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Afees A. Salisu, Lateef O. Akanni and Rasheed O. Azeez

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Could this be a fiction? Bitcoin forecasts most tradable currency pairs better than ARFIMA

Afees A. Salisu[a*], Lateef O. Akanni [a,b,#] , Rasheed O. Azeez[c,%]

[a] Centre for Econometric & Allied Research, University of Ibadan, Nigeria.
[b] Department of Economics, University of Lagos, Nigeria.
[#] Email: akanniolat@yahoo.com; Phone: +234(0)8057907425.
[c] Department of Economics, University of Ibadan, Nigeria.
[%] Email: azrash2013@gmail.com; Phone: 234(0)7068182050.
*Corresponding Author:
Email: adebare1@yahoo.com; aa.salisu@cear.org.ng;
Phone: +234(0)8034711769.

Abstract

In this paper, we attempt to exploit any inherent useful information in Bitcoin to predict the future path of the most tradable currency pairs in the world. We also verify whether the forecast outcomes can compare favourably with the time series model such as the fractionally integrated autoregressive moving average (ARFIMA) model. We follow the Lewellen (2004) and Westerlund and Narayan (2102, 2015) approaches that account for any statistical effect that could bias the regression estimates. Our results suggest that Bitcoin is a good predictor of the selected currency pairs and more importantly, its forecast results outperform the time series model judging by the Diebold and Mariano test regardless of the data sample and forecast horizon. Although, recent evidence in the literature seems to suggest that the Bitcoin bubble will soon burst, its connection with the considered currency pairs may be exploited while it lasts.

Keywords: F31, F37, G15
JEL Classification: Bitcoin, Exchange rates, Forecast evaluation

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1.0 Introduction

The question of whether or not Bitcoin is a perfect substitute for existing tradable financial assets, such as stocks, foreign exchange, bonds and commodities, among others, has remained a topical issue in the literature. While the discussions on this subject are quite recent, contributions from academic researchers and policy makers are rapidly increasing. The emerging evidence from the empirical studies can be explained in two strands. The first strand argues that cryptocurrencies are closely related to the conventional assets, hence, cannot be completely isolated (see for example, Dyhrberg, 2016; Bouri et al., 2018). The second strand is of the opinion that both are uncorrelated or have low correlations as they are assumed to operate somewhat distinctively particularly in terms of returns, volatility and correlation characteristics (see for example, Baur et al., 2017a,b; Corbet et al., 2017; Kurka, 2017). A cursory review of the relevant literature is provided in Table 1 and it highlights the different cryptocurrencies and financial assets analysed, methodological approaches employed and empirical findings.

One area that has remained relatively uninvestigated on the subject is whether there are some underlying characteristics of the cryptocurrencies which can be utilized to produce better out-of-sample forecasts for the conventional financial assets using most tradable currency pairs as a case study. All the known studies on digital currencies involve impact (in-sample) analyses which cannot be generalized for out-of-sample forecasts.[1] This is the contribution of our study. Information about the probable out-of-sample predictive powers of cryptocurrencies may help in investment and policy decision purposes. If it is true that such predictive powers are inherent in the unconventional currencies, investors and policy makers can utilize such information when making future decisions which may minimize risks and uncertainties associated with financial assets.

Consequently, we construct a predictive model that captures Bitcoin as a predictor of most tradable currency pairs in the world. In addition, we account for the peculiar characteristics of the predictors such as persistence, endogeneity and conditional heteroscedasticity as evident in most financial series[2]. Ignoring these features when they are found to be significant have implications on the forecast performance of a predictive model (Lewellen, 2004; Westerlund and Narayan, 2012, 2015; Nayaran and Gupta, 2015; Salisu and Isah, 2017; Salisu et al., 2018). For completeness, the proposed predictive model is compared with the fractionally integrated autoregressive moving average (ARFIMA) processes using standard forecast performance measures. This comparison is particularly important given the findings of Moosa and Burns (2014a,b,c). These studies have raised doubts about the ability of any exchange rate model to outperform the autoregressive models including random walk in out-of-sample forecasting except where the lagged term of the dependent variable is introduced in the former which amounts to trying to beat a random walk with another random walk model. Thus, while accounting for the underlying statistical properties of the relevant variables, the approach followed in this paper to predict the major tradable currency

[1] To the best of our knowledge, the only exception is the work of Peng et al. (2018); however, it only evaluates different volatility models for forecasting singly the traditional currencies and the cryptocurrencies. In our study, the intention is to engage the information in the latter to forecast the former.

