS_t are also weighted the same way to obtain the Size-Weighted PES

[3]Most of the snapshots in the order books are given every minute at the start of the period and the frequency increases towards 30 seconds towards the end.

[4]We have 345 trading days times 288 five-minute intervals per day, which gives 99360 intervals. By rejecting the intervals with less than 3 trades we manage to keep 97% of the intervals. The rejected intervals ranged from 1% to 5% of the total number of 5 minute intervals for each cryptocurrency. There was no clear pattern in the time distribution of the rejected intervals.

(SWPES) and Size-Weighted PTS (SWPTS) respectively.[5] Finally, the last aggregation method that we use consists in weighting each PQS_t by the number of seconds its corresponding quote remains unchanged. This gives the Time-Weighted Proportional Quoted Spread TWPQS.

We identify the daily volatility regime as low, intermediate or high, based on the daily values of the VCRIX, a volatility index on cryptocurrencies. Just as the VIX index is induced from option prices in the S&P500 index, VCRIX is calculated from option prices on the CRIX.[6] We classify the daily volatilities into one of the three regimes by using the 33$^{\text{rd}}$ percentile and the 67$^{\text{th}}$ percentile of the VCRIX as lower and upper bounds respectively.

2.3. Descriptive statistics

We report summary statistics for all the key variables computed from the trades and order book datasets. Based on their price levels, there are two groups of cryptos: XRP and EOS, on the one hand; BTC, ETH and BCH, on the other hand. There is indeed a big difference in the average trade price between these two groups in our sample. The average trade price was $1.04 and $9.59 for XRP and EOS, while the average trade price was $617.68, $1,354.47 and $9,482.31 for ETH, BCH and BTC respectively.

Table 2 gives some cross-sectional statistics for the six liquidity measures defined above. Consistent with previous results in the literature, we observe right skewness in the distribution of our proxies. All the medians for all proxies are indeed lower than their respective means.

[5] The procedure is slightly different in the case of SWPTS. We compute the weighted averages of our proportional traded spreads *PTS* and weight them by their respective trades amount. We then add these two weighted averages to construct our SWPTS.

[6] CRIX stands for crypto-currency index and it is made freely available by Humboldt University of Berlin.

Table 2: Aggregate liquidity measures - Summary statistics

Liq. Proxy	Mean	Median	Stdev	AC(1)
EWPQS	0.0008	0.0004	0.0011	0.76
EWDEPTH	1,767.9540	28.8419	5,489.4700	0.50
SWPQS	0.0008	0.0004	0.0012	0.70
SWPES	0.0012	0.0007	0.0017	0.56
SWPTS	0.0017	0.0007	0.0015	0.52
TWPQS	0.0008	0.0004	0.0011	0.76

This Table reports some descriptive statistics for each liquidity proxy. See Section 2.2 for the definition of variables.

We also observe that the proportional effective spread and the proportional traded spread appear to be larger than the proportional quoted spread. This points to some form of price deterioration as we take the trade price into account. This is typically not the case for more liquid assets such as stocks.

Finally, we can see that among all the liquidity proxies, the quoted spread measures display the highest autocorrelation coefficients of order 1, equal or greater than 70%.

We provide the same summary statistics conditioned on the volatility regimes in Table 3 while removing intraday seasonality for all the liquidity proxies as explained in Hasbrouck and Seppi (2001) and Corwin and Lipson (2011). This explains the negative signs for the means and medians in Table 3.

The most attractive volatility regime in terms of liquidity is the intermediate one. In other words, there seems to be an optimal level of volatility which benefits liquidity the most. When market activity in cryptocurrencies is not high enough, volatility remains subdued and spreads are wider than in the intermediate regime. When comparing both regimes, the only more attractive feature in the low volatility regime is the higher level of depth. However, wider spreads with higher depth are still arguably less desirable than tighter spreads with lower depth.

