Economics Letters 163 (2018) 6–9

Contents lists available at ScienceDirect

Economics Letters

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

A new look at Cryptocurrencies

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HIGHLIGHTS

- Cryptocurrencies show predictable patterns with mostly oscillating persistence.
- They also display mild leverage effects, varied kurtosis and volatility clustering.
- With no counter-party credit risk, Ripples shows the weakest leverage effect.
- Being easier to transact, Ethereum and Dash have a smaller kurtosis than Bitcoin.

ARTICLE INFO

Article history:
Received 18 October 2017
Received in revised form 10 November 2017
Accepted 13 November 2017
Available online 26 November 2017

JEL classification:
C5
C22
G1

Keywords:
Long memory
Stochastic volatility
Leverage
Heavy tails
Cryptocurrency
Bitcoin

ABSTRACT

The complexities of Cryptocurrencies are yet to be fully explored. New evidence suggests the most popular Cryptocurrency, Bitcoin, displays many diverse stylized facts including long memory and heteroskedasticity. This note combines many of these attributes into a single model to conditionally measure the varied nature of Cryptocurrencies. Understanding these properties helps us to evaluate their investability. We fit our model to 224 different Cryptocurrencies in order to determine which of these properties exist. It is found that Cryptocurrencies in general have several unique properties including leverage effects and Student-*t* error distributions.

1. Introduction

Academic interests in anonymous communications research date back to the early 1980s (Chaum, 1981), and the first digital currency, *DigiCash*, was launched in 1990 which offered anonymity through cryptographic protocols. Nakamoto (2008) resurrected philosophies of Chaum (1981) with the addition of crowd sourcing and peer-to-peer networking which both avoid centralized control. Today, this has manifested itself into a growing Cryptocurrency community which now includes banks, hedgefunds and even Government. The most popular Cryptocurrency and largest by market capitalization is Bitcoin. A $1000 USD investment in Bitcoin in July of 2010 would have returned $81,000,000 just 7 years later (BNC, 2017). Bitcoin, or Cryptocurrencies in general face scrutiny as being speculative (Cheah and Fry, 2015). Conversely, there is evidence to suggest the Cryptocurrency market is still in its infancy and is inefficient (Urquhart, 2016), with properties such as price clustering (Urquhart, 2017). There is however a strong growing network of Bitcoin users and academics who are shedding light on this new technology. In this work, we discuss a large investable sample of Cryptocurrencies, and conditionally measure some important stylized facts.

The remainder of this note is organized as follows: in Section 2, we discuss our data source and the model; in Section 3 we discuss our empirical findings and conclude with Section 4.

2. Data and methodology

The long memory effect of Hosking (1981) was identified in Bitcoin by Bariviera (2017). We extend these findings to model and conditionally measure the generalized long memory effect of Gray et al. (1989). Another important feature found in financial time

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https://doi.org/10.1016/j.econlet.2017.11.020
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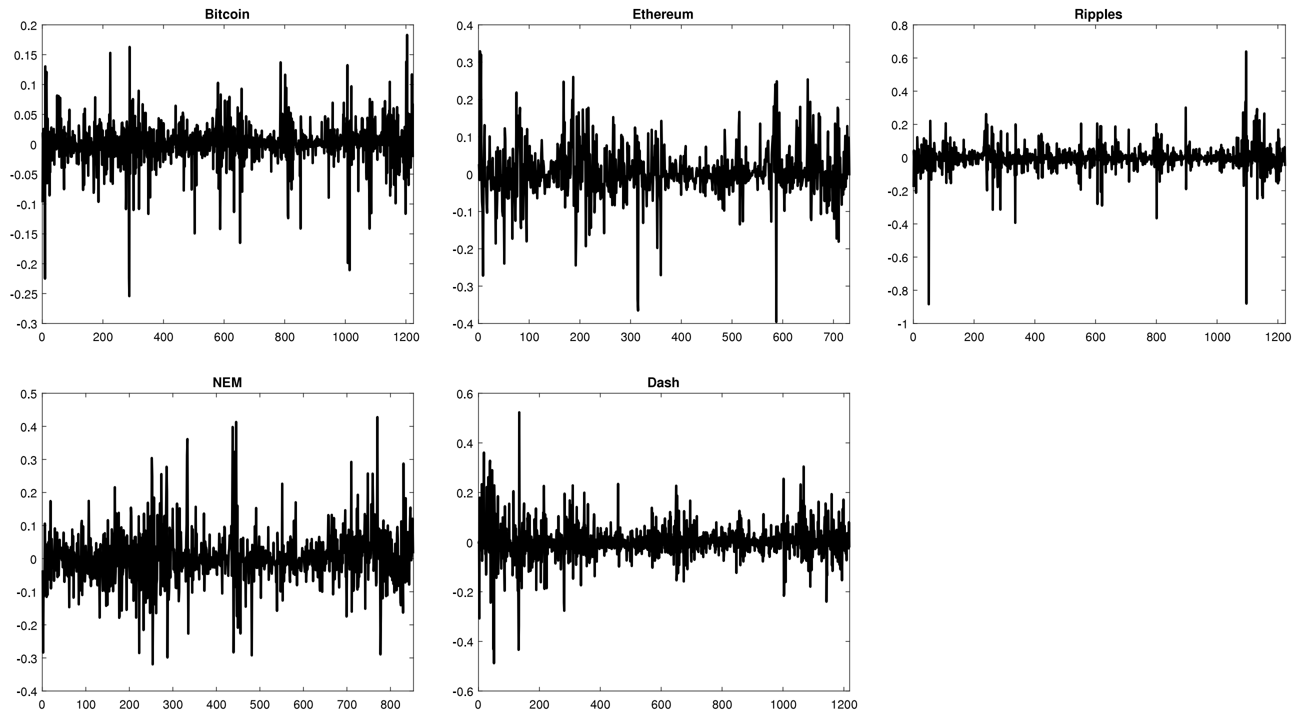