[2] This approach is increasingly gaining relevance in the literature particularly those involving forecasting. Examples of these studies include, but not limited to Makin et al. (2014); Bannigidadmath and Narayan (2015); Narayan and Bannigidadmath (2015); Narayan and Gupta (2015); Phan et al. (2015); Sharma (2016); Devpura et al. (2017); Salisu and Isah (2017) and Salisu et al. (2018).

pairs with Bitcoin, refrains from modelling exchange rate by including the lagged term of the dependent variable as suspected by Moosa and Burns (2014a,b,c).

Foreshadowing our results, we find that Bitcoin is a good predictor of the major tradable currency pairs in the world. More importantly, the out-of-sample forecast results suggest that the former contains useful information that can help determine the probable future path that the latter can follow, *ceteris paribus*. In addition, the predictive model outperforms the ARFIMA model regardless of data sample, forecast horizon and currency pair.

The remainder of this study is organized as follows: Section 2 describes the model and estimation procedure for the analysis; Section 3 provides information on the data used and some preliminary analyses; Section 4 presents and discusses the main results while Section 5 concludes the paper.

Table 1: A summary of recent literature

Author/Year	Data Scope/country	Variables	Methodology	Findings
Dyhrberg (2016)	19th July 2010- 22nd May 2015	Bitcoin returns, federal funds rate, USD EUR, USD GBP, FTSE Index, and gold prices	GARCH Model Exponencial GARCH Model	Bitcoin and gold respond similarly to some of the variables used as they have similar hedging capabilities and react symmetrically to good and bad news, though the frequency may be higher for Bitcoin as trading is faster and reaction to market sentiment are quick.
Baur et al. (2017a)	Daily data (July 2010- June 2015)	US equities (S&P500, S&P600), precious metals, commodities, energy, bonds and EUR USD, JPY USD, GBP USD, CNY USD etc	Descriptive Statistics and correlation matrix	Bitcoin is uncorrelated with traditional asset classes such as stocks, bonds and commodities both in normal times and periods of financial turmoil. Cryptocurrencies are mainly used as a speculative investment rather than an alternative currency and medium of exchange
Baur et al. (2017b)	July 19 2010 - July 14 2017	Bitcoin returns, federal funds rate, USD EUR, USD GBP, FTSE 100, and gold prices, trade-weighted currency indices (US dollar and the euros) and global equity index(MSC))	Descriptive statistics, Asymmetric GARCH (TGARCH) model without exogenous variables in the variance equation	Bitcoin exhibits distinctively different return, volatility and correlation characteristics compared to other assets including gold and the US Dollar.
Corbet et al. (2017)	2013-2017	Bitcoin, Ripple, Litecoin, MSC GSCI total returns index, US$ Broad Exchange Rate, SPS500Index, COMEX closing price, VIX and the market ITTR10 Index	Generalized Variance Decomposition Method	They explain that cryptocurrency are better if isolated from other financial assets because the values for directional returns and volatility from other assets to cryptocurrency markets are very low.

Peng et al. (2018)	January 4th 2016-July 31st 2017.	Bitcoin, Ethereum, Dash market price, euro, british pound, Japanese yen (in US dollar)	SVR-GARCH, GARCH, EGARCH, GJR-GARCH	Results showed that SVR-GARCH models managed to outperform GARCH, EGARCH and GJR-GARCH models with Normal, Student's t and Skewed Student's t distributions. For all variables and both time frequencies, the SVR-GARCH model exhibited statistical significance towards its superiority over GARCH and its extensions.
Kurka (2017)	June 2011-December 2015	Bitcoin, EUR/USD forex, JPY/USD forex, Gold, Crude oil, S&P 500 Stock index, US 2-year T-note	FEV (Forecast Error Variance Decomposition) SAM (Spillover Asymmetry Measure)	There exists a low level of connectedness between the main cryptocurrency and the selected financial assets except gold which receives a reasonable degree of shock of cryptocurrency. There is significant positive asymmetry of spillover among the studied assets.
Bouri et al. (2018)	July 19, 2010-October 31 2017	MSCI World, MSCI Emerging markets, MSCI China, S&P GSCI Commodity, S&P GSCI energy, one ounce of gold, US dollar index, and US 10-year treasury yields	Bivariate GARCH-in-mean (BTGARCH-M) model Smooth Transition Vector Autoregressive (STVAR), Dynamic Conditional Correlation (DCC), Wald test	Bitcoins are significantly closely related to other conventional assets, hence, cannot be completely isolated. Bitcoin receives more volatility than it transmit

