Economics Letters 168 (2018) 21–24

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Liquidity and market efficiency in cryptocurrencies

Wang Chun Wei

UQ Business School, University of Queensland, Brisbane, Australia

HIGHLIGHTS

- We examine 456 cryptocurrencies.
- Return predictability diminishes as liquidity increases in cryptocurrencies.
- Volatility decreases as liquidity increases in cryptocurrencies.
- There are no signs of an illiquidity premium.

ARTICLE INFO

Article history:
Received 12 March 2018
Received in revised form 26 March 2018
Accepted 2 April 2018
Available online 5 April 2018

JEL classification:
C01
G12
G14

Keywords:
Bitcoin
Cryptocurrency
Market efficiency
Market liquidity

ABSTRACT

We examine the liquidity of 456 different cryptocurrencies, and show that return predictability diminishes in cryptocurrencies with high market liquidity. We show that whilst Bitcoin returns are showing signs of efficiency, numerous cryptocurrencies still exhibit signs of autocorrelation and non-independence. Our findings also show a strong relationship between the Hurst exponent and liquidity on a cross-sectional basis. Therefore, we conclude that liquidity plays a significant role in market efficiency and return predictability of new cryptocurrencies.

1. Introduction

Since the seminal work of Nakamoto (2008) on electronic payment system based on cryptographic proof, a plethora of various cryptocurrencies have emerged over the last two years via initial coin offerings (ICOs). The explosion in interest in cryptocurrencies have offered speculators and investors a diverse spectrum of electronic crypto assets to trade in. In recent times, interest in cryptocurrency markets have not been limited to technology enthusiasts and those who value anonymity. Despite prevailing skepticism, investment banks and asset managers have been releasing their own research notes on cryptocurrencies to clients.

Understandably, research in this fledging topic has been experimental in nature, and most have not made it into academic journals. Few papers have examined a large cross-section of the cryptocurrencies universe. Academic research, to date, have focused solely on Bitcoin. Several papers have examined the nature of Bitcoin, with Selgin (2015) and Baeck and Elbeck (2015) arguing that the cryptocurrency resembles a speculative commodity rather than a currency. Peterson (2017) and Van Vliet (2018) examine Metcalfe's Law for valuing Bitcoins based on the size of the user network. Grinberg (2012) discusses the impact of macroeconomic factors on Bitcoin price.

This short paper examines market efficiency in cryptocurrencies. In particular, we wish to extend this analysis to incorporate the numerous *altcoins* that have emerged in recent years. Urquhart (2016) was first to test weak form efficiency of Bitcoin, the cryptocurrency with the largest market capitalization. Utilizing five different tests, it was concluded that Bitcoin returns were indeed market inefficient, which confirmed the intuition of many bitcoin observers about the fledging new market.[1] Bitcoin rivals such as Ripple, Ethereum, Litecoin and Cardano all have market

E-mail address: w.wei@business.uq.edu.au.

[1] Nadarajah and Chu (2017) suggest transforming Bitcoin returns with an odd integer power would result in a series that passes Urquart's (2016) battery of statistical tests for weak-form efficiency. However, the resulting return series would not represent the returns market participants experience as the distributional characteristics have changed.

