Cryptocurrencies: Do they exhibit properties of an Asset or Fiat currency?

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***Abstract*—Cryptocurrencies exploded onto the scene in 2009 with the first digital currency, Bitcoin. Its success heralded the arrival of many more such currencies. Price volatility has been a feature of these currencies and has lead to debates in both media and academia as to whether such currencies are being used as originally intended, that is a secure method of payment to rival traditional fiat currencies or as an investment asset. The current study uses price-range estimators including Parkinson, Garman-Klass, Rogers-Satchell and Yang Zhang to gain an understanding of the underlying features of this volatility. Cryptocurrencies are represented by Bitcoin and Litecoin, while fiat currencies are represented by Euro, Dollar and Yen as they represent the major currencies in each continent and hard assets are represented by gold, silver and platinum. Results found that cryptocurrencies are a unique asset class unto their own. They are a hybrid asset class which exhibit traits of both fiat currencies and speculative assets. Moving forward this is a consideration which needs to be considered by regulators if they are ever to achieve widespread adoption.**

Keywords: volatility, cryptocurrencies, fiat currencies,, price range-estimators, hard assets, commodities, hybrid asset classes

I. Introduction

Bitcoin is a peer-to-peer electronic payment system based on cryptographic proof instead of trust, allowing any two willing parties to transact directly with each other without the need for a trusted third party [1]. Therefore the purpose of Bitcoin is to act as a secure form of digital money which eliminates the need for banks so that parties can transact directly with each other. Since its foundation in 2009, Bitcoin has seen its price soar with a current market capitalisation of $153,778,009,226 as of 23 April 2018 and a circulating supply of 16,998,375 (coinmarketcap.com, 2018). This success has encouraged the introduction of other cryptocurrencies such as Litecoin, Namecoin, Peercoin and Zero Coin which operate similarly to Bitcoin with some minor modifications [2]. This has been endorsed by [3] who argues Bitcoins success has ignited an exposition of new alternative currencies referred to as Altcoins, however, these currencies contain many of the same issues as fiat currencies such as money laundering and other uses by criminals.

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According to [4], Bitcoin behaves more like an investment asset than functioning currency for transaction purposes due to its very high levels of market volatility. This perspective is given weight by [5] who found many first time Bitcoin purchasers kept their coins in the exchange wallets for speculative purposes and had little intention of using their Bitcoins for payment purposes. A similar conclusion was reached by [6] who found that a third of Bitcoins are held by investors who receive them, but do not send them to others suggesting that they are held for investment purposes rather than being used for transactions and hence as a medium of exchange, one of the key functions of fiat currencies. According to [7], the limited number of daily transactions suggests that Bitcoin fails in serving as a medium of exchange capable of being traded for a wide variety of goods and services concluding that Bitcoin does not have the key attributes of a currency and should be regarded as a very liquid asset instead. This perspective is further endorsed by [8] who warn investors should be cautious about the lack of liquidity in Bitcoin relative to conventional assets.

Bitcoin has been called digital gold as many feel it behaves like gold acting as a store of value [9]. According to [10], the reason Bitcoin has been compared to gold is due to its similarity regarding scarcity of supply, finite nature, high price volatility and the fact it remains outside of government control. However, [8] cautions that Bitcoin also differs from gold in several aspects including the fact it remains an intangible asset and that it bears a significant counterpart risk which was tested when one of the most widely used exchanges Mt. Gox collapsed. [2] argues Bitcoin fails as a store of value and as a unit of account due to its volatility and it therefore doesnt perform the functions of a currency. In addition, it has no intrinsic value as it simply anchored on a computer program and it simply derives its value from being a speculative commodity [2]. This sentiment is supported by [11] who argue the key difference between a commodity currency such as gold standard and Bitcoin is that demand for Bitcoin is driven solely by its value in future exchange, whereas the demand for commodity currency is driven by both its intrin-sic value and its value in future exchange. A similar conclu-sion was reached by [12] who found Bitcoins are 26 times more volatile than the SP 500 Index and regarding the ques-tion as to whether Bitcoin should be considered an invest-ment or speculative vehicle, they concluded that at present it is more of a speculative vehicle as it is internally driven by buyers and sellers who are not influenced by fundamental economic factors.