Source: Compiled by authors

2.0 The model and estimation procedure

As demonstrated in the immediate succeeding section, we find evidence of persistence, endogeneity and conditional heteroscedasticity for the Bitcoin, although this is not unexpected for high frequency series. Similar evidence has been reported for oil price (see Narayan and Gupta, 2015; Phan et al., 2015; Salisu and Isah, 2017; Salisu et al., 2018); financial data such as Dividend-payout ratio, Earnings-price ratio, Dividend-price ratio, Dividend yield and Book-to-market ratio (see Narayan and Bannigidadmath, 2015; Bannigidadmath and Narayan, 2016), among others. Thus, we employ the Westerlund and Narayan [WN hereafter] (2012, 2015) estimator which is an extension of the Lewellen (2004) estimator to account for these effects in the estimation process. The latter simultaneously allows for both persistence and endogeneity effects in the predictive model while the former extends these effects to include conditional heteroscedsticity, which is a prominent feature of most high frequency series.

Following the WN approach, we specify the following predictive model for a typical exchange rate:

$$e_t = \alpha + \beta^{adj} x_{t-1} + \gamma\left(x_t - \rho_0 x_{t-1}\right) + \eta_t \qquad (1)$$

where e_t is defined as the log of exchange rate, x_t is a potential predictor of exchange rate which is described as the log of the Bitcoin (in this study) and η_t is distributed as zero mean and variance σ_η^2. The parameter $\beta^{adj} = \beta - \gamma\left(\rho - \rho_0\right)$ is the bias adjusted OLS estimator of Lewellen (2004) which corrects for any persistence effect in the predictive model. The additional term $\gamma\left(x_t - \rho_0 x_{t-1}\right)$ corrects for any endogeneity bias resulting from the correlation between x_t and η_t. Accounting for endogeneity bias here is important since there could be several determinants of exchange rate which are suppressed in equation (1). Such omissions could introduce endogeneity bias resulting from probable correlations between x_t and η_t.

According to WN (2012, 2015), $\rho = 1 + \dfrac{c}{T}$ [where $c \leq 0$] is a drift parameter that measures the degree of persistence in x_t. To resolve the conditional heteroscedasticity effect, WN (2012, 2015) suggest pre-weighting all the data by $1/\hat{\sigma}_\eta$ and estimating the resulting equation with the Ordinary Least Squares (OLS). This modified OLS estimator is described as Feasible Quasi GLS estimator in WN (2012, 2015).

For the purpose of out-of-sample forecasts, we use both the 50% and 75% of the total observations and the rolling window approach is used to produce the forecast results. Two forecast measures are employed to evaluate the forecast results. We use the popular Campbell and Thompson (2008) and Diebold and Mariano (1995) test which are usually employed to estimate the forecast performance of two competing models. In our case, we compare the forecast performance of equation (1) with the fractionally integrated autoregressive moving average process specified as[3]:

$$\left(1-\sum_{i=1}^{p}\rho_i L^i\right)(1-L)^d \pi_t = \mu + \left(1-\sum_{i=1}^{q}\phi_i L^i\right)\varepsilon_t \tag{2}$$

where μ is the drift parameter, L denotes the lag operator, p is the maximum lag for e_t which is fixed at one for simplicity while the $(1-L)^d$ is described as the fractional differencing operator defined by:

$$(1-L)^d = \sum_{k=0}^{\infty}\frac{\Gamma(k-d)L^k}{\Gamma(-d)\Gamma(k+1)} \tag{3}$$

where $\Gamma(\cdot)$ denotes the generalized factorial function.