https://doi.org/10.1016/j.econlet.2018.04.003

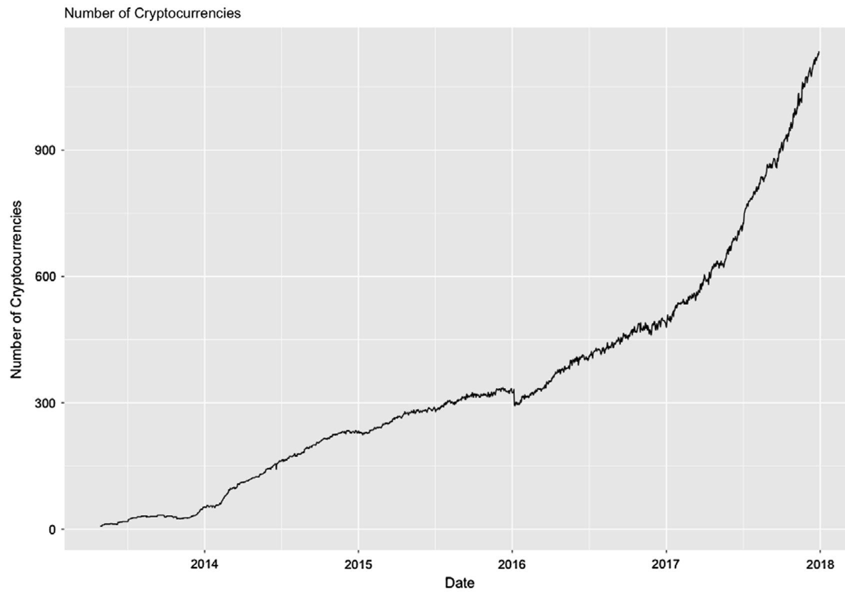

Fig. 1. The number of cryptocurrencies *'listed'* across time. We plot the number of cryptocurrencies that posted a daily price on www.coinmarketcap.com over a period of circa 5 years. This chart illustrates the explosive interest in cryptocurrencies throughout 2017.

capitalizations in excess of 5 billion USD.[2] We examine whether these altcoins are also weak-form inefficient.

Furthermore, we explore the relationship between liquidity and market efficiency in a large cross-section of cryptocurrencies. We expect market efficiency to be stronger in more liquidity markets as active traders are more likely to arbitrage any signs of return predictability. Illiquid cryptocurrencies incur greater costs for investors and speculators to buy and sell due to higher spreads and higher transaction costs. We hypothesize that if cryptocurrency market-makers have limited risk-bearing capacity and inventory constraints (which is very likely given many individual algorithmic traders act as market-makers in the altcoin market), an temporary asymmetric order shock will lead to significant price deviation even in periods where there is no fundamental change in news on the cryptocurrency. Active traders detecting these large deviations may submit 'arbitrage trades' to convergence prices back to 'fundamental values' given there is no news. However, their efforts would be hampered if underlying liquidity is low. We also believe that in very illiquid cryptocurrency markets, the lack of active traders also means it would take longer for market participants to act on new information, resulting in market inefficiency.

Therefore, our aim is two-fold. Firstly, we follow up Urquhart (2016) and extend his analysis on bitcoin efficiency to 456 different cryptocurrencies. We find that for the year 2017, Bitcoin returns showed some signs of improvement in efficiency, which is consistent with findings from the second test period in Urquhart (2016). However, a significant number of *altcoins* still showed statistically significant autocorrelations and non-independence. Secondly, we document the relationship between liquidity and market efficiency in cryptocurrency markets. Return predictability diminishes via 'arbitrage trading', which we believe to be more effective in markets that are more liquid. We divide our sample set into quantiles based on liquidity, and show for altcoins with high liquidity, its returns exhibit more signs of efficiency.

2. Data

Numerous cryptocurrency exchanges exist globally. For instance, Bitcoin alone is traded on at least 387 markets worldwide in various currency cross pairs. Instead of sourcing our data from hundreds of cryptocurrency exchanges around the world, we collect data from www.coinmarketcap.com which aggregates and reports the trading activity of 1500+ cryptocurrencies in 8900+ exchanges globally. Price is calculated to be the volume weighted average of all active currency pairs converted to USD.[3] This is an important distinction to simply looking at cryptocurrencies trading with USD base, because many of these active cross pairs are with KRW, JPY or EUR or other cryptocurrencies. Currency pairs traded on cryptocurrency futures exchanges, such as BitMEX, are excluded in this sample.

We calculate daily cryptocurrency returns to be:

$$R_t = \ln(P_t) - \ln(P_{t-1})$$

where $\ln(P_t)$ is the natural logarithm of the close price at time t. Furthermore, we collect data on aggregate daily volume traded (in USD) of the cryptocurrencies. These can then be used to estimate and compare the market liquidity measures of various cryptocurrencies.

Fig. 1 shows an explosion of the number of cryptocurrencies in the global market. For our purposes, we select 456 cryptocurrencies in our data set that has full price and aggregate volume data history for the year 2017. The names of these cryptocurrencies are documented in Table 1. They are grouped based on liquidity, which is explained in the methodology section.

3. Methodology

Our method involves testing the efficient market hypothesis on the returns of various cryptocurrencies sorted for market liquidity. The tests used to examine market efficiency are based on Urquhart (2016), whilst proxy for liquidity is the Amihud's illiquidity ratio (Amihud, 2002).