Liquidity clearly deteriorates as volatility enters the high regime. Depth decreases and all spread measures increase, pointing to a lower willingness to provide liquidity in stressful market conditions in terms of both price and quantity. This is also clearly revealed by all the proxies for spread which exhibit positive signs once seasonality is accounted for. The more volatile the market, the higher the spreads, which is consistent with Pástor and Stambaugh (2003). Reciprocally, the more volatile the market, the lower the depth. The comparison between the intermediate and high volatility regimes show an inverse relationship between liquidity and volatility for our set of cryptocurrencies. The same results are documented for stocks in Beaupain et al. (2010). As it is the case for traditional markets as well, autocorrelation tends to reach its lowest value during highly volatile days.

Table 3: Liquidity measures and volatility regimes : Summary Statistics

Liq. Proxy	Mean	Median	Stdev	AC(1)
Low volatility regime				
EWPQS	-0.1423	-0.4335	0.8768	0.6565
EWDEPTH	0.1663	-0.1070	1.0709	0.3047
SWPQS	-0.1375	-0.4545	0.8660	0.5801
SWPES	-0.0670	-0.2923	0.9293	0.4543
SWPTS	-0.0739	-0.2616	0.9247	0.4273
TWPQS	-0.1415	-0.4370	0.8784	0.6544
Intermediate volatility regime				
EWPQS	-0.1707	-0.4970	0.9036	0.6666
EWDEPTH	-0.0096	-0.1966	0.9245	0.2615
SWPQS	-0.1585	-0.4885	0.8980	0.5962
SWPES	-0.1434	-0.4045	0.9180	0.4881
SWPTS	-0.1458	-0.3600	0.9234	0.4108
TWPQS	-0.1723	-0.5007	0.9020	0.6628
High volatility regime				
EWPQS	0.4498	0.1343	1.1282	0.5708
EWDEPTH	-0.1444	-0.3360	1.0307	0.3007
SWPQS	0.4228	0.0680	1.1582	0.5016
SWPES	0.3266	0.0690	1.1221	0.4628
SWPTS	0.3377	0.1202	1.1136	0.4037
TWPQS	0.4517	0.1334	1.1282	0.5642

This Table reports some descriptive statistics for each liquidity proxy and for each volatility regime (low, intermediate, and high). See Section 2.2 for the definition of variables.

When analysing the absolute value of size-weighted spread measures, we observe that the average quoted spread is systematically greater than the average traded spread which in turn is greater than the average effective spread. This is often the case for more traditional equity markets as well, since market participants trade between quotes.

Looking at the quoted spreads, we see that they are wider when they are averaged according to the available quantities in both the low and intermediate regimes, since equally-weighted proportional quoted spreads and time-weighted proportional quoted spreads are lower. In other words, when larger quantities are available, spreads are on average wider in low and intermediate regimes, which is not unusual. What is more interesting is the opposite outcome in the high volatility regime. Market participants tend to show tighter spreads on average when they post larger quantities. This points to positive market dynamics by participants who help stabilize liquidity in stressful market conditions. These tighter spreads with larger quantities are nevertheless available for shorter periods of time as indicated by the higher time-weighted proportional quoted spread.

2.4. Methodology

To assess liquidity co-movements within each of the five crypto markets, we first follow Chordia et al. (2000) using Equation 5. We run 'market model' time series regressions, in which the liquidity proxy of an individual crypto is regressed on the class-wide liquidity proxy. The class-wide liquidity proxy is the value-weighted average of individual liquidity measures of all cryptos belonging to the same market capitalisation class, excluding the dependent-variable crypto. The model is:

$$L_{j,t} = \alpha_j + \beta_{1,j} L_{M,t} + \beta_{2,j} L_{M,t-1} + \beta_{3,j} L_{M,t+1} + \gamma_j V_{j,t} + \sum_{i=-1}^{+1} \delta_{i,j} R_{M,t+i} + \epsilon_{j,t} \tag{5}$$

where $L_{j,t}$ denotes a liquidity proxy for cryptocurrency j at time-interval t, $L_{M,t}$ is the associated market liquidity proxy at time t computed as the mean change in the liquidity proxy of all cryptocurrencies, excluding cryptocurrency j. The control (or nuisance) variables are $V_{j,t}$, i.e., the concurrent change in the volatility of cryptocurrency j at time t, and $R_{M,t}$, i..e, the market log-return at time t.