The Campbell and Thompson (C-T) test which is described as the out-of-sample R-squared (OOS_R^2) statistic is computed as $OOS\_R^2 = 1-\left(M\widehat{S}E_1 / M\widehat{S}E_0\right)$, where $M\widehat{S}E_1$ and $M\widehat{S}E_0$ are the mean square errors (*MSE*) of the out-of-sample prediction from the unrestricted and restricted models, respectively. Here, the restricted model is the ARFI model while the unrestricted is equation (1). A positive value for the statistic, that is, $OOS\_R > 0$ suggests that the unrestricted model outperforms the restricted model while the reverse is the case if $OOS\_R < 0$.

[3] The ARFI model is often used to address a situation where time-series exhibit too much long-range dependence to be classified as I(0) but are not I(1).

While the C-T test gives the difference between two forecasts, it says nothing about whether the difference is statistically significant or not. Hence the need to consider the Diebold and Mariano (D-M) test which is prominently used in this regard. The D-M test is computed as:

$$\text{D-M stat} = \frac{\bar{d}}{\sqrt{\frac{1}{T}V(d)}} \sim N(0,1) \tag{4}$$

$$d_t = f(\eta_t) - f(\varepsilon_t) \tag{5}$$

$$\bar{d} = \tfrac{1}{T}\sum_{t=1}^{T}\left[f(\eta_t) - f(\varepsilon_t)\right] \tag{6}$$

where (5) is the loss differential while (6) is the mean value of (5); $V(d)$ is the unconditional variance of d. The $\{\eta_t\}_{t=1}^{T}$ and $\{\varepsilon_t\}_{t=1}^{T}$ denote the forecast errors associated with equations (1) and (2) respectively. The null hypothesis of equal forecast accuracy for the two models is that $E[d_t]=0$. In other words, there is relative equality between the two forecasts if the null hypothesis of the D-M test is not rejected; otherwise, the two forecasts are not identical.

3.0 Data sources and description

We utilize data covering six majorly traded currency pairs against the United States Dollar (USD). These include the British pound (GBP/USD), the Euro (EUR/USD), the Canadian Dollar (CAD/USD), the Australian Dollar (AUD/USD), the Chinese Yuan (YUA/USD) and the Japanese Yen (YEN/USD) (See also Salisu and Ndako, 2017 and Wali et al., 2017). Like the currency pairs, we also consider the foremost traded and highly ranked cryptocurrency – Bitcoin (see Dyhrberg, 2016; Corbet et al., 2018 and Phillip et al., 2018). Besides, Bitcoin is the single largest cryptocurrency asset with its market value of above one billion USD and it also has sufficiently large daily datasets compared to other cryptocurrencies. The Exchange rate data were collected from the Federal Reserve Bank of St. Louis website (https://fred.stlouisfed.org/) while data on

Bitcoin prices was collected from Coin Metrics (https://coinmetrics.io/data-downloads/). The data scope showing the start and end dates is presented in Table 2.

Table 2: Frequency Table

	Full Sample			50% of Full Sample			75% of Full Sample		
Variables	**Start Date**	**End Date**	**Obs.**	**Start Date**	**End Date**	**Obs.**	**Start Date**	**End Date**	**Obs.**
Bitcoin	29/04/13	21/02/18	1206	29/04/13	23/09/15	603	29/04/13	06/12/16	905
Exchange Rates									
AUD/USD	29/04/13	21/02/18	1206	29/04/13	23/09/15	603	29/04/13	06/12/16	905
YUA/USD	29/04/13	21/02/18	1206	29/04/13	23/09/15	603	29/04/13	06/12/16	905
YEN/USD	29/04/13	21/02/18	1206	29/04/13	23/09/15	603	29/04/13	06/12/16	905
GBP/USD	29/04/13	21/02/18	1206	29/04/13	23/09/15	603	29/04/13	06/12/16	905
EUR/USD	29/04/13	21/02/18	1206	29/04/13	23/09/15	603	29/04/13	06/12/16	905
CAD/USD	29/04/13	21/02/18	1206	29/04/13	23/09/15	603	29/04/13	06/12/16	905

Note: The Start and End dates are written in the format [dd/mm/yy]. Obs. represents the number of observations. The 50% and 75% represent part of the total observations used for the in-sample analyses while the balances therefrom are used for out-of-sample forecast evaluation at forecast horizons 10, 20 and 30 periods.