Acknowledging that Bitcoin is usually considered a purely speculative asset, [3] concluded that standard fundamental factors such as its use in trade, money supply and price level played a role in Bitcoin price over the long-term in line with standard economic theory, specifically monetary economics and the quantity theory of money. Additionally, [3] found prices were driven by investor interest in the cryptocurrency and this fact tended to lead to a situation whereby during periods of explosive prices such interest tended to drive prices higher and conversely when prices were in rapid decline, such investor interest tended to push prices further down. The overall conclusion reached is that Bitcoin is a unique asset which possesses properties of both standard financial assets and speculative assets [3].

According to [13], gold is often considered a good hedge and a safe haven during periods of extreme financial distress and as the price of gold in the US tends to increase when stock prices fall it has the potential to compensate investors for losses on their stocks, provided they already hold the gold. Those that purchased the gold at the time of the extreme financial shock tended to lose money if they held it longer than fifteen days [13]. [7] compared Bitcoin price returns to gold returns and other world currencies and found it had very low or insignificant correlations with other global currencies and gold returns, reinforcing the conclusion that Bitcoin does not behave like a currency. These results lead [7] to conclude that Bitcoin could be used as a diversifier for an investment port-folio. Research by [14] found a low correlation between Bitcoin and both traditional assets (stocks, bonds and fiat currencies) and alternative investments (commodities, hedge funds, property) suggesting Bitcoin has good diversification benefits despite its volatility [14]. [15] found Bitcoin shared many similarities with both gold and the dollar and that it reacted significantly to the federal funds rate which suggests that Bitcoin acts like a currency, although [15] argues its de-centralised and unregulated state will ensure that it never behaves exactly like currencies on the market today. Lack of consensus as to whether Bitcoin is a currency or a commodity or both remains [16].

Academics and scholars alike have examined Bitcoins ability to act as a hedging tool and whether it more of a traditional asset class or opportunity for speculation. To our knowledge there are no studies examining cryptocurrencies volatility using historical data to see if they are closer to fiat currencies or hard assets. Therefore, we propose to examine the volatility of cryptocurrencies (Bitcoin and Litecoin) using price-range estimators to see whether they share properties with fiat currencies or hard assets.

II. Related Work

According to [17] measuring volatility is not like measuring price. Instantaneous volatility is unobservable. It needs time to manifest itself [17]. Traditionally, many researchers calculated volatility using the daily squared mean of market closing prices. However, such an approach may result in poor Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model performance for volatility forecasting [18]. More recent studies argue failure of GARCH models to pro-duce accurate forecasts could be attributed to the inappropri-ate use of ex-post squared returns as opposed to inherent fail-ure of the GARCH model themselves [18]. [19] warns against using only closing prices such as GARCH and stochastic vol-atility (SV) models as they can be inaccurate and inefficient as they ignore the path of the price inside the reference period when volatility is estimated. This is especially so on very turbulent trading days that are characterised by drops and recoveries, the traditional close-to-close volatility estimators indicate that volatility for that day was low which the daily price range estimators correctly capture that volatility was in fact high [19].

There are also major practical advantages to using price ranges as for many assets daily opening, highest, lowest and closing prices are readily available and most data suppliers provide daily highest/lowest as summaries of intra-day activity, therefore range-based volatility proxies are easily calculated [19]. In addition, traders and those in the trading community make use of the many institutional and free charting tools of asset prices showing open, high, low and close prices in the form of bar charts which make such studies more appealing [20]. It is generally accepted that while high/low prices do require continuous monitoring during the trading period to establish their value they contain more information regarding volatility than do open/close prices which merely provide a snapshot of the process [21]. This perspective is supported by [19] who argue using such data provides a greater understanding of the real underlying processes even if the whole pathway of the asset price remains unknown.

Parkinson proposed an estimator that assumed no drift and no opening price jumps which claimed to be 2.5 to 5.2 times more efficient [25]. However, according to [18] Garman and Klass improved the Parkinson estimator by using the opening, closing prices in addition to high and low prices. This is supported by [22] who argue the Garman-Klass estimator aims to enhance the efficiency of range-based estimators by including opening and closing prices into the estimation. According to [25] not only is the Garman-Klass estimator more efficient than the Parkinson estimator, but it is about 8 times more efficient than the historical volatility. According to [21] continuous price observations are curtailed by the fact that transactions often occur only at discrete points in time and stock exchanges close during certain periods of time. For this reason, the Garman-Klass model like Parkinson, assumes continuous brownian motion is followed between transactions and during exchange closure, even though prices cannot be observed during such periods [21].