The Amihud illiquidity measure is chosen based on its robustness and simplicity. It requires only daily trade data, allowing for easy computation and comparison between traded assets, especially in circumstances where market microstructure data is not readily available. Furthermore, it does not require full market

[2] As of the 4th of March, 2018, the market capitalization of Ethereum, Ripple, Litecoin and Cardano are 83.2 bn, 35.5 bn, 11.6 bn and 7.5 bn USD respectively.

[3] For instance, for Bitcoin's price, the price is the volume weighted average of 387 currency cross pairs as of 4th March, 2018 converted to USD (with OKEx's BTC/USDT taking the greatest market share at 8.59%).

Table 1
Coins in the sample. We document the tickers of 456 cryptocurrencies we use in our empirical analysis for 2017, categorized into five groups sorted by their Amihud illiquidity ratio. Group 1 cryptocurrencies are the most liquid, whilst Group 5 are the most illiquid cryptocurrencies in our sample.

Group 1		Group 2		Group 3		Group 4		Group 5	
BTC	NEO	CPC	ABY	PDC	XTO	SRC	FJC	SUPER	PIZZA
USDT	SBD	PIVX	ZET	BIT	QTL	SMC	EMD	BSC	DES
ETH	BURST	AUR	PASC	UIS	ICO	GAP	JWL	MND	MOTO
LTC	BITCNY	MONA	CREVA	EL	XRC	ARG	MANNA	VAL	UNIC
XMR	DGD	NOTE	XST	FST	BOLI	GPU	SPT	TEK	WARP
DASH	NLG	GCR	VRM	8BIT	MAX	ACOIN	CHESS	PURA	BIOS
ETC	VTC	AEON	OBITS	PAK	SOIL	FC2	1337	XQN	CMT
XRP	NXS	GLD	INCNT	THC	VLT	CBX	SONG	ANC	TTC
ZEC	XPM	BITUSD	PEPECASH	TIT	SWING	REE	HODL	I0C	DLC
FCT	XAUR	START	KRB	GAM	C2	GCC	RED	FLT	MXT
MAID	RVR	UNO	SAFEX	DSH	RBIES	SLG	KLC	CRX	IMPS
DOGE	BCY	USNBT	DGC	BRX	MINT	BIP	ION	AMBER	CON
REP	FLDC	CLOAK	SXC	BLOCKPAY	BUCKS	SMLY	BCF	ORLY	JIN
XEM	VASH	DOT	EAC	QRK	NLC2	QCN	PEX	HYP	REGA
XLM	NVC	UBQ	BYC	BLC	$PAC	EVO	BTQ	PR	ARB
BTS	XHI	XBC	BRK	SWIFT	IFC	ARCO	XCT	XCRE	PHO
LSK	ZCL	LMC	GOLOS	TRIG	MOON	AC	YAC	BLRY	CASH
GAME	GBYTE	EGC	ERC	ADCN	BTCS	CNO	DP	SDP	XPD
NXT	SIB	YOC	BLOCK	UNB	ZEIT	ZNY	XNG	BUMBA	EGO
ICN	SLR	EFL	BLITZ	BITBTC	CJ	LTB	XRE	LIR	NODC
STEEM	IOC	CRB	DEM	BERN	ENT	BOST	611	HYPER	BLZ
SC	VIA	SHIFT	TRUST	MEME	ADC	ELE	SDC	BTCR	OS76
STRAT	BAY	XMG	GEO	BITS	DIME	PKB	CHC	TGC	CALC
PPC	BTCD	OK	BTA	ORB	808	CF	QORA	FUZZ	PND
WAVES	XVC	ADZ	ARC	XCN	HUSH	PXC	AU	PLNC	DLISK
EDR	RADS	VTR	XVG	CDN	NET	J	EVIL	WAY	DGCS
ARDR	RBY	MEC	GB	SJCX	VLTC	NYAN	MST	ZOI	HVCO
POT	EMC2	POST	MOIN	COVAL	IXC	TROLL	LEA	VIP	UNIT
SYS	FTC	QWARK	ATOM	EXCL	BITGOLD	ATX	NKA	BRAIN	LDOGE
GNT	BTM	MUE	DOPE	SPHR	PLU	NTRN	KB3	DBTC	LTCR
AMP	GRC	IOP	MZC	GCN	KURT	NEWB	KOBO	QBT	TOKEN
BLK	RIC	DMD	SLS	PXI	2GIVE	DOLLAR	HMP	BSTAR	SANDG
DCR	VRC	VSL	PTC	TRK	NEVA	ZUR	RCN	POP	AIB
NAV	XDN	WDC	INFX	GP	LANA	FRC	MAD	ZNE	BITZ
NMC	NEOS	BSD	GRS	MOJO	CESC	SPACE	PIGGY	NYC	CUBE
EMC	XMY	ENRG	XWC	UTC	BASH	MNM	ACP	ARI	VC
XCP	BBR	SEQ	SPR	42	ASAFE2	XRA	IMS	ECC	CV2
LEO	OMNI	CANN	TAG	NOBL	TAJ	ZYD	CRT	XCO	COXST
LBC	BELA	CRW	NSR	HEAT	BPC	CCN	GRN	MTLMC3	PX
1ST	PINK	TRC	TIPS	BTB	BLU	$$$	TRI	ALTC	P7C
DGB	CURE	TRUMP	BSTY	TES	UNITY	HTC	HAL	FRK	VTA
EXP	BCN	SNRG	VRS	ESP	XJO	STV	BRIT	XPY	STEPS
XZC	HUC	RDD	FAIR	HBN	EUC	DUO	XBTS	BXT	TALK
CLAM	FLO	RISE	WBB	SAC	SYNX	GBC	BUN	XBTC21	SH
LKK	SNGLS	TX	FCN	LOG	RBT	FRN	SHORTY	JOBS	VPRC
NXC		PUT		BITSILVER		GUN		TAGR	ISL