In this model, we run three statistical tests. The first test is a Wald test, testing $H_0 : \beta_{1,j} + \beta_{2,j} + \beta_{3,j} = 0$. While the magnitude of class-wide liquidity co-movements is measured by the individual betas, the Wald test gives information on the pervasiveness of liquidity co-movements within the crypto class over time. We apply a second Wald test with the null hypothesis defined as $H_0 : \gamma_j = \delta_{-1,j} = \delta_{0,j} = \delta_{1,j} = 0$. This test evaluates the influence of all the other (nuisance) variables not directly related to market liquidity in Equation 6. The third test is simply a basic F-test, testing whether the fit of the intercept-only model is equivalent to the fit of the stated model.

The second step of our analysis consists in conditioning liquidity co-movements upon volatility regimes. We follow the methodology of Beaupain et al. (2010) in which three volatility regimes are defined, i.e. high, intermediate and low, using the following equation :

$$L_{j,t} = \sum_{k=1}^{3} D_{k,t}(\alpha_{j,k} + \beta_{j,k} L_{M,T} + \gamma_{j,k} L_{t-1} + \phi_{j,k} V_{j,t} + \sum_{i=-1}^{+1} \delta_{i,j,k} R_{M,t+i}) + \epsilon_{j,t} \tag{6}$$

where $D_{1,t}$, $D_{2,t}$ and $D_{3,t}$ are indicator variables that equal 1 in low, intermediate and high volatility regimes respectively. These dummy variables are derived from the classification of daily volatility regimes as explained in Section 2.2. This equation includes a dummy variable $D_{k,j}$ as an indicator of volatility regimes (1 for low volatility, 2 for intermediate volatility, 3 for high volatility). For each market-liquidity proxy variable, we consider the intermediate volatility regime as the reference category against which the two other regimes are compared, since perfect colinearity would make it impossible to estimate the model otherwise. So, $\beta_{j,1}$ measures the average sensitivity of individual crypto liquidity to contemporaneous class-wide liquidity in the low volatility regime (i.e., in quiet markets), while $\beta_{j,3}$ measures the average sensitivity of individual crypto liquidity to contemporaneous class-wide liquidity in the high volatility regime (i.e., in stressful markets).

For all the regressions conditioned on volatility, we make two unilateral t-tests. We check wheter there is any statistical difference between the average sensitivity of individual crypto liquidity to contemporaneous class-wide liquidity in low and high volatility regimes. The alternative hypotheses are $H_1 : \beta_{j,1} <$ or $> \beta_{j,3}$ against its corresponding opposite one-sided null hypothesis, i.e., $H_0 : \beta_{j,1} \geq$ or $\leq \beta_{j,3}$.

3. Empirical results

Results of Equation 5 are shown in Table 4, by liquidity proxy and cryptocurrency. There is strong evidence of co-movements in liquidity. All β coefficients are statistically significant for all five cryptocurrencies at the 5% confidence level. They all point to strong positive liquidity commonalities, both contemporaneously and asynchronously.