According to [24] the Garman-Klass estimator is biased when the number of transactions per day is less than 1000. Similar-ly, a downward bias occurs when the Parkinson estimator is used to calculate volatility for securities that are less-liquid or not continuously traded [18]. In addition, the Parkinson estimator tends to over-estimate true volatility in the pres-ence of non-zero drift [22]. [25] concurs, arguing the assump-tion of drift-less price processes in the Parkinson and Gar-man-Klass estimators is more likely to lead to over-estimation of volatility when security prices exhibit a distinct trend such as those in a bearish or bullish market. Rogers and Satchell proposed an estimator that allowed for price drift and when a security price has a drift, the Rogers-Satchell estimator is claimed to be more efficient than both the Parkinson and Garman-Klass estimators [18]. According to [26] the no drift assumption of Parkinson and Garman-Klass estimators may not be valid if the time period is not small such as those contained in weekly or monthly time-series. In addition, [26] argues that ignoring the opening jumps will under-estimate the volatility and in reality both drifts and opening jumps do exist. Therefore, [26] constructed what is known as the Yang Zhang estimator which is independent of both drift and opening jumps of the underlying price movement and is considered 14 times more accurate than the other estimators [25].

27] investigated the relative performance of historical volatility estimators and their applicability to market data as few studies to date have empirically tested the accuracy of range estimators using market data. They found that all four range estimators provide a good estimation of true variance when prices follow a geometric Brownian motion with a small drift and no opening price jump. However, if the drift term is large, both the Parkinson and Garman-Klass estimator signif-icantly over-estimate the true variance, whereas the Rogers-Satchell estimator and the Yang Zhang estimator are drift independent. The Yang Zhang is the only one that can give an accurate estimate if there is a large opening price jump. The Parkinson, Rogers-Satchell and Garman-Klass are all down-ward biased which is proportional to the size of the opening jump. In addition, [27] found that range estimators were able to capture the short-run dynamics of volatility variation and were robust against microstructure noise. This confirmed the findings of [28] who concluded that range estimators are fair-ly robust toward microstructure effects.

An empirical analysis of the relative bias, efficiency and forecasting properties of the close-to-close and extreme value volatility estimators for SP 500 futures prices was conduct-ed by [29]. It was found the Parkinson estimator contained little empirical bias relative to close-to-close volatility esti-mator, suggesting actively traded instruments with small price increments do not suffer the same discrete-time and discrete-price trading problems discussed by Garman and Klass. In addition, both the Parkinson and Garman-Klass es-timators exhibited very little downward bias and were found to be much more efficient than the traditional close-to-close estimator. Weekly data forecasts show that neither of the estimators perform that well, but when using monthly data in a forecasting context, the extreme value volatility estimators perform better than the close-to-close estimator [29].

III. Methodology

A. Research Hypothesis

This paper examines whether the properties of cryptocurrencies are closer to assets or fiat currencies, using volatility estimators including Parkinson, Garman-Klass, Rogers-Satchell and Yang-Zhang.

B. Data

Volatility estimators require historical information regarding opening/closing and high/low prices, therefore datasets were chosen on this basis. The scope of the study was determined by Litecoins foundation in 2013 as it has comparable trading activity to Bitcoin which sets the benchmark for other cryptocurrencies since its foundation in 2009. Each dataset was selected from the historical section of the chosen website and filters were applied from 29/04/2013 to 26/03/2018.

Datasets for Bitcoin and Litecoin were obtained from Coinmarketcap.com who calculate prices by taking the volume weighted average of all prices reported at each market. Coinmarketcap collects information regarding Bitcoin prices and 24 hour trading volumes for Bitcoin against its trading pair from a number of exchanges including OKex, Binance, Bitfinex, Huobi, Upbit, bitFlyer, GDAX, Bitstamp, Bithumb, BCEX, BTCC, BTCBOX. It does likewise for all quoted cryptocurrencies including Litecoin. It excludes markets that do not charge transaction fees as this practice can lead to a situation where traders or bots trade back and forth with themselves and generate fake volumes without penalty. As it is impossible to ascertain how much of the volume is fake, Coinmarketcap.com excludes it entirely from their calculations. All data is collected, recorded and reported in UTC time (Universal Time Coordinated) and all prices are quoted in US dollars.