3.1 Preliminary analyses

The standard practice in the literature is to explore the historical information derivable from series by graphical illustrations. This will permit some insights into their possible co-movements and detection of likely responses to structural adjustments. Figure 1 provides the various plots where each of the currency pairs is graphed against the Bitcoin currency after taking their natural logarithms. A cursory look at the graphs reveals a somewhat negative comovement between Bitcoin and the selected currency pairs.

The summary statistics of the series are reported in Table 3. The average prices in USD for Bitcoin is approximately 1469.80 over the period under consideration. Similarly, its standard deviation stood at 2925.15, indicating a very high deviation of the series from its average. The skewness value is positive while its Jacque-Bera statistics shows that it is non-normal.

For the exchange rates, the mean values are 1.24, 0.84, 0.69, 1.22, 6.41 and 110 per USD respectively for Australian Dollar, Euro, British Pound, Canadian Dollar, Chinese Yuan and Japanese Yen. The standard deviation estimates shows that Japanese Yen with the highest average value also exhibit the highest deviation with its value at approximately 7.87. The skewness value is negative for some of the currency pairs (AUD, EUR, and CAD) and positive for others (GBP, YUA and YEN). Lastly, the exchange rate values are also non-normal as shown by the significance of the Jarque-Bera statistics. Thus, the regression error in equation [1] is allowed to follow a non-normal distribution.

Figure 1: Plots of currency pairs against Bitcoin

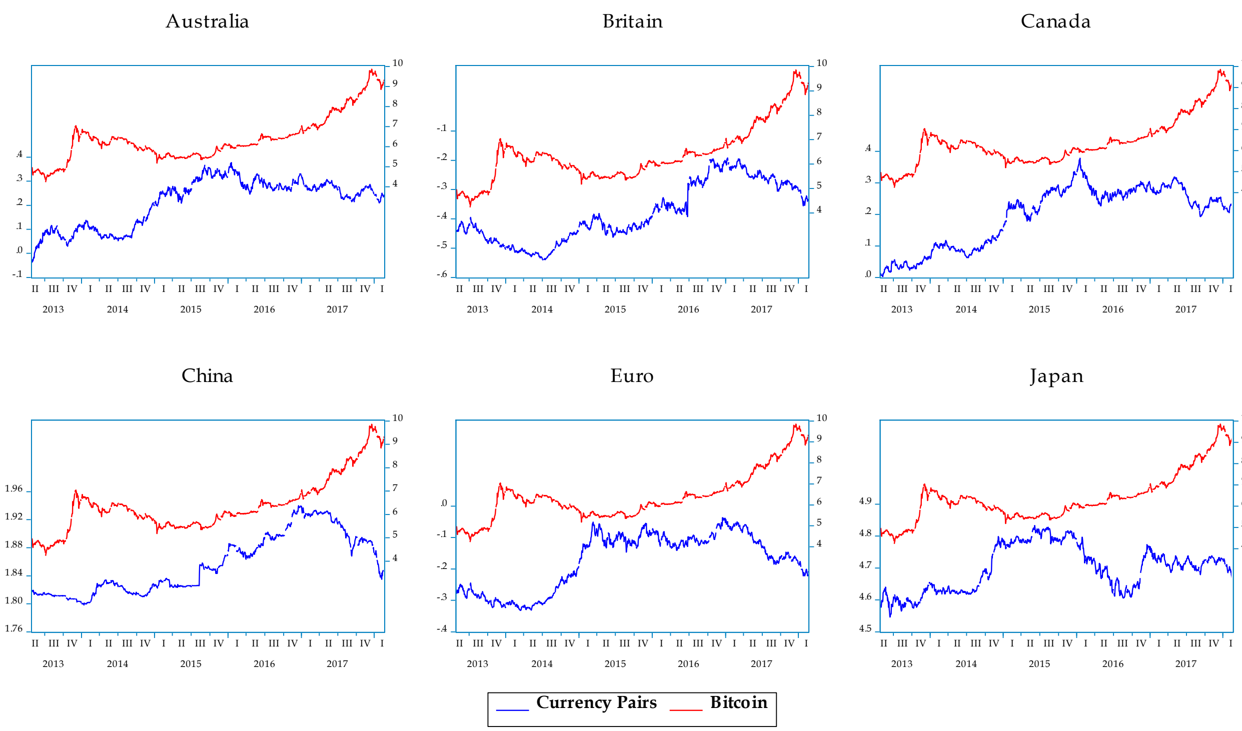


Table 3: Summary statistics

	Bitcoin	AUD	EUR	GBP	CAD	YUA	YEN
Mean	1469.80	1.2438	0.8444	0.6871	1.2215	6.4093	110.09
Median	479.50	1.2887	0.8763	0.6628	1.2565	6.3471	110.57