Table 4: Liquidity co-movements - Unconditioned upon volatility regime

EWPQS	BCH	BTC	EOS	ETH	XRP
$\boldsymbol{L_{M,t}}$	0.2440	0.1788	0.2412	0.1761	0.2588
p-val	***	***	***	***	***
$\boldsymbol{L_{M,t-1}}$	0.1960	0.1621	0.2416	0.1692	0.2570
p-val	***	***	***	***	***
$\boldsymbol{L_{M,t+1}}$	0.2047	0.1563	0.2303	0.1609	0.2558
p-val	***	***	***	***	***
Adj. $\mathbf{R^2}$	0.3860	0.3212	0.4528	0.2945	0.5157
$H_0 : \beta_{1,j} + \beta_{2,j} + \beta_{3,j} = 0$ (p-val)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
$H_0 : \gamma_j = \delta_{-1,j} = \delta_{0,j} = \delta_{1,j} = 0$ (p-val)	0.0054	<0.0001	0.0014	<0.0001	<0.0001
F-test (p-val)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
SWPQS	BCH	BTC	EOS	ETH	XRP
$\boldsymbol{L_{M,t}}$	0.2166	0.1675	0.2256	0.1631	0.2425
p-val	***	***	***	***	***
$\boldsymbol{L_{M,t-1}}$	0.1823	0.0336	0.2313	0.1475	0.2514
p-val	***	***	***	***	***
$\boldsymbol{L_{M,t+1}}$	0.2006	0.1315	0.2235	0.1430	0.2436
p-val	***	***	***	***	***
Adj. $\mathbf{R^2}$	0.3255	0.2625	0.3953	0.2359	0.4489
$H_0 : \beta_{1,j} + \beta_{2,j} + \beta_{3,j} = 0$ (p-val)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
$H_0 : \gamma_j = \delta_{-1,j} = \delta_{0,j} = \delta_{1,j} = 0$ (p-val)	0.0006	<0.0001	0.0186	<0.0001	<0.0001
F-test (p-val)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
TWPQS	BCH	BTC	EOS	ETH	XRP
$\boldsymbol{L_{M,t}}$	0.2398	0.1816	0.2405	0.1738	0.2585
p-val	***	***	***	***	***
$\boldsymbol{L_{M,t-1}}$	0.1981	0.1593	0.2360	0.1711	0.2538
p-val	***	***	***	***	***
$\boldsymbol{L_{M,t+1}}$	0.2057	0.1530	0.2270	0.1608	0.2512
p-val	***	***	***	***	***
Adj. $\mathbf{R^2}$	0.3834	0.3195	0.4405	0.2942	0.5042
$H_0 : \beta_{1,j} + \beta_{2,j} + \beta_{3,j} = 0$ (p-val)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
$H_0 : \gamma_j = \delta_{-1,j} = \delta_{0,j} = \delta_{1,j} = 0$ (p-val)	0.0033	<0.0001	0.0006	<0.0001	<0.0001
F-test (p-val)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
SWPES	BCH	BTC	EOS	ETH	XRP
$\boldsymbol{L_{M,t}}$	0.1705	0.2038	0.1861	0.2165	0.2377
p-val	***	***	***	***	***
$\boldsymbol{L_{M,t-1}}$	0.1460	0.0147	0.1705	0.1275	0.1754
p-val	***	ns	***	***	***
$\boldsymbol{L_{M,t+1}}$	0.1169	0.0745	0.1463	0.1658	0.1905
p-val	***	***	***	***	***
Adj. $\mathbf{R^2}$	0.2841	0.2343	0.2614	0.2929	0.3923
$H_0 : \beta_{1,j} + \beta_{2,j} + \beta_{3,j} = 0$ (p-val)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
$H_0 : \gamma_j = \delta_{-1,j} = \delta_{0,j} = \delta_{1,j} = 0$ (p-val)	0.0272	0.0001	<0.0001	0.1136	0.0001
F-test (p-val)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
SWPTS	BCH	BTC	EOS	ETH	XRP
$\boldsymbol{L_{M,t}}$	0.1705	0.1664	0.2035	0.2055	0.2329
p-val	***	***	***	***	***
$\boldsymbol{L_{M,t-1}}$	0.1424	0.0879	0.1519	0.1464	0.1827
p-val	***	***	***	***	***
$\boldsymbol{L_{M,t+1}}$	0.1295	0.0866	0.1292	0.1581	0.1742
p-val	***	***	***	***	***

Adj. $\mathbf{R^2}$	0.2507	0.2117	0.2217	0.2556	0.3385
$H_0 : \beta_{1,j} + \beta_{2,j} + \beta_{3,j} = 0$ (p-val)	<0.0001	0<0.0001	<0.0001	<0.0001	<0.0001
$H_0 : \gamma_j = \delta_{-1,j} = \delta_{0,j} = \delta_{1,j} = 0$ (p-val)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
F-test (p-val)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
EWDEPTH	BCH	BTC	EOS	ETH	XRP
$\boldsymbol{L_{M,t}}$	0.0383	0.0158	0.0462	0.0143	0.0520
p-val	***	**	***	ns	***
$\boldsymbol{L_{M,t-1}}$	0.0353	0.0036	0.0605	-0.0035	0.0722
p-val	***	ns	***	ns	***
$\boldsymbol{L_{M,t+1}}$	0.0439	0.0101	0.0697	0.0014	0.0630
p-val	***	ns	***	ns	***
Adj. $\mathbf{R^2}$	0.0072	0.0074	0.0170	0.0043	0.0172
$H_0 : \beta_{1,j} + \beta_{2,j} + \beta_{3,j} = 0$($p$-val)	<0.0001	0.0034	<0.0001	0.2718	<0.0001
$H_0 : \gamma_j = \delta_{-1,j} = \delta_{0,j} = \delta_{1,j} = 0$ (p-val)	0.5248	<0.0001	0.0008	<0.0001	0.3946
F-test (p-val)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001