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In order to achieve a balanced representation of commodities, datasets for gold, silver and platinum were obtained from investing.com. Contemplation was initially given to solely using gold prices for this study, however, research indicated that gold prices can be skewed due to its reliance as a safe-haven during economic, financial, political, and geopolitical crisis and it has less industrial uses, in contrast to other commodities such as copper and oil. In addition, gold can sometimes attract emotional, speculative investors who might amplify its price gyrations creating disruptive spikes in peaks and troughs in the market. Therefore, the scope of this study was widened to include silver and platinum as they have more industrial uses (jewelry, photography, coins, auto

[1] https://coinmarketcap.com/
[2] https://www.investing.com/

catalyst, petroleum and plastics) and consequently are more representative of actual commodity markets. Therefore, future contracts datasets were obtained from investing.com from the historical data section and filters were applied to ensure unison with the cryptocurrencies time frames. Prices quoted are per troy ounce and are obtained from market mak-ers and quoted in US dollars.

Datasets for Fiat currencies were obtained from tick-data.com. In order to achieve good representation from each of the global regions, exchange rate datasets for Euro/USD and Euro/YEN were selected.
[3]

The data which was acquired had one important feature which could not be ignored. Each had a different trading time-frame. FX and Commodity markets trade over 252 days a year, whereas cryptocurrency markets trade 365 days a year. Therefore the datasets were interpolated to ensure uniformity across the time-series datasets using R-Clean, a tool available in R-Studio. The analysis was conducted in Python Notebook using R.

C. Application

Before proceeding to the empirical results, we need to introduce the key concepts used to obtain them. According to [17] measuring volatility is not like measuring price. Instantaneous volatility is unobservable. It needs time to manifest itself. As alluded to earlier in the related work using only closing prices such as GARCH and stochastic volatility models can be inaccurate and inefficient as they ignore the path of the price inside the reference period when volatility is estimated. Traditional close-to-close volatility estimators indicate that volatility for a day was low when in fact if OHLC data was applied then the volatility was in actual fact high[19]. High, Low prices do require more attention but give a better snapshot of volatility than traditional open close prices

$$r_i = \ln\left(\frac{C_{i+1}}{C_i}\right)$$
$$\bar{r} = \frac{r_1 + r_2 + \dots r_{n-1}}{n-1}$$
$$\sigma = \sqrt{\frac{Z}{n-2}\sum_{i=1}^{n-1}(r_i - \bar{r})^2}$$

Fig. 1. Close to close Volatility Estimator.

Historical volatility is a quantifiable number which is based on past changes to the price of a stock or futures contract. To calculate it, take the past prices and price changes (from close to close), then take an average of those price changes in percentage terms. Below is the Parkinsons Volatility Estimator which extends the regular volatility calculation by incorporating the low and high price of a security during the day. To calculate Parkinson volatility the high and low prices of the period are divided and follow the natural log by taking the power of 2. Sum the results over the observed series and the result should be multiplied by a certain factor. The square root then gives you Parkinsons volatility. This volatility estimator takes into account some intraday high and low prices to calculate volatility which as a result gives more information about how volatile a security is. The Parkinson

$$\sigma = \sqrt{\frac{Z}{n 4 \ln 2}\sum_{i=1}^{n}\left(\ln\frac{H_i}{L_i}\right)^2}$$

Fig. 2. Parkinsons Volatility

volatility estimator does not take into account the opening and closing price. Since markets are most active during the opening and closing of a trading session this is a serious shortcoming of this estimator. The Garman Klass estimator for estimating historical volatility assumes Brownian motion with zero drift and no opening jumps (i.e. the opening = close of the previous period). This estimator is 7.4 times more efficient than the close-to-close estimator but it is not robust for opening jumps in prices. Overnight jumps in price bias the estimate and as such is not ideal for use. The

$$\sigma = \sqrt{\frac{Z}{n}\sum\left[\tfrac{1}{2}\left(\ln\frac{H_i}{L_i}\right)^2 - (2\ln 2 - 1)\left(\ln\frac{C_i}{O_i}\right)^2\right]}$$