capitalization data, which is necessary for turnover based metrics, which can be problematic to source for lesser known altcoins. As shown in Amihud (2002), this ratio is positively and strongly related to microstructure estimates of illiquidity for equity markets.

The Amihud illiquidity ratio is defined as,

$$\mathrm{ILLIQ}_T^i = \frac{1}{D_T}\sum_{t=1}^{D_T}\frac{|R_t^i|}{P_t^i V_t^i}$$

where D_T is the number of traded days in year T (this is 364 days for most cryptocurrencies in 2017), $R_{t,T}^i$ is the daily return of asset i on day t in USD, V_t^i is the daily volume traded of asset i on day t, and P_t^i is the daily price of asset i on day t in USD. This measure provides an understanding on the relationship between volume and price change, providing us with a proxy on the price impact of daily aggregate trades.

To examine market efficiency of cryptocurrency returns, we focus on examining the predictability of its returns. Following Urquhart (2016), we employ the same set of statistical tests for randomness. Firstly, return autocorrelation is examined using Ljung–Box test (Ljung and Box, 1978). Secondly, the runs test and the Bartels test (Bartels, 1982) are used to further test if the cryptocurrency returns are independent. Thirdly, we employ Lo and MacKinlay's (1988) variance ratio test to examine if the standard deviation of returns scales by $\sqrt{T}$. To implement the variance ratio test, we utilize the wild-bootstrapped automatic variance test (AVR) suggested by Kim (2009). We also utilize the non-parametric BDS (Brock et al., 1996) test on serial dependence. Following Urquhart (2016), we choose embedding dimension from 2 to 5 and report the average p-values across different specifications. We also report the R/S Hurst exponent to examine long memory of returns. Time-series momentum is exhibited in the return series if the Hurst exponent is greater than 0.65 and time-series mean reversion (or anti-persistence) is exhibited when the Hurst exponent value is less than 0.45.

4. Results

In Table 2, we sort our cryptocurrencies based on the Amihud ratio into 5 groups, with group 1 being most liquid and group 5 being least liquid, and report their return characteristics. We note a strong relationship between liquidity and volatility among cryptocurrencies. This is consistent with our belief that for liquid markets with more active traders, price efficiency is stronger resulting in lower volatility. We do not observe signs of an illiquidity premium in cryptocurrencies, suggesting crypto-investors are not necessarily demanding a return premium to hold illiquid assets.

Table 2
Return characteristics of cryptocurrencies sorted by liquidity. Average returns characteristics sorted by the Amihud illiquidity ratio on daily returns denominated in USD are reported.