This Table reports our estimation for regression 5. Newey and West (1994) heteroskedasticity and autocorrelation robust standard errors are calculated using automatic lag truncation parameter selection. Significance levels: $*** \leq 0.001$, $** \leq 0.01$, $* \leq 0.05$ and ns > 0.05.

The strongest evidence of liquidity co-movements is found when liquidity is proxied by the three quote-based liquidity measures (EWPQS, SWPQS and TWPQS) and the β coefficients are very similar, as expected. Commonalities measured in terms of the size-weighted effective (SWPES) and traded (SWPTS) spreads are nevertheless somewhat higher when it comes to Ethereum (ETH), pointing to the usefulness of using various spread measures. Depth (EWDEPTH) shows the weakest evidence of co-movements in liquidity irrespective of the crypto currency market. Interestingly, the same results are observed for equity securities.

A remarkable result is how similar are both the magnitude and pervasiveness of the comovements among these cryptos, compared to what Chordia et al. (2000) and Beaupain et al. (2010) estimate for large US stocks 10 to 20 years ago. Not only the β coefficients are in line with what they document, but this is also the case for the level of significance as well as the model fit. Overall, the model fit is higher for quote-based measures, followed by trade-based measures and depth. The best R^2 are obtained for the equally-weighted proportional quoted spreads (EWPQS), ranging between

29% and 52% and are followed closely by the other two quote-based spread measures.

We also report the Wald joint test on the βs, showing that liquidity co-movements within the crypto class are pervasive over time. There is evidence of momentum over time since H_0 : $\beta_{1,j} + \beta_{2,j} + \beta_{3,j} = 0$ is rejected at the 0.1% significance level. This means that the common movements are not just instantaneous; they persist over time as well. Out of 30 regressions, the null hypothesis is always rejected, except in the case of depth on the Ethereum (ETH) market.

Regarding the control (or nuisance) variables such as volatility and market returns, they do bear on liquidity. They are significant at the 5% confidence level in all cases, except in the case of the SWPES on the Ethereum (ETH) market. And the F-test of overall significance is rejected every time, as expected.

Table 5 shows the results when liquidity co-movements are conditioned on volatility regimes, as in Equation 6. Following Beaupain et al. (2010), we choose the intermediate volatility regime as benchmark and show the coefficient estimates for the low and high volatility regimes, for each cryptocurrency and liquidity proxy.

First, we observe that all our $\beta_{j,3}$ are statistically greater than 0 at a significance level of 5%, meaning that there is evidence of positively correlated liquidity co-movements in high volatility setups for all cryptocurrencies, irrespective of the variabkes used to estimate liquidity. This is less the case in the low volatility regime. Both the magnitude and pervasiveness of commonalities are overall weaker in the low volatility regime when liquidity is arguably more idiosyncratic, affecting cryptos differently and leading to more disconnected movements in liquidity at the market level. This is especially the case for trade-based measures and depth.