Fig. 3. Garman-Klass Volatility

Rogers-Satchell volatility estimator outperforms the preceding estimators (Parkinson's Garman-Klass) when the underlying follows a geometric Brownian motion (GBM). This is where the historical data mean returns different from zero. This provides a better volatility estimation but does not account for jumps in price and assumes no opening jump. Yang and Zhang

$$\sigma = \sqrt{\tfrac{Z}{n}\sum\left[\ln\tfrac{H_i}{C_i}\ln\tfrac{H_i}{O_i} + \ln\tfrac{L_i}{C_i}\ln\tfrac{L_i}{O_i}\right]}$$

Fig. 4. Rogers-Satchell

derived an extension to the Garman-Klass historical volatility estimator that allows for opening jumps. It assumes Brownian motion with zero drift. This is currently the preferred version of open-high-low-close volatility estimator for zero drift and has an efficiency of 8 times the classic close-to-close estimator. Note that when the drift is nonzero, but instead relative large to the volatility, this estimator will tend to overestimate the volatility.
[4] [5]

[3]https://www.tickdata.com/product/historical-forex-data/

[4]https://web.archive.org/web/20090105181213/http://www.sitmo.com/eq/409.pdf

[5]http://breakingdownfinance.com/finance-topics/risk-management/garman-klass-volatility/

$$\sigma = \sqrt{\frac{Z}{n}\sum\left[\left(\ln\frac{O_i}{C_{i-1}}\right)^2 + \frac{1}{2}\left(\ln\frac{H_i}{L_i}\right)^2 - (2\ln 2 - 1)\left(\ln\frac{C_i}{O_i}\right)^2\right]}$$

Fig. 5. Yang-Zhang

IV. Evaluation

In order to determine whether cryptocurrencies exhibit trademarks of either asset classes using the volatility estimators we need to examine the asset classes, namely the FX data (EUR_USD, EUR_JPY) and Litecoin and Bitcoin datasets. The authors examined the datasets from 09/06/2014 until 25/02/18 for the FX data. The reason for this was that was the furthest back the authors could obtain FX data which had Open, High, Low and Close data. As previously discussed our volatility estimators rely on Open, High, Low and Close data in order to measure volatility. Evolution of the price index for both Bitcoin and Litecoin we can observe that both prices are dominated by periods of explosive bubbles followed by corrections. (See Fig. 6 and Fig.7) An observation made from these prices is that the prices never return to their starting value from before the bull run.

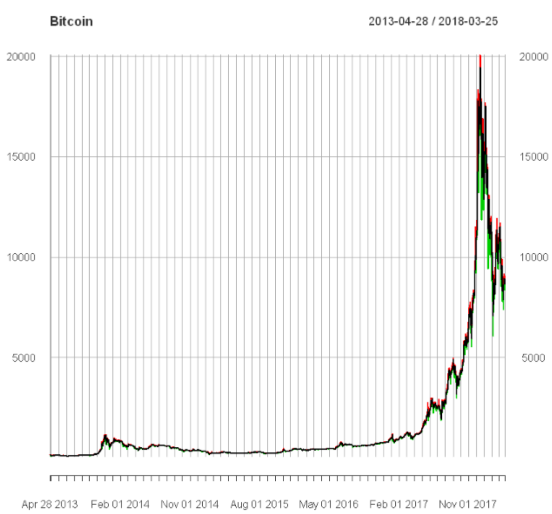

Fig. 6. Bitcoin OHLC Historical Prices

The price index of the commodities Gold, Silver, and Platinum (see Fig.8-19) show how silver and platinum are far more stable assets as they attract less emotional investors as previously stated. Gold just like Bitcoin attracts speculative emotional investors. This can be see in the volatility exhibited by Gold in comparison to other 2 commodities from 2016 to present where the prices of platinum and silver demonstrate less volatility. This can be attributed to the practical nature of these 2 precious metals.As [13] alluded to gold is often considered a good hedge and a safe haven during periods of extreme financial distress and as the price of gold in the US tends to increase when stock prices fall it has the