Sort by liquidity			Return characteristics			
	Group	Amihud	Mean	Std. Dev	Skewness	Kurtosis
High liquidity	1	<0.00001	0.010	0.106	0.928	11.422
	2	0.00011	0.010	0.160	1.167	18.162
	3	0.00191	0.009	0.234	0.906	17.409
	4	0.00960	0.009	0.282	0.742	20.276
Low liquidity	5	0.03581	0.010	0.366	0.301	10.829

Table 3
Market efficiency and the Hurst coefficient for cryptocurrencies sorted by liquidity. Average *p*-values for the five return efficiency tests (see Urquhart, 2016) after sorting for the Amihud illiquidity ratio are reported.

Sort by liquidity			Average *p*-values					Hurst
	Group	Amihud	Ljung–Box	Runs	Bartel	AVR	BDS	
High liquidity	1	<0.00001	0.35	0.44	0.40	0.41	0.02	0.53
	2	0.00011	0.11	0.27	0.19	0.25	0.01	0.50
	3	0.00191	0.05	0.12	0.04	0.09	0.01	0.46
	4	0.00960	0.02	0.09	0.02	0.03	0.02	0.44
Low liquidity	5	0.03581	0.01	0.04	0.01	0.02	0.01	0.41

This is interesting and contrary to traditional asset classes. We also note strong positive skew and high levels of kurtosis in returns. The former is reflective of significant levels of optimism among investors in our sample period whilst the latter is a confirmation of Urquhart's (2016) findings.

In Table 3, we document the average *p*-values of the five efficiency tests along with the average Hurst coefficient for the 5 liquidity sorted groups.

We find that the lowest quintile cryptocurrencies (with the lowest liquidity) on average reject the null hypothesis of randomness in all tests. The average *p*-values increases in higher liquidity quintiles suggesting greater market efficiency in markets where liquidity is high. Furthermore, the Hurst exponent shows evidence of anti-persistence in illiquid markets (<0.5) which confirms the findings of Urquhart (2016) to be prevalent for most cryptocurrencies. Smaller *altcoins* exhibit mini boom-bust cycles as speculators sway from being overly optimistic to pessimistic. However, in the higher liquidity quintiles the Hurst exponent is close to being a random walk (0.5), showing better efficiency relative to Urquhart's (2016) study.

5. Conclusions

We test market efficiency in a wide cross-section of cryptocurrencies. We find that efficiency is stronger, and volatility lower, in liquid markets as active traders are more likely to arbitrage away signs of return predictability. Higher transaction costs in markets where turnover is low impacts the ability for traders to act quickly and readily, resulting in market inefficiency. We also find that illiquid cryptocurrencies exhibit strong return anti-persistence in the form of a low Hurst exponent. Our findings suggest that whilst established cryptocurrencies are improving in terms of market efficiency, fledging new altcoins with limited liquidity continue to struggle.

References

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Markets 5, 31–56.
Baeck, C., Elbeck, M., 2015. Bitcoins as an investment or speculative vehicle? A first look. Appl. Econ. Lett. 22, 30–34.
Bartels, R., 1982. The rank version of von Neumann's ratio test for randomness. J. Amer. Statist. Assoc. 77 (377), 40–46.
Brock, W.A., Dechert, W.D., Schieinkman, J.A., LeBaron, B., 1996. A test for independence based on the correlation dimension. Econom. Rev. 15, 197–235.
Grinberg, R., 2012. Bitcoin: an alternative digital currency. Hastings Sci. Technol. Law J. Winter, 159–208.
Kim, J.H., 2009. Automatic variance ratio test under conditional heteroskedasticity. Finance Res. Lett. 3, 179–185.
Ljung, G.M., Box, G.E.P., 1978. On a measure of the lack of fit in time series models. Biometrika 65 (2), 297–303.
Lo, A.W., MacKinlay, C., 1988. Stock market prices do not follow random walks: Evidence fro a simple specification test. Rev. Financ. Stud. 1, 41–66.
Nadarajah, S., Chu, J., 2017. On the inefficiency of Bitcoin. Econom. Lett. 150, 6–9.
Nakamoto, S., 2008. Bitcoin: A peer-to-peer electronic cash system, working paper.
Peterson, T., 2017. Metcalfe's law as a model for Bitcoin's value, working paper.
Selgin, G., 2015. Synthetic commodity money. J. Financ. Stab. 17, 92–99.
Urquhart, A., 2016. The inefficiency of Bitcoin. Econom. Lett. 148, 80–82.
Van Vliet, B., 2018. An alternative model of metcalfe's law for valuing Bitcoin. Econom. Lett. 165, 70–72.