The Efficacy of Bitcoin as an Investment and Diversification Tool

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Abstract

Cryptocurrencies have been the subject of much scholastic research in the last few years with many still fascinated with the phenomenon. This is especially so in the case of Bitcoin, arguably the most influential one. Some of these papers look at the market efficiency of such quasi-currencies while others hypothesise on the very definition of such assets, with many concluding their existence to hover between being a full-fledged currency and an investment asset. In this paper, we use several robust volatility estimators to compare the volatility and returns of Bitcoin vis-à-vis a selected number of other traditional assets and currencies to ascertain its risk diversification capability relative to these other assets and currencies. Further, we measure the risk per unit of return of the assets using the volatility estimates generated. We find Bitcoin to be one of the more attractive investment tool and test its risk diversification capabilities using the Markowitz Portfolio Theory. We propose an optimal portfolio allocation consisting of Bitcoin, stock and bond index.

Keywords: Bitcoin, Investment Returns, Risk Diversification, Portfolio Management

JEL Classification: G0, G11, G12, G15

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1. Introduction

Cryptocurrencies have been the subject of much research interest in recent years. This is not surprising given that the speculative forces that followed such “assets” (or digital money) have seen the market value of them soaring to ridiculous levels. Touted as the world’s currency – a logical and necessary alternative to national currencies, cryptocurrencies thrive on those sceptical of the true value of national denominated monies whose values they believed are compromised as a result of irresponsible government policy-led inflation. While many may understand the basic definition of a cryptocurrency, not many would when it comes to understanding the actual mechanism and technological intricacies that are responsible in such digital monies. Taking Bitcoin as an example, it is a product of digital “blocks” that are created by algorithm writers, i.e., miners. Such “blocks” are essentially bundles of data but are of permanent communication of each other, each well aware of the protocols of the Bitcoin chain thus ensuring an exchange system that is not only highly exclusive but also one that can function with little or no supervision and more importantly, one that can exist and thrive without the fear of being shut down by any regulator.

Given the controversies surrounding Bitcoin, many investors have remained sceptical of its potential. One of the key issues is related to its high volatility - it has been constantly associated with speculative activity and bubbles formation. Many have pointed out its extreme volatility, as compared to other assets or currencies. Baek and Elbeck (2015) found the standard deviation of detrended ratio of Bitcoin (from 2010 to 2014) to be 26 times more volatile than the S&P 500 Index while Baur et al. (2018) reported the daily volatility of Bitcoin's return (from 2010 to 2015) being 8 times more than the S&P 500 Index and 7 times more riskier than gold. However, many of these studies were solely focused on the risk aspect of cryptocurrencies while giving little appreciation to the high returns that it could potentially generate.

Further, the issue as to whether cryptocurrencies can be in fact, classified as a commodity or money is itself divisive and a much contested subject. In essence, it has the features of gold given its limited supply. In the case of Bitcoin, it has a finite supply of 21 million coins and requires a complicated mathematical process to mine these coins, known as Blockchain. In this sense, it fulfils the “unit of account” function of money. However, it suffers from acceptability issues and quite possibly, it does not have (or able to maintain) a stable store of value due to its price volatility. Wu and Pandey (2014) question the viability of Bitcoin as a currency given the limited functions that it served. That said, these do not discourage many from investing in Bitcoin or the other cryptocurrencies. Since cryptocurrencies carry hybrid features of both commodity and money, we believe it is both useful and interesting to compare the returns of cryptocurrencies against major stock indices and currencies. While there are many different types of cryptocurrencies in the market, we selected Bitcoin (to represent cryptocurrency) in our analysis given its market share leadership.

Most of the literatures on cryptocurrencies focused on the risk aspect rather than the returns of cryptocurrencies. This is interesting since the very fundamental principle of finance would inform that returns are essentially compensation for risk-bearing, i.e., they are positively correlated, which is the very essence of the high-risk high-return theory. For instance, in the case of Bitcoin, given its volatile price swings (its price went from $1,000 at the start of 2017 to $19,000 twelve months later!), one would be expected to internalise its returns as well when interpreting the riskiness. One simple but useful tool to do so is the coefficient of variation (CV), which interprets risk per unit of return – this would provide another layer of analysis on the returns from investing.