Fig. 7. Litecoin OHLC Historical Prices

potential to compensate investors for losses on their stocks, provided they already hold the gold. Cryptocurrencies attract emotional investors just like gold does. They believe that this "digital gold" will be the new gold for speculative asset holders in the future. It is therefore crucial that both are tested against cryptocurrencies to see whether or not this emotional attachment plays any factor in their respective volatility scores. One factor which cannot be overlooked in this research is the fact that standard currencies USD, EUR and JPY have limited data attached to them. Bitcoin, Litecoin and other cryptocurrencies however have unlimited data on the number of coins in circulation and what transactions have taken place on a daily basis. Such data availability allows for more precise statistical analysis. We examine Bitcoin prices considering various aspects that might influence the price or that are often discussed as drivers of the Bitcoin exchange rate.[3]

Fig. 8. Gold OHLC

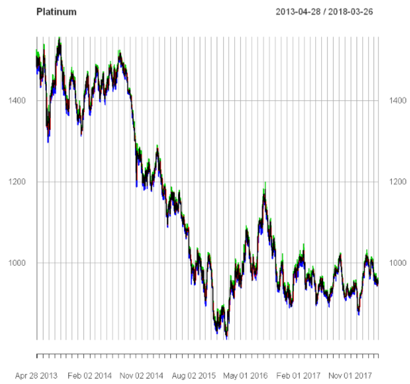

Fig. 9. Platinum Historical Prices

Fig. 10. Silver Historical Prices

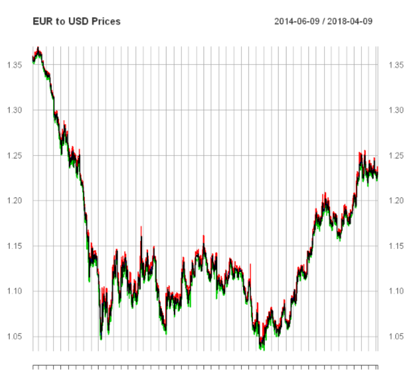

Fig. 11. EURUSD

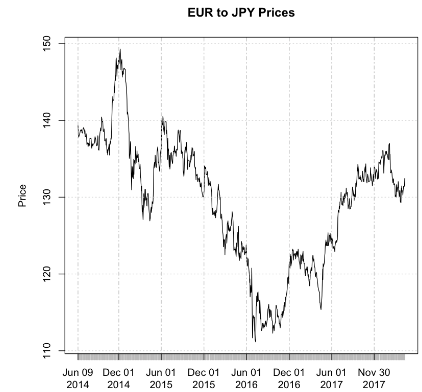

Fig. 12. EURJPY

A. Results

The choice of which estimator to build the authors model around was decided by measuring their respective performance against each other. [27] investigated the relative performance of historical volatility estimators and their applicability to market data as few studies to date have empirically tested the accuracy of range estimators using market data. They found that all four range estimators provide a good estimation of true variance. The authors measured the variance between the 3 estimators by using Bitcoin historical data and then building a model using the Garman-Klass, Rogers-Satchell and Yang-Zhang estimators. The results were that there was little between them as can be seen in Fig.13. As the Yang-Zhang

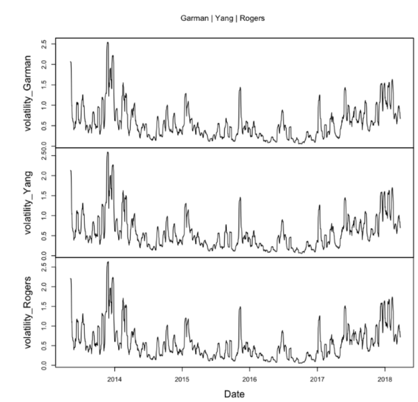

Fig. 13. Measure of Volatility Estimators Performance

estimator is the only one of the 3 that can accurately measure if there is a large opening jump in price it was the obvious choice to build our models around. Firstly the authors measured the volatility of the Bitcoin data set against the Euro_US Dollar using the Yang-Zhang volatility estimator. Using the Root mean squared errors regression model the authors obtained a score of **.6450** This was repeated for the Eur_JPY dataset which produced a similar score of **0.6383**.