Fig. 1. Time series plots of the price percentage change for the five largest Cryptocurrencies measured by market capitalization.

series is the leverage effect which has its roots in the asymmetric return–volatility relationship attributed to financial leverage or debt-to-equity ratios. The leverage effect is the notion of a negative correlation between one-day ahead volatility and returns. Generalized autoregressive conditional heteroscedastic (GARCH) models have been successfully used to measure time-varying volatility in Bitcoin data (Katsiampa, 2017). We however plan to do this using the stochastic volatility model of Taylor (1986) to describe the time varying nature of volatility typically found in financial returns. See Shephard (2005) for a detailed comparison of the two approaches.

An additional stylized fact of financial returns of assets such as stocks and currencies is they are not normally distributed. The usual treatment to measure this feature is to modify the observation and/or the latent equation to include a heavy-tailed distribution (Chib et al., 2002; Omori and Watanabe, 2008). Incorporating all of these features commonly found in financial time series, we construct a model which describes all of these properties.

The data for this analysis is sourced from the Brave New Coin (BNC) Digital Currency indices (BNC, 2017). BNC surveys hundreds of trading platforms and currently records 2796 Cryptocurrency time-series indices. However, some of these have market capitalizations which are small (<$1,000,000 USD) and traded very little. Of the 2796 data sets available on the BNC database, only 224 of these have been exchanged at least once per day since inception. The time series y_t is defined as the daily index price percentage change $y_t = (P_t - P_{t-1})/P_{t-1}$, where P_t is the daily index value at time t. It should be noted that alternative transformations to de-trend the data can be used, such as $y_t = \log(P_t/P_{t-1})$. Although Cryptocurrencies were first introduced in 2008, BNC only reports price points when more formalized exchanges for each respective currency could be measured with reliability. As such, the number of observations recorded for each Cryptocurrency vary, but all end on the 31st of July, 2017.

The time series model fitted in this note measures Generalized long memory (GLM), stochastic volatility (SV), leverage (LVG) and heavy tails (HT). Let $y_t, t = 1, 2, \ldots, T$ be a stochastic process satisfying the equations

$$\text{GLM} : (1 - 2uB + B^2)^d y_t = \varepsilon_t, \tag{1}$$

$$\text{SV} : h_{t+1} = \alpha + \beta(h_t - \alpha) + \eta_{t+1}, \tag{2}$$

$$\text{LVG-HT} : \begin{pmatrix} \varepsilon_t \\ \eta_{t+1} \end{pmatrix} \sim t_\nu \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} e^{h_t} & \sigma\rho e^{h_t/2} \\ \sigma\rho e^{h_t/2} & \sigma^2 \end{pmatrix} \right). \tag{3}$$

It is known that y_t has long memory effects when $(\{|u| < 1, 0 < d < 0.5\} \cup \{|u| = 1, 0 < d < 0.25\})$. There is assumed to be a leverage effect between the errors of the observation equation (1) and the latent equation (2) such that $\mathbb{E}[\varepsilon_t \eta_{t+1}] = \rho$. Further, these components are assumed to follow a bivariate Student-t distribution. Clearly, h_t is the log-volatility, which evolves according to the state equation (2) for $t = 1, \ldots, T$, α is the constant level of the volatility, β is the persistence of the volatility process and σ^2 is the volatility of volatility. We assume $|\beta| < 1$ so h_{t+1} is stationary.