The aim of this paper is to examine the volatility and returns of Bitcoin vis-à-vis other traditional assets and currencies to ascertain its risk diversfication capability relative to those of other assets. We start with the conventional approach to measure volatility, i.e., the standard deviations based on close-to-close price data. Next, we employ four other range-based volatility estimators, namely the Parkinson, Garman-Klass, Roger-Satchell and Yang-Zhang volatility estimators to provide further measurement of volatility. These range-based estimators, which incorporates the daily high, low and opening price data, are essential as results that relied on only close-to-close price data to measure the volatility of cryptocurrencies have the potential of either underestimating or overestimating volatility (since intraday volatility is ignored). Further, the coefficient of variation (CV) is calculated to enable the comparative analysis of risk-return performance of Bitcoin against various traditional assets and currencies. Except for bonds, we find that Bitcoin demonstrates superior risk-return performance than those of other traditional assets and currencies. In addition, we also find that Bitcoin possess risk diversification attributes when combined in a portfolio. Lastly, we employed the Markowitz Portfolio Theory to construct the optimal investment portfolio.

The paper is organised as follows – section 1 is the introduction while the related literatures are reviewed in section 2. Section 3 covers the data and methodology while the findings are reported in section 4. Section 5 concludes.

2. Literature Review

Dyhrberg (2016) argues that Bitcoin is similar to gold as it possess similar hedging capabilities while its medium of exchange attributes and its correlation to the federal funds rate indicate currency qualities. Her paper concludes with Bitcoin being a hedging instrument that is useful for portfolio management and particularly so for risk-averse investors in anticipation of bad news. Wu and Pandey (2014) meanwhile examined the role of Bitcoin as a currency and its investability by comparing it against major world currencies, gold and other major investable assets. Although they found Bitcoin to be the most volatile, it had low or insignificant correlations with major currencies and assets. As such, they concluded that Bitcoin can potentially enhance the performance of the portfolio when held as a minor component of a well-diversified portfolio.

Baur et al. (2018) also profess of Bitcoin being an effective tool for portfolio risk diversification given that its returns are uncorrelated to traditional asset classes during both normal and crisis periods. However, the paper also highlighted Bitcoin's speculative traits as did Baek and Elbeck (2015). The latter further argued that Bitcoin's volatility is internally driven by buyers and sellers and not by economic fundamentals. They concluded that factors such as consumer price index, industrial production, real personal consumption expenditures, S&P 500 index, 10-year Treasury note, euro exchange rate and unemployment rate are not significant when it comes to the determination of returns of Bitcoin thus relegating it to a mere speculative investment tool.

However, Blau (2017) did not find high levels of speculative trading in Bitcoin, contrary to what is perceived from the observations of the stylized data thus suggesting Bitcoin being more aligned to a currency rather than a speculative investment tool. Further, Gandal et al. (2018) examining the leaked data from Mt. Gox's trading (which at the time was the largest Bitcoin trading exchange), found evidence of price manipulation during 2013. They found that the price of Bitcoin rose by an average of 4 to 5 percent on days when suspicious trading activities took place. In contrast, on days without suspicious trading activities, the price remains flat or even decreased slightly. They concluded that the volatility was due to fraudulent transactions as opposed to market forces.

Finally, in terms of the market efficiency of Bitcoin exchanges, Urquhart (2016) found non-randomness of returns in the the Bitcoin market thus deeming such markets as inefficient. However, some evidence of market efficiency was detected in a subsample consisting of data from the later period of the whole sample thus suggesting possible eventual efficiency in such markets in the later years of the sample period. Following this, Wei (2018) examined the liquidity and market efficiency of cryptocurrencies, found Bitcoin returns to exhibit signs of efficiency improvement, a finding that supports Urquhart's (2016) results.