A replica evaluation method was applied to the Gold and Platinum Data sets against Bitcoin with a score of **0.5555** and **0.5380** respectively. With a score of 1 demonstrating indicating a perfect prediction the authors can conclude that both fiat currencies and commodities lie in the same percentile of volatility as against Bitcoin thus making it a hybrid of the 2 assets. This sentiment is shared by [3] who concluded that cryptocurrencies are a unique asset which possess properties of both standard financial assets and speculative assets .

V. Conclusions and Future Work

Giving value to cryptocurrencies is difficult, if we consider it to be an exchange currency like the fiat currencies examined in this research then their value would depend on their relationships with other currencies. This is not a justified a comparison in the authors opinion. There is a different and disproportionate valuation between them as there is not widespread adoption of cryptocurrencies like fiat currencies. However, if you consider cryptocurrencies to be an asset like shares in a company, bonds or a barrel of oil then you need to apply a unique classification as all of these assets are classified differently according to their characteristics. Cryptocurrencies differ from other assets in terms of their politico-economic profile, price independence and risk-reward. As such it is important from a regulatory standpoint to classify cryptocurrencies accordingly and monitor their behaviour so they are given the proper financial classification. Expanding on this body of work the authors would like to measure the volatility estimators using mean squared errors regression model instead of root mean squared errors which can exacerbate any errors in a model and lead to skewed results. Leveraging the existing results with more assets and currencies against multiple cryptocurrencies could prove to be a worthwhile endeavour moving forward.

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References

[1] S. Nakamoto, "Bitcoin: A Peer-to-Peer Electronic Cash System", Bitcoin.org, 2009. [Online]. Available: https://bitcoin.org/bitcoin.pdf. [Accessed: 13- Mar- 2018].

[2] A. Cheung, E. Roca and J. Su, Crypto-currency bubbles: an application of the PhillipsShiYu (2013) methodology on Mt. Gox bitcoin prices, Applied Economics, vol. 47, no. 23, p. 2348-2358, 2015 [Online]. Avail-able: Business Source Complete, EBSCOhost. [Accessed April 24, 2018].

[3] L. Kristoufek, 2015. What are the main drivers of the Bitcoin price? Evidence from wavelet coherence analysis, PloS one, vol. 10, no. 4, April 2015 [Online]. Available: http://journals.plos.org/plosone/article?id=10.1371/journal.pone.0123923. [Accessed April 24, 2018].

[4] J. Obnesorge, A primer on Blockchain Technology and its potential for financial inclusion. Bonn: German Development Institute, 2018, pp. 1-43.

[5] F. Glaser, K. Zimmermann, M. Haferkorn, M.C.Weber and M. Siering, Bitcoin - Asset or Currency? Revealing Users' Hidden Intentions, Twenty Second European Conference on Information Systems, 2014, Tel Aviv, Israel.

[6] D.G. Baur, K. Hong and A.D. Lee, Bitcoin: Medium of Exchange or Speculative Assets?, Journal of International Financial Markets, Institu-tions and Money, 21, December 2017. [Online]. Available: https://doi.org/10.1016/j.intfin.2017.12.004. [Accessed April 24, 2018].

[7] C.Y. Wu and V.K. Pandey, The Value of Bitcoin in Enhancing the Efficient of an Investors Portfolio, Journal of Financial Planning, vol. 27, no. 9: p. 44-52, September 2014.

[8] E. Bouri, G. Azzi, and A.H. Dyhrberg, On the return-volatility relationship in the Bitcoin market around the price crash of 2013, Economics, vol. 11, no. 2, February 2017

[9] 9. N.Popper, Digital gold: Bitcoin and the inside story of the misfits and millionaires trying to reinvent money. New York, Harper, 2015.

[10] A.H. Dyhrberg, Bitcoin, gold and the dollarA GARCH volatility analysis, Finance Research Letters, vol. 16, October 2015. [Online]. Available:

[11] P. Ciaian, M. Rajcaniova and D. Kancs, The digital agenda of virtual currencies: Can BitCoin become a global currency?, Information Systems & E-Business Management, vol. 14, no. 4, p. 883-919, 2016

[12] 12. C. Baek and M. Elbeck, Bitcoins as an investment or speculative vehi-cle? A first look, Applied Economics Letters, vol. 22, no. 1, p. 30-34, 2015.