3. Empirical results

Firstly, we focus on the 5 largest Cryptocurrencies measured by market capitalization on the 31st of July, 2017 (BNC, 2017) (see Table 1). As expected, we see that currencies with lower market capitalizations exhibit larger variability. The Ljung–Box (L–B) tests of $|y_t|$ and y_t^2 show strong evidence of long memory and time-dependent volatility respectively. The Kolmogorov–Smirnov test for normality is also rejected. The L–B test, the normality test, the high level of kurtosis and the volatility clustering in Fig. 1 all confirm the need for model (1)–(3).

Model (1)–(3) is estimated using the filtered investable universe of 224 different Cryptocurrency indices.[1] We also plot the names of the top 5 Cryptocurrencies to show where they stand relative to their counterparts.

As evidenced in Fig. 2(a), most estimates of $\hat{u}$ are negative. As $\hat{u}$ approaches -1 from the right, the sample autocorrelation function

[1] The list of names is in the appendix attached to this letter.

Table 1
Summary statistics of the global weighted average indices for each relevant Cryptocurrency. *P*-values of the relevant columns are reported in parentheses. L–B: Ljung–Box Q-test for residual autocorrelation.

	Rank	Market Cap. ($B)	No. of obs	Mean	Std.	Skewness	Kurtosis	Min.	Max.	L–B ($\lvert y_t \rvert$)	L–B (y_t^2)	Normality test
Bitcoin	1	67.7602	1225	0.0009	0.0362	−1.0460	11.9590	−0.2543	0.1830	439.1810	211.8933	4320.1650
										(< .0001)	(< .0001)	(< .0001)
Ethereum	2	28.4994	732	0.0054	0.0742	−0.0981	7.4296	−0.3959	0.3293	244.3408	122.0188	599.6219
										(< .0001)	(< .0001)	(< .0001)
Ripples	3	6.7727	1225	−0.0003	0.0751	−2.0852	40.6985	−0.8844	0.6393	460.2791	89.1193	73426.8413
										(< .0001)	(< .0001)	(< .0001)
NEM	4	2.3565	853	0.0046	0.0831	0.5260	7.0738	−0.3196	0.4279	227.0109	135.8583	629.1816
										(< .0001)	(< .0001)	(< .0001)
Dash	5	1.5033	1219	0.0020	0.0724	0.0827	11.7466	−0.4881	0.5232	902.6657	586.7064	3887.1329
										(< .0001)	(< .0001)	(< .0001)

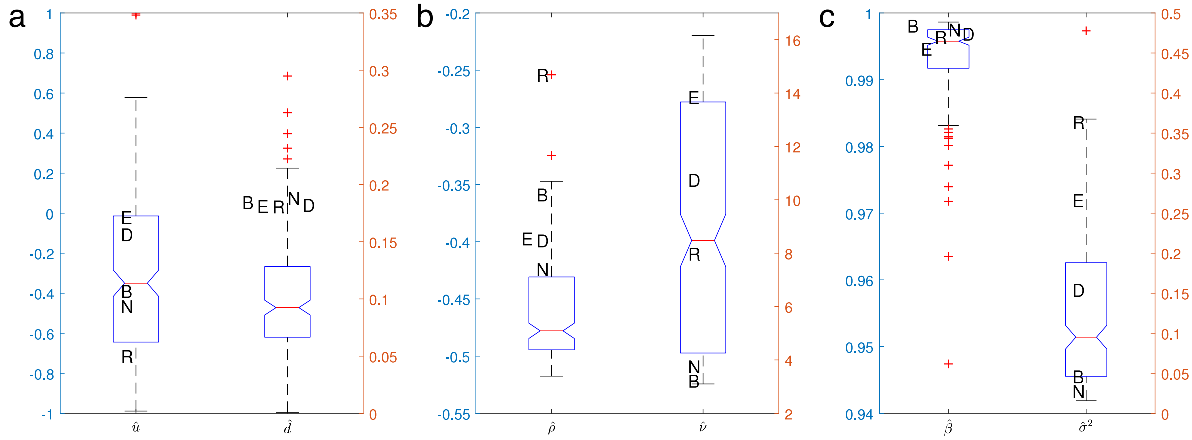

Fig. 2. Notched boxplots of parameter estimates of 224 different cryptocurrency data sets under the GLM-SV-LVG-HT model. B: Bitcoin, E: Ethereum, R: Ripples, N: NEM, D: Dash. (a) $[\hat{u}, \hat{d}]$. (b) $[\hat{\rho}, \hat{\nu}]$. (c) $[\hat{\beta}, \hat{\sigma}^2]$.