3. Data and Methodology

3.1. Data

We use the daily price data of Bitcoin, the S&P500 index, the Vanguard Total Bond Market (TBM) Index Fund and four pairs of currencies; Euro (EUR), British pound (GBP), Chinese Yuan (CNY) and Japanese Yen (JPY). The daily close, open, highest and lowest prices covering the period from 1 January 2015 to 31 December 2019 are obtained and are all quoted in USD. The prices of Bitcoin are sourced from CoinMarketCap (www.coinmarketcap.com), an open source cryptocurrencies database provider which quotes cryptocurrency prices on a volume-weighted average approach. Meanwhile, the price data for the four selected currencies, the stock index and the bond index are obtained from the Yahoo finance (www.yahoofinance.com). The 30-day US Treasury-bill rate is used as a proxy for risk-free rate and is obtained from the U.S. Department of Treasury website (https://home.treasury.gov/).

3.2. Methodology

3.2.1. Daily returns

We begin by computing the daily returns using closing prices.

$$r_t = \left(\frac{c_t}{c_{t-1}}\right) - 1,$$

where rt is the return at time t, c_t and c_{t-1} are the closing price at time t and t-1 respectively.

3.2.2. Conventional Measure of volatility

The volatility of these daily returns are then being measured using the the conventional standard deviation formula.

$$\sigma_C = \sqrt{\sum_{i=1}^{N} \frac{(r_t - \bar{r})^2}{N-1}},$$

where $\bar{r}$ is the mean returns over N number of daily observations.

3.2.3. Range-based volatility estimators

Apart from the conventional standard deviation computations to measure volatility, four other range-based volatility estimators are employed in this paper – i.e., the Parkinson, Garman-Klass, Roger-Satchell and Yang-Zhang volatility estimators. Unlike the conventional standard deviation, these range-based volatility estimators are able to capture intraday volatility and are argued to be more efficient (Shu and Zhang, 2006). For example, the Parkinson estimator uses the high-low prices instead of closing prices to measure volatility. Overall, the list of volatility measurements employed and their respective data range coverage is summarized in Table 1 below.

Table 1. Volatility Measurements and their Data Range

No.	Measurement	Close	Opening	High	Low
1	Standard Deviation	✓			
2	Parkinson			✓	✓
3	Garman-Klass	✓	✓	✓	✓
4	Rogers-Satchell	✓	✓	✓	✓
5	Yang-Zhang	✓	✓	✓	✓

The Parkinson volatility estimator, σPARK, is measured by

$$\sigma_{PARK} = \sqrt{\frac{1}{4N\ ln2} \sum_{t=1}^{N} \left(ln \frac{h_t}{l_t}\right)^2},$$

where h_t and l_t are the highest price and lowest price of the day.

Building on the work of Parkinson (1980), Garman and Klass (1980) and Rogers and Satchell (1991) went on to improve the variance estimator by incorporating closing and opening prices, these in addition to the highest and lowest prices of the day. Garman and Klass (1980) aptly pointed out that the inclusion of other information besides the closing prices will help to improve the efficiency of the estimation. Sinclair (2013) argue that the Parkinson, Garman-Klass and Yang-Zhang estimators are about 5, 8 and 14 times more efficient respectively in estimating volatility as compared to the close-to-close estimator.[1] Further, Rogers and Satchell (1991) enhanced the models by Parkinson (1980) and Garman and Klass (1980) by allowing for non-zero drift, as previous assumptions of these works were built on the assumption of zero drift.

The formulae for the Garman-Klass, σ_{GK} and Rogers-Satchell, σ_{RS} estimators are as follows:

$$\sigma_{GK} = \sqrt{\frac{1}{2N}\sum_{t=1}^{N}\left(ln\frac{h_t}{l_t}\right)^2 - \frac{(2\,ln2-1)}{N}\left(ln\frac{c_t}{o_t}\right)^2},$$

$$\sigma_{RS} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left[\left(ln\frac{h_t}{c_t}\right)\left(ln\frac{h_t}{o_t}\right) + \left(ln\frac{l_t}{c_t}\right)\left(ln\frac{l_t}{o_t}\right)\right]},$$

where c_t is the closing price, o_t is the opening price of the day.

Following Rogers and Satchell (1991), Yang and Zhang (2000) further refined the volatility estimator and their model is the only one among the four range-based volatility estimator that is able to capture volatility from opening price jumps. Prior estimators ignore the overnight volatility and thus resulting in the volatility measures being underestimated. Their refined volatility estimator is measured as the sum of the overnight volatility, σ_O^2, the open-to-close volatility, σ_C^2, and a weighted-average of the Roger-Satchell estimator (Bennett and Gil, 2012).