Maximum	19114.20	1.4588	0.9639	0.8252	1.4592	6.9580	125.58
Minimum	68.430	0.9641	0.7180	0.5826	1.0023	6.0402	94.29
Std. Dev.	2925.19	0.1196	0.0746	0.0699	0.1143	0.2719	7.8695
Skewness	3.5741	-0.4448	-0.3707	0.3924	-0.3951	0.4650	0.1059
Kurtosis	16.2866	1.8258	1.6453	1.8224	1.7680	1.8415	1.8365
JB-Stat	11438.36***	109.04***	119.85***	100.64***	107.64***	110.91***	70.28***

Note: The probability values for the Jarque-Bera test are in parentheses and the null hypothesis of the test is that series is normally distributed

Table 4: Serial correlation and conditional heteroscedasticity tests

	Q-stat	**Q-stat²**	**ARCH**	**Q-stat**	**Q-stat²**	**ARCH**	**Q-stat**	**Q-stat²**	**ARCH**
Lags		5			10			20	
Bitcoin	14.163**	83.794***	14.2711***	28.567***	128.33***	8.7077***	47.538***	217.39***	6.7529***
Exchange rates									
AUD	8.936	8.683	1.5782	22.643**	30.005***	2.4885***	37.933***	85.960***	2.8497***
CAD	5.500	12.294**	2.2327**	14.245	53.146***	4.4255***	28.820*	101.71***	3.2695***
EUR	1.343	36.919***	6.2081***	9.976	77.903***	5.6953***	21.205	132.70***	3.6136***
GBP	11.187**	59.384***	10.9149***	19.098**	64.343***	5.8440***	29.497*	69.154***	3.0818***
YUA	15.250***	45.779***	8.5964***	23.488***	48.882***	4.4921***	35.544**	54.131***	2.4447***
YEN	6.629	34.925***	5.9215***	27.286***	74.123***	5.4588***	45.932***	131.86***	4.1932***

Note: ***, ** and * denote 1, 5 and 10% levels of significance respectively. The serial correlation test conducted involves the use of Ljung-Box Q-stat and Q-stat². The underlying null hypothesis for the two tests is that there is no serial correlation. The ARCH-LM test of Engle (1982) is used to test for conditional heteroscedasticiy with the null hypothesis is that there is no presence of conditional heteroscedasticity. The F-statistic is reported for the ARCH-LM test. Both Serial Correlation and Conditional Heteroscedasticty tests are conducted at different lag orders of 5, 10, and 20 for robustness.

Table 5: Testing for persistence and endogeneity in the predictors

	Persistence	**Endogeneity**
AUD	1.000871***	0.0371
CAD	1.000871***	0.0152
EUR	1.000871***	0.0350**
GBP	1.000871***	0.0432
YUA	1.000871***	0.0211*
YEN	1.000871***	-0.0149

Note: The persistence test is done by regressing a first order autoregressive process for the predictor $\left(x_t = \theta + \rho x_{t-1} + \varepsilon_{x,t}\right)$ using OLS estimator. The first order autocorrelation coefficient $\left(\rho\right)$ captures the persistence effect and it is reported for the predictors. The null hypothesis is that $H_0 : \rho = 0$ while the alternative is given as $H_1 : \rho \neq 0$. The test follows a three-step procedure: First, we run the following predictive regression model: $e_t = \alpha + \beta x_{t-1} + \varepsilon_{e,t.}$, where x_t represents exchange rate and x_t is the predictor variable which is Bitcoin here. In the final step, the relationship between the two error terms from x_t and e_t equations is captured using the following regression: $\varepsilon_{e,t} = \lambda \varepsilon_{x,t} + \eta_t$. If the coefficient λ is statistically different from zero at any of the conventional chosen levels of significance such as ***, ** and * for 1%, 5% and 10%, respectively; then, including the predictor variable in the regression will introduce endogeneity bias.