Table 5: Liquidity co-movements - Conditioned upon volatility regime

EWPQS	BCH	BTC	EOS	ETH	XRP
$\boldsymbol{L_{M,1}}$ "low volatility"	0.0090	0.0877	0.1274	0.2223	-0.0770
t-stat	(0.32)	(3.60)	(3.08)	(11.06)	(-1.96)
p-val	ns	***	**	***	*
$\boldsymbol{L_{M,3}}$ "high volatility"	0.2654	0.1946	0.3171	0.0819	0.3053
t-stat	(11.14)	(11.50)	(9.70)	(8.215)	(8.09)
p-val	***	***	***	***	***
Adj. $\mathbf{R^2}$	0.4908	0.4029	0.5300	0.5260	0.6392
Reject $H_0 : \beta_1 \leq \beta_3$?	*no*	*no*	*no*	*yes*	*no*
Reject $H_0 : \beta_1 \geq \beta_3$?	*yes*	*yes*	*yes*	*no*	*yes*
SWPQS	**BCH**	**BTC**	**EOS**	**ETH**	**XRP**
$\boldsymbol{L_{M,1}}$ "low volatility"	0.3565	0.0993	0.1145	0.2311	-0.0864
t-stat	(1.28)	(4.06)	(3.00)	(10.67)	(-2.35)
p-val	ns	***	**	***	*
$\boldsymbol{L_{M,3}}$ "high volatility"	0.2419	0.1574	0.3100	0.0723	0.3018
t-stat	(10.52)	(10.08)	(10.66)	(6.89)	(8.58)
p-val	***	***	***	***	***
Adj. $\mathbf{R^2}$	0.4067	0.3383	0.4507	0.4279	0.5544
Reject $H_0 : \beta_1 \leq \beta_3$?	*no*	*no*	*no*	*yes*	*no*
Reject $H_0 : \beta_1 \geq \beta_3$?	*no*	*yes*	*yes*	*no*	*yes*
TWPQS	**BCH**	**BTC**	**EOS**	**ETH**	**XRP**
$\boldsymbol{L_{M,1}}$ "low volatility"	0.0203	0.0859	0.1304	0.2122	-0.0770
t-stat	(0.74)	(3.55)	(3.21)	(10.54)	(-1.96)
p-val	ns	***	**	***	*
$\boldsymbol{L_{M,3}}$ "high volatility"	0.2579	0.1912	0.3123	0.0834	0.3082
t-stat	(10.99)	(11.38)	(9.76)	(8.27)	(8.22)
p-val	***	***	***	***	***
Adj. $\mathbf{R^2}$	0.4865	0.4040	0.5217	0.5250	0.6270
Reject $H_0 : \beta_1 \leq \beta_3$?	*no*	*no*	*no*	*yes*	*no*
Reject $H_0 : \beta_1 \geq \beta_3$?	*yes*	*yes*	*yes*	*no*	*yes*
SWPES	**BCH**	**BTC**	**EOS**	**ETH**	**XRP**
$\boldsymbol{L_{M,1}}$ "low volatility"	0.0436	0.0138	0.0563	0.0006	-0.0568
t-stat	(1.77)	(0.52)	(1.58)	(10.55)	(-2.17)
p-val	ns	ns	ns	***	*
$\boldsymbol{L_{M,3}}$ "high volatility"	0.1954	0.1917	0.2216	2.0e-5	0.2529
t-stat	(9.99)	(9.41)	(9.85)	(8.29)	(10.99)
p-val	***	***	***	***	***
Adj. $\mathbf{R^2}$	0.3741	0.2936	0.3191	0.522	0.5043
Reject $H_0 : \beta_1 \leq \beta_3$?	*no*	*no*	*no*	*no*	*no*
Reject $H_0 : \beta_1 \geq \beta_3$?	*yes*	*yes*	*yes*	*yes*	*yes*
SWPTS	**BCH**	**BTC**	**EOS**	**ETH**	**XRP**
$\boldsymbol{L_{M,1}}$ "low volatility"	0.0734	0.0166	0.006	0.0792	-0.0220
t-stat s	(3.17)	(0.76)	(0.22)	(2.87)	(-1.01)
p-val	**	ns	ns	**	ns
$\boldsymbol{L_{M,3}}$ "high volatility"	0.1842	0.1952	0.2700	0.2080	0.2440
t-stat	(11.87)	(12.48)	(17.66)	(12.67)	(14.33)
p-val	***	***	***	***	***
Adj. $\mathbf{R^2}$	0.3063	0.2620	0.2522	0.2852	0.4232
Reject $H_0 : \beta_1 \leq \beta_3$?	*no*	*no*	*no*	*no*	*no*