becomes instantaneously oscillating. Twenty five percent of our investable universe have a positive $\hat{u}$, among which the largest is 0.6 corresponding to a period of around 7 days. Remarkably, the top 5 Cryptocurrencies by market capitalization have a value of $\hat{d}$ which is clustered around 0.18. This is suggestive that as Cryptocurrency markets mature, they tend to have similar long memory persistence characteristics. All estimates of $\hat{\rho}$ are negative and tend to cluster between -0.4 and -0.5, which implies that one day ahead volatility and returns are negatively correlated. This too is the assumed case in most financial time series to have a negative ρ, and therefore shows that Cryptocurrencies also share this behaviour. The *volatility of volatility* estimate $\hat{\sigma}^2$ shows the existence of a stochastic volatility process. Some commonly traded Cryptocurrencies, such as Ripples, show extreme volatility characteristics. The estimated parameter $\hat{\beta}$ reflects volatility persistence over time and is highly suggestive that all Cryptocurrencies in our investable universe show evidence of volatility clustering. This further validates the volatility clustering shown in Fig. 1. After allowing for these various effects, the errors show a diverse level of kurtosis with $\hat{\nu}$ ranging from 3 for Bitcoin showing extreme kurtosis to 16 showing moderate level of kurtosis.

Interestingly, Ripples is not dependent on any third party for redemption, and as such, it is the only currency with no counterparty credit risk. Due to this safety feature, Ripples has been increasingly used by banks and large corporations as their preferred settlement infrastructure technology due to minimized future exchange rate volatility risk — this is indeed in line with our findings as it has the lowest $|\rho|$ indicating it has the weakest leverage effect amongst all Cryptocurrencies.

The main features of Ethereum (ETH) and Dash compared to all other Cryptocurrencies is they are more user-friendly. There is a larger community based approach with computer programmers actively making both Cryptocurrencies easier, safer and quicker to use. The biggest criticism of BTC is that transacting money can be an extremely slow process, sometimes taking up to 48 h for Bitcoins to be sent from one user to another. ETH uses smart contracts to use blockchains in comparison to BTC which does not. Also, Dash is the only currency that uses instant transactions ('InstantSend'). InstantSend is a feature of Dash which allows for almost near-instant transactions, which solves the longer confirmation time problem of Bitcoin. This can be perceived that ETH and Dash have lower liquidity risk than BTC. This is indeed consistent with our findings since both ETH and Dash have a higher value of ν, which implies their error distributions behave closer to a Gaussian distribution with smaller kurtosis than BTC which nearly has the lowest value of ν. While BTC has a relatively low value of σ^2 which is similar to other financial returns, it is clear that most of the variability of BTC can be attributed to a heavy tailed distribution.

4. Conclusion

This work is deeply motivated by the unique characteristics found in Cryptocurrency data, which are drawing media and academic attention. The empirical data analysis shows Cryptocurrencies exhibit long memory, leverage, stochastic volatility and heavy tailedness. We further shed light on a larger scope of the Cryptocurrency universe by expanding our analysis to cover 224 Cryptocurrency indices. Although still in its infancy, we contribute a deeper understanding surrounding Cryptocurrencies for the upcoming regulators, investors and governments to explore further on the topic.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econlet.2017.11.020.

References

Bariviera, Aurelio F., 2017. The inefficiency of Bitcoin revisited: A dynamic approach. Econ. Lett. 161, 1–4.
Brave new coin price indices, 2017. www.bravenewcoin.com.
Chaum, David L., 1981. Untraceable electronic mail, return addresses, and digital pseudonyms. Commun. ACM 24 (2), 84–90.
Cheah, Eng-Tuck, Fry, John, 2015. Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. Econ. Lett. 130 (Suppl. C), 32–36.
Chib, Siddhartha, Nardari, Federico, Shephard, Neil, 2002. Markov chain monte carlo methods for stochastic volatility models. J. Econom. 108 (2), 281–316.
Gray, Henry L., Zhang, Nien-Fan, Woodward, Wayne A., 1989. On generalized fractional processes. J. Time Ser. Anal. 10 (3), 233–257.
Hosking, J.R.M., 1981. Fractional differencing. Biometrika 68 (1), 165–176.
Katsiampa, Paraskevi, 2017. Volatility estimation for Bitcoin: A comparison of GARCH models. Econ. Lett. 158 (Suppl. C), 3–6.
Satoshi Nakamoto, 2008. Bitcoin: A peer-to-peer electronic cash system. www.bitcoin.org.
Omori, Yasuhiro, Watanabe, Toshiaki, 2008. Block sampler and posterior mode estimation for asymmetric stochastic volatility models. Comput. Statist. Data Anal. 52 (6), 2892–2910.
Shephard, Neil, 2005. Stochastic Volatility: Selected Readings. Oxford University Press.
Taylor, Stephen, 1986. Modelling Financial Time Series. Wiley, Chichester [West Sussex]; New York, ISBN: 0471909939, 9780471909934.
Urquhart, Andrew, 2016. The inefficiency of Bitcoin. Econ. Lett. 148 (Suppl. C), 80–82.
Urquhart, Andrew, 2017. Price clustering in Bitcoin. Econ. Lett. 159 (Suppl. C), 145–148.