The formula for the Yang-Zhang estimator , σ_{YZ} is as follows:

$$\sigma_{YZ} = \sqrt{\sigma_O^2 + k\sigma_C^2 + (1-k)\sigma_{RS}^2},$$

where

$$k = \frac{0.34}{1.34 + \frac{N+1}{N-1}}$$

$$\sigma_O^2 = \frac{1}{N-1}\sum_{t=1}^{N}\left(ln\left(\frac{o_t}{c_{t-1}}\right) - \frac{1}{N}\sum_{t=1}^{N}ln\left(\frac{o_t}{c_{t-1}}\right)\right)^2$$

$$\sigma_c^2 = \frac{1}{N-1}\sum_{t=1}^{N}\left(ln\left(\frac{c_t}{o_t}\right) - \frac{1}{T}\sum_{t=1}^{N}ln\left(\frac{c_t}{o_t}\right)\right)^2$$

$$\sigma_{RS}^2 = variance\ of\ Rogers - Satchell\ volatility$$

3.2.4. Coefficient of variation (CV)

To allow for meaningful comparison of the risk-return tradeoffs of selected assets, the coefficient of variation (CV) is employed. The CV is basically the ratio of standard deviation to the mean return. The CV measurement is useful as it indicates the asset's risk per percentage of return. This is especially important in making investment selection or comparison among assets of varying levels of risk and returns. Essentially, given the same level of risk, the asset with the higher return is preferred or given the same level of return, the asset with the lower risk is preferred. However, under the

[1] Efficiency is defined as the ratio of the close-to-close volatility to the volatility of the range-based estimators.

scenarios whereby the level of risk and returns among assets vary greatly, the use of CV should then be employed instead.

3.2.5. Markowitz Portfolio Theory

The essence of the Modern Portfolio Theory (MPT) lies in portfolio diversification and Markowitz was the first to formalise this concept into a mathematical equation (Rubinstein, 2002). Through portfolio diversification, the overall risk can then be minimised without compromising the expected portfolio return. The crucial condition to achieve portfolio diversification is to combine assets of low correlation into a portfolio. The expected portfolio return, r_p, and the portfolio standard deviation, σ_p, are as follows:

$$r_p = \sum_i w_i E(r_i),$$

$$\sigma_p = \left[\sum_{i=1}^{n} w_i^2 \sigma_i^2 + \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \sigma_{i,j}\right]^{\frac{1}{2}},$$

where w_i is the portfolio weight of asset i, $E(r_i)$ is the expected return of asset i, σ_i^2 is the variance of asset i, $\sigma_{i,j}$is the covariance between asset i and j and n is the number of assets in the portfolio.

Using the above mathematical equation, three optimal portfolios will be constructed with the aim to examine the role of Bitcoin as a tool to diversify risk. The construction of the optimal portfolios involves a two-step process. Firstly, two other top performing assets in terms of the CV results (assets with the low CV) are bundled together with Bitcoin to form a portfolio. Secondly, the weightages assigned to the respective assets are conditioned to maximise the Sharpe ratio of the overall portfolio. The formula for the Sharpe ratio is as follows:

$$Sharpe\ ratio = \frac{r_p - r_f}{\sigma_p}$$

This optimisation process will enable us to identify the optimal asset allocations that maximises the portfolio's risk premium for any given level of risk.

4. Results

Table 2 provides the descriptive statistics for the selected assets and currencies.

In contrast to some earlier findings (Wu and Pandey, 2014, Baur et al., 2018 and Phillip et al., 2018), the returns of Bitcoin were found to be slightly positively skewed. The long right-tail distribution indicates infrequent large positive returns while the high level of kurtosis gives rise to a leptokurtic distribution thus indicating a greater chance of an extreme outcome. This result is consistent with Nadarajah and Chu (2017) where the skewness of Bitcoin returns is found to be positive using more recent data but when earlier price data is used, the results showed negative skewness instead.