The choice of the WN estimator requires that we pre-test the series of interest in our study for the heteroscedasticity, serial correlation, persistence and endogeneity. Table 4 shows the summarised results for the conditional heteroscedasticity and serial correlation tests, while the persistence and endogeneity test results are summarised in Table 5. The serial correlation test is carried out using the Ljung-Box Q-statistic and its squared statistics for robustness purpose. On the other hand, the conditional heteroscedasticity test is done using the Engle's ARCH LM test with both tests conducted at three lag orders – 5, 10 and 20 to ensure further robustness of the obtained results. With the exception of the Australian Dollar, there is evidence of serial correlation and conditional heteroscedasticity for all the series being analyzed. Even for the AUD/USD, the non-rejection of homoscedasticity and serial independence is only limited to the 5th lag order as higher lag orders resoundingly reject the null hypothesis for the two effects. Also the results for the persistence test indicate the presence of persistence effect in Bitcoin and therefore the series may be assumed to exhibit long memory. Lastly, the endogeneity test shows mixed results for the currency pairs. Endogeneity bias is only noticed for Euro and Yuan implying that there are some important fundamentals underlying the two currency pairs and ignoring them may bias the estimates. Hence, there is a need to control for such endogeneity effect in the estimator process.

4.0 Discussion of results

We begin the discussion of empirical results with the in-sample predictability in order to ascertain the significance of the cryptocurrencies in the predictability of US currency pairs with other globally traded currencies. Following the discussion of the in-sample predictability in section 4.1, we evaluate the forecast performance of the in-sample results at both 50% and 75% in section 4.2. As earlier noted the forecast evaluation is conducted using the C-T and D-M tests[4]. Lastly, the out-of-sample predictability results following the same procedure as the in-sample results are discussed in section 4.3.

4.1 In-sample predictability

Starting with the coefficients and significance of the cryptocurrencies predictability of exchange rates, the results summarised in Table 6 reveal that the relationship between the two variable is largely negative. Except for few instances when the 75% data sample is used, the relationship between Bitcoin and each of the currency pairs is negative and statistically significant. The negative coefficients could imply that increasing (decreasing) value of Bitcoin will lead to the appreciation (depreciation) USD against the currency pairs. This is intuitive as Bitcoin and other cryptocurrencies are mostly quoted and traded in USD denominations and hence its increasing volume of transaction could sprout increasing demand for the USD. Besides, these results further elucidate the argument in the extant literature that cryptocurrencies could serve as an instrument for hedging against the conventional foreign exchanges, particularly USD (see Dyhrberg, 2016).

Table 6: In-Sample Predictability Results

	50% of Sample	75% of Sample
AUD	-0.0092*** [0.0044]	0.0624*** [0.0042]
CAD	-0.0381*** [0.0016]	-0.0439*** [0.0019]
EUR	-0.0741*** [0.0034]	-0.0569*** [0.0018]
GBP	-0.0330*** [0.0018]	-0.0177*** [0.0029]
YUA	-0.0069*** [0.0006]	0.0002 [0.0009]
YEN	-0.0431*** [0.0026]	-0.0598*** [0.0057]

Note: the standard errors are in brackets and ***, ** and * denote 1, 5 and 10% levels of significance respectively.

4.2 In-sample forecast evaluation

Here, we evaluate the forecast performance of the predictive model involving Bitcoin relative to the ARFIMA model using the C-T and the D-M tests and the results are presented in Table 8. The C-T statistic is positive for nearly all the currency pairs (except

[4] See also Salisu and Isah (2017) and Salisu et al. (2018).

for Euro) using the 50% data sample while the evidence is mixed for the 75% data sample. Nonetheless, the D-M test reveals that, irrespective of the data sample, the predictive model that incorporates Bitcoin when forecasting the currency pairs outperforms the ARFIMA model.

In additional to the C-T and D-M tests, we also provide figures that illustrate how the Bitcoin-based exchange rate model is able to track the actual data relative to the ARFIMA model (see Figures 2a and 2b for 50% and Figures 3a and 3b for 75%). The figures resoundingly corroborate the D-M test where the exchange rate model with Bitcoin as a predictor tracks the actual data far better than the ARFIMA model for both data samples.