$H_0 : \beta_1 \geq \beta_3$?	*yes*	*yes*	*yes*	*yes*	*yes*
EWDEPTH	BCH	BTC	EOS	ETH	XRP
$\boldsymbol{L_{M,1}}$ "low volatility"	-0.0639	-0.0676	- 0.0089	-0.0417	0.0085
t-stat	(-3.25)	(-5.47)	(-0.49)	(-2.12)	(0.50)
p-val	$**$	$***$	ns	$*$	ns
$\boldsymbol{L_{M,3}}$ "high volatility"	0.0775	0.0320	0.0707	0.0356	0.0554
t-stat	(4.20)	(4.00)	(4.85)	(3.11)	(4.84)
p-val	$***$	$***$	$***$	$**$	$***$
Adj. $\mathbf{R^2}$	0.0824	0.1236	0.0839	0.1043	0.1148
Reject $H_0 : \beta_1 \leq \beta_3$?	*no*	*no*	*no*	*no*	*no*
Reject $H_0 : \beta_1 \geq \beta_3$?	*yes*	*yes*	*yes*	*yes*	*yes*

This Table reports our estimation for regression 6. Newey and West (1994) heteroskedasticity and autocorrelation robust standard errors are calculated using automatic lag truncation parameter selection. Significance levels: $*** \leq 0.001$, $** \leq 0.01$, $* \leq 0.05$ and ns > 0.05.

When analysing the changes in liquidity co-movements between high and low volatility regimes, Ripple (XRP) shows the greatest beta variations. The level of idiosyncraticity in the low regime for the Ripple is particularly noticeable since its $\beta_{j,1}$ coefficients are always negative, except for DEPTH. Also, the null hypothesis according to which liquidity comovements are equal or higher in the low regime is always rejected in favour of the one-sided alternative.

For order-book-based measures, when analysing the t-stats of $\beta_{j,1}$'s, we have strong evidence that liquidity co-movements are greater in magnitude when volatility is higher. $H_0 : \beta_1 \leq \beta_3$ is never rejected, except in 3 cases out of 25 in the case of Ethereum. Alternatively, $H_0 : \beta_1 \geq \beta_3$ is rejected in all the cases, except 4 out of 25. 3 of these 4 exceptions concern the same cryptocurrency, i.e., Ethereum.

Finally, we notice that the R^2 increases significantly when we condition the analysis of liquidity comovements on volatility regimes using order-book-based variables. For example, we obtain the highest R^2 for the EWPQS proxy, ranging from 40% to 64%, while the worst fit for the regressions is obtained when EWDEPTH is used to estimate liquidity.

3.1. Robustness checks

An extensive set of robustness checks have been performed. First, we have estimated the models without controlling for seasonality, i.e., without standardizing the variables. Second, we have computed the liquidity proxies as weighted medians instead of weighted means. Third, the market liquidity proxies have been weighted by market capitalization instead of using equal weights. Fourth, we have aggregated our proxies over 10, 15, 30 and 60 minute intervals. Fifth, we have simulated order-book values by linear interpolation so that they match to the timing of each trade, using both the mean and the median as aggregation rule and working with 30 minutes intervals instead of 15 minutes. All these methodological variations had only very minor impacts on the results. To save space, we do no report these robustness checks but they are available upon request.

4. Conclusion

Using trades and order book data for the five major cryptocurrencies traded on the Bitfinex exchange between August 2017 and July 2018, we find significant evidence of liquidity commonalities among cryptos. The strongest evidence of co-movements is identified when liquidity is estimated by using order-book-based variables.

It is striking to observe how similar are both the magnitude and pervasiveness of the comovements among these cryptos, compared to what Chordia et al. (2000) and Beaupain et al. (2010) estimate for large US stocks 10 to 20 years ago. Not only the coefficients are in line with what they document, but this is also the case for the level of significance as well as the model fit.

When we introduce volatility regimes based on the VCRIX volatility index on cryptocurrencies, we find stronger liquidity co-movements in high volatility regimes across all cryptocurrencies and for all liquidity proxies. The magnitude and pervasiveness of commonalities are indeed weaker in the low volatility regime when liquidity is arguably more idiosyncratic, affecting cryptos differently and leading to more disconnected movements relative to market liquidity.

We conclude that the liquidity co-movements among cryptos are not orthogonal to what was observed in the past for more centralized markets. There was indeed no obvious sign overall of dysfunctionality when it came to estimating systematic liquidity risk on this market.

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