Table 2. Descriptive Statistics

Asset/Currencies	No. of Observations	Mean Returns	Std. Dev.	Kurtosis	Skewness
BTC	1825	0.25%	3.88%	5.38	0.11
S&P 500 index	1257	0.04%	0.85%	3.82	-0.45
Vanguard TBM index	1257	0.01%	0.20%	3.82	-0.15
EUR	1300	0.00%	0.53%	2.87	0.05
GBP	1300	0.01%	0.60%	21.03	-1.44
CNY	1299	0.01%	0.25%	6.66	-0.28
JPY	1300	0.01%	0.53%	2.64	-0.31

The standard deviation of Bitcoin is 3.8 percent while the standard deviation of the S&P 500 is 0.85 percent. This makes the volatility of Bitcoin to be around 4.6 times the volatility of the S&P 500. In contrast to earlier studies by Wu and Pandey (2014), Baek and Elbeck (2015), and Baur et al. (2018), our results show a much smaller gap. Such sharp reduction in the volatility of Bitcoin returns coupled with the transition in its skewness in recent years may explain the increased attractiveness and interest in Bitcoin as an investment tool among investors.

When we use more robust estimators for volatility, some interesting results are observed (see Table 3). Firstly, the results from the more robust volatility estimators for Bitcoin show little difference from those computed using the conventional close-to-close data except for the Garman-Klass estimator. Otherwise, results from all three others saw a slight drop in the volatility for Bitcoin. As for the stock and bond index, the general trend of the four estimators point towards an overestimation of volatility when the conventional method is employed while in contrast, the reverse is observed in the case of the four pairs of currencies. In fact, from the Yang-Zhang results (given that it is the most efficient amongst the range-based estimators), Bitcoin, while still the most volatile among the assets and currencies in our list, is only just over 3.9 times more volatile than the pound sterling (its volatility is more than 6 times when the conventional method is used). While this does not necessarily mean that Bitcoin is any closer to being deemed as a currency per se but at the very least, provides some evidence to downplay its speculative qualities.

Table 3. Volatility Estimates

Assets/Currency	Conventional	Parkinson	Garman-Klass	Roger-Satchell	Yang-Zhang
BTC	3.88%	3.62%	4.26%	3.52%	3.56%
S&P 500 index	0.85%	0.68%	0.80%	0.65%	0.73%
Vanguard TBM index	0.20%	0.14%	0.17%	0.14%	0.21%
EUR	0.53%	0.45%	0.53%	0.64%	0.79%
GBP	0.60%	0.51%	0.60%	0.73%	0.91%
CNY	0.25%	0.28%	0.33%	0.35%	0.48%
JPY	0.53%	0.45%	0.53%	0.66%	0.81%

Further, from the CVs estimated using the conventional standard deviation and Yang-Zhang estimator, Bitcoin recorded the lowest figure among all the selected assets and currencies (see Table 4). This shows that Bitcoin investors are better compensated for the risk borne as compared to all the other selected assets and currencies. In fact, when using the other range-based estimators (i.e., Parkinson, Garman-Klass and Roger-Satchell), Bitcoin still ranks second thus indicating Bitcoin having one of the lowest risk per percentage of return. Overall, results from Table 4 indicate that all four pairs of currencies are comparatively riskier as compared to Bitcoin, stock and bond investments across all five measurements. In any case, the CV results affirm Bitcoin's risk-return performance to be above both stock and currency investments. As such, we argue that Bitcoin is indeed an attractive and useful investment tool when considering its risk-return trade-off.

Table 4. Coefficient of Variations (CV)

Asset/Currency	Conventional	Parkinson	Garman-Klass	Roger-Satchell	Yang-Zhang
BTC	15.7	14.6	17.2	14.2	14.4
S&P 500 index	21.5	17.2	20.3	16.5	18.4
Vanguard TBM index	16.3	11.7	13.8	11.7	16.9
EUR	116.5	100	117.7	142	175.2
GBP	52.2	44.4	52.3	64	79.1
CNY	28.6	31.3	36.9	39.1	53.8
JPY	89.5	76	89.5	110.9	135.9

Following the CV results in Table 4, we proceed to examine the diversification capability of Bitcoin. We begin by examining the correlations of Bitcoin against all the other selected assets and currencies. Except for the slight positive correlation between Bitcoin and stock, the rest of the assets and currencies appears to be negatively correlated with Bitcoin. The results are very much consistent with Wu and Pandey (2018) where the correlation of Bitcoin with traditional assets were found to be either low or negative. This suggests that Bitcoin possess the ability to diversify risk. All in all, results from our analysis underline the potential contribution of Bitcoin to investors, in line with the arguments from Dyhrberg (2016) who suggested that the inclusion of Bitcoin in a portfolio can benefit investors in that it allows them to make more informed decisions while also providing them with another useful hedging instrument.

Table 5. Correlation Matrix

	BTC	S&P	Bond	EUR	GBP	JPY
S&P	0.0235	-				
Bond	-0.0021	-0.2428	-			
EUR	-0.0199	0.0267	-0.0518	-		
GBP	-0.0395	0.067	-0.0649	0.5178	-	
JPY	-0.0399	0.019	-0.027	-0.3729	-0.0963	-
CNY	-0.027	0.0231	-0.0203	0.2158	0.2036	-0.0782

Besides the correlation results presented above, we proceed to construct three optimal portfolios which are made up of assets with varying compositions (see Table 6). Bitcoin, bonds and stocks investments are included in the portfolios since these three assets recorded superior CV results (see table 4).

Table 6. Portfolio Weightage

Portfolio	Bitcoin	Stock	Bond
1	4.08%	17.24%	78.68%
2	24.36%	75.64%	-
3	6.39%	-	93.61%

The performance of the three optimal portfolios and individual assets and currencies are presented in a single diagram (see Fig. 1). As can be seen from the slope of the capital market line (CML), Portfolio 1 has the steepest slope indicating that it yields the highest portfolio excess return per unit of risk. This is followed by Portfolio 3, Portfolio 2, Bitcoin, bond and stock investments, in descending order. As for the four pairs of currencies, it can be observed that they are closely clustered at the bottom of the diagram, indicating the poorest Sharpe ratio. It is evident that the risk-return performance of all three portfolios are superior to any of the individual assets or currencies as seen in their locations (P1, P2 and P3). The portfolios are located in the upper-left side of the diagram (maximizing return while minimizing risk), above the positions of other single assets or currencies.

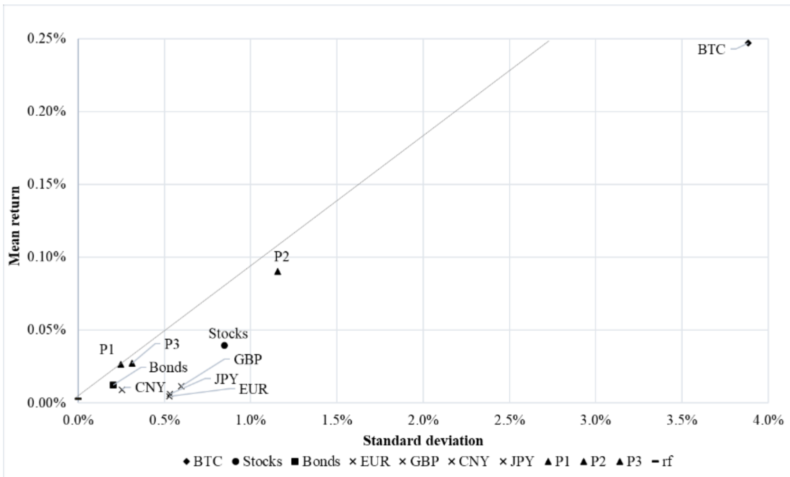

Figure 1. Risk-Return Performance

Our results confirm that the inclusion of Bitcoin as part of a portfolio can indeed enhance the overall risk-return performance of a particular portfolio. Nevertheless, the proportion of Bitcoin in the portfolio is found to be small. Despite that Portfolio 1 boasts the highest Sharpe ratio, the optimal Bitcoin allocation is a mere 4.08 percent. This is consistent with Wu and Pandey (2014) who argue that Bitcoin has the potential to enhance the performance of an investment portfolio albeit as a minor component. We find the role of Bitcoin as a risk diversifer increases substantially in a portfolio comprising of only stocks and Bitcoin (Portfolio 3).