Table 8: In-sample forecast evaluation results

	Campbell Thompson		Diebold & Mariano	
	50%	**75%**	**50%**	**75%**
AUD	0.0071	0.0493	-1.8858*	-2.2614**
CAD	0.4773	0.4985	-24.866***	-38.503***
EUR	-0.0446	-0.0011	-41.490***	-38.575***
GBP	0.0089	-0.0601	-15.676***	-24.747***
YUA	0.0038	0.0159	-9.487***	-38.149***
YEN	0.0025	-0.0044	-28.795***	-3.1360***

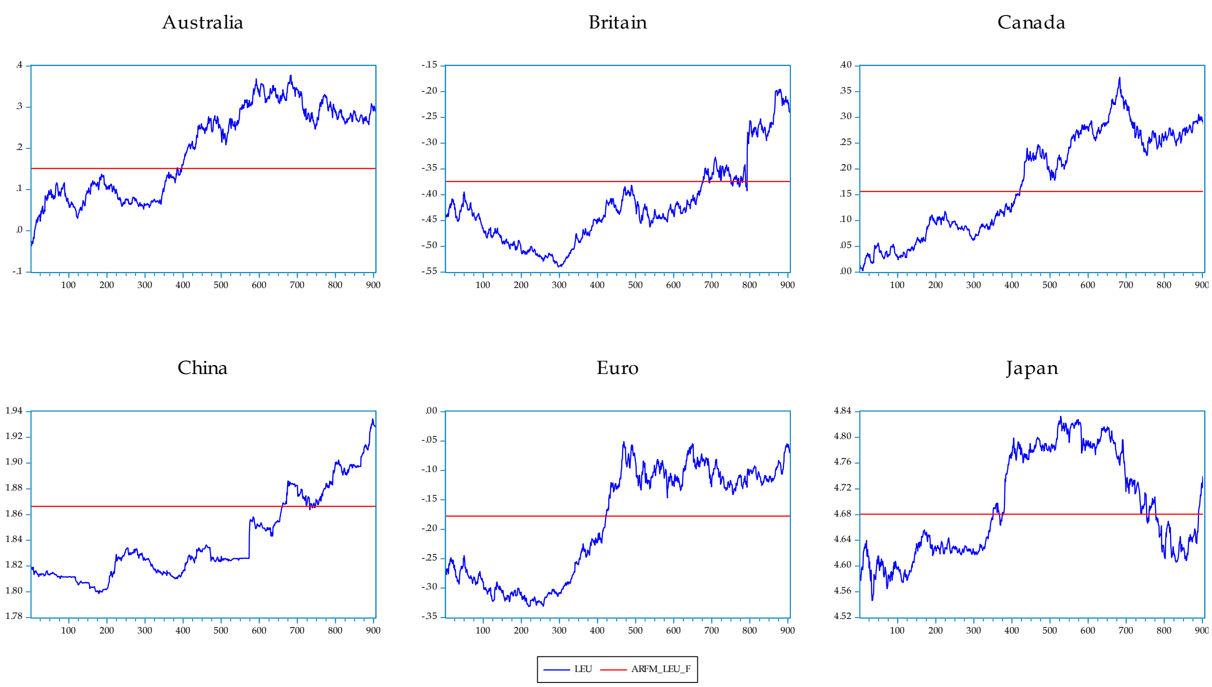
Note: The way the C-T test is constructed here, the model that incorporates Bitcoin is the unrestricted model while the ARFIMA model is the restricted model. Thus, a positive value implies that the unrestricted model outperforms the alternative model; otherwise, it does not. However, the reverse is the case for the D-M test. That is, a statistically significant negative D-M statistic implies that the unrestricted model outperforms the restricted model; however, the two forecast models are relatively identical in terms of forecast accuracy if the D-M statistic is not statistically significant.

Figure 2a: Predictability graphs for Bitcoin [50%]

Figure 2b: Predictability graphs for ARFIMA [50%]

Figure 3a: Predictability graphs for Bitcoin [75%]

Figure 3b: Predictability graphs for ARFIMA [75%]



4.3 Out-of-sample forecast evaluation