[13] 13. D. Baur and B. Lucey, Is Gold a Hedge or a Safe Haven? An Analysis of Stocks, Bonds and Gold, Financial Review, vol. 45, no. 2, p. 217-229, 2010

[14] M. Brire, K. Oosterlinck and A. Szafarz, Virtual currency, tangible return: Portfolio diversification with bitcoin, Journal of Asset Management. vol. 16, no. 6, pp.365-373. 2015.

[15] A.H. Dyhrberg, Hedging capabilities of bitcoin. Is it the virtual gold?, Finance Research Letters, vol. 16, October 2015.

[16] S. Lo and C.J. Wang, Bitcoin as Money?, Current Policy Perspectives, 14(4), Federal Reserve Bank of Boston, Boston MA, 2014.

[17] E. Sinclair, Volatility Trading, Hoboken, N.J.: Wiley, 2008. [E-Book] Available: EBSCOhost

[18] .J. Hung, T. Lou, Y. Wang and J. Lee, Evaluating and improving GARCH-based volatility forecasts with range-based estimators, Ap-plied

[19] R.Y. Chou, H. Chou and N. Liu, Range volatility models and their applications in finance, in Handbook of quantitative finance and risk management, Boston, MA: Springer, 2010, pp. 1273-1281.

[20] I.L. Kliakhandler, Execution edge of pit traders and intraday price ranges of soft commodities, Applied Financial Economics, vol. 17, no. 5, p. 343-350, 2007. [Online]. Available: Business Source Complete, EBSCOhost. [Accessed April 15, 2018].

[21] M.B. Garman and M.J. Klass, On the Estimation of Security Price Volatilities from Historical Data, The Journal Of Business, vol. 53, no. 1, p. 67-78, 1980. [Online]. Available: JSTOR Journals, EBSCOhost. [Accessed April 10, 2018].

[22] I. Jiang, J. Hung and C. Wang, Volatility Forecasts: Do Volatility Estimators and Evaluation Methods Matter?, Journal Of Futures Markets, vol. 34, no. 11, p. 1077-1094, 2014. [Online]. Available: Business Source Complete, EBSCOhost. [Accessed April 23, 2018].

[23] M. Parkinson, The Extreme Value Method for Estimating the Variance of the Rate of Return, Journal Of Business, vol. 53, no. 1, p 61-65, 1980. [Online]. Available: Entrepreneurial Studies Source, EBSCOhost. [Accessed April 23, 2018].

[24] Z. Chen, R. Daigler and A. Parhizgari, Persistence of volatility in futures markets, Journal Of Futures Markets, vol. 26, no. 6, p. 571-594, 2006. [Online]. Available: Business Source Complete, EBSCOhost. [Accessed April 10, 2018].

[25] Vipul and J. Jacob, Forecasting performance of extreme-value volatility estimators, Journal Of Futures Markets, vol. 27, no. 11, p. 1085-1105, 2007. [Online]. Available: Business Source Complete, EBSCOhost. [Accessed April 23, 2018].

[26] D. Yang, and Q. Zhang, Driftindependent volatility estimation based on high, low, open, and close prices, The Journal of Business, vol. 73, no. 3, p.477-492, 2000. [Online]. Available: Business Source Complete, EBSCOhost. [Accessed April 23, 2018].

[27] S. Jinghong and J. Zhang, Testing range estimators of historical volatility, Journal Of Futures Markets, vol. 23, no. 3, p. 297-313, 2006. [Online]. Available: Business Source Complete, EBSCOhost. [Accessed April 15, 2018].

[28] 28. S. Alizadeh, M.W. Brandt and F.X. Diebold, Rangebased estimation of stochastic volatility models, The Journal of Finance. vol. 57, no. 3, pp. 1047-1091, 2002.

[29] J.B. Wiggins, Estimating the Volatility of SP 500 Futures Prices Using the Extreme-Value Method, Journal Of Futures Markets, vol. 12, no. 3, p. 265-273, 1992. [Online]. Available: Business Source Complete, EBSCOhost. [Accessed April 10, 2018].