In addition to the static correlations calculated over a five year period, a 1-year rolling correlation is presented in Figure 2.

The general pattern of the correlation between Bitcoin and stocks suggest that there is a downward trend in recent years while the correlation between Bitcoin and bonds shows an upward trend. The weakening correlation between Bitcoin and stocks further strenghtens the efficacy of Bitcoin to diversify risk arising from stock investments. Although the correlation between Bitcoin and bonds is on the rise, it is still far from unity (perfect positive correlation). As such, there is still much to be gained from diversification as demonstrated in the risk-return performance of Portfolio 3 in Figure 1.

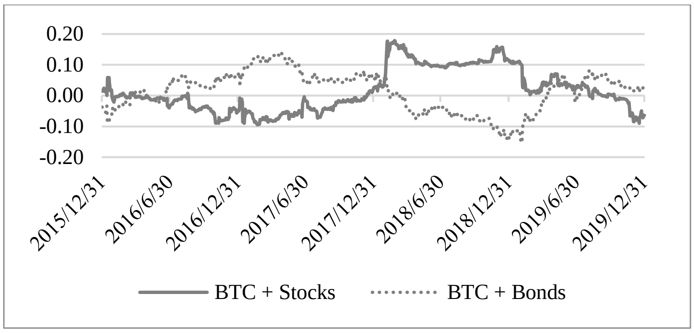

Figure 2. Correlations between Bitcoin and Stocks and Bitcoin and Bonds

Finally, we also performed an autocorrelation test to ascertain the efficiency of Bitcoin markets – i.e., testing for any serial correlation in the case of the Bitcoin returns in our sample. We decompose our Bitcoin returns series into two phases; phase 1 covers the period from 30 April 2013 to 2 April 2017 while phase 2, 3 April 2017 to 3 April 2020, similar to the approach by Urquhart (2016). Although marginal serial correlation was detected in the first sample, the second period, nevertheless, tested insignificant for autocorrelation[2]. Our results support the findings by Urquhart (2016), who found improvements in efficiency of Bitcoin returns, specifically the later period of his data, confirming Bitcoin's market efficiency improvements from 2013-2016. With its efficient market

[2] We use the correlogram to test for serial correlation of Bitcoin returns. For the period (from 30 April 2013 to 2 April 2017), the returns (natural log) did not exhibit strong interdependency although the lag orders of 1 to 5 were significant (36 lags were used). Nonetheless, the Durbin-Watson (DW) statistics showed no evidence of serial correlation (1.9935). For the second period (3 April 2017 to 3 April 2020), neither the correlogram test nor the DW test (1.996) found any evidence of serial correlation.

pricing qualities, we argue that Bitcoin should not be viewed as speculative and volatile but rather as a useful investment and diversification tool.

5. Conclusion

Our results suggest that Bitcoin is a good investment tool in that its volatility is not as extreme as how it is made up in many media outlets. Its CVs are consistently lower than stocks and currencies in all the estimators with only bonds faring better, this being so (i.e., bonds having lower CVs than Bitcoin) only in the case of the Parkinson, Garman-Klass and Roger-Satchell estimators. As such, it appears that Bitcoin may prove to be an attractive investment tool once the returns were factored into the risk assesment – the returns earned for every risk borne is substantially higher than currencies and even stock index3. In this context, we argue that it is a useful investment tool for risk averse investors. On a more broader note, our paper's findings also support the previous works by Blau (2017) and Dyhrberg (2016) in that Bitcoin appears to be a good tool for investment and portfolio management. Finally, using the Markowitz Portfolio Theory, we constructed the optimal portfolio to include Bitcoin, Stocks and Bonds. However, Bitcoin's share in the portfolio is small (at around 4% only), suggesting a more restraint role for it when it comes to portfolio management despite its growing prominence as an investment and diversification tool among investors.

[3] We refer to the inverse of CV here. Essentially, the compensation for bearing more risks would technically be represented by the inverse of the CV, meaning the returns per unit of risk taken (Holgersson et al., 2012). The inverse CV figures are not reported in the paper but the CV figures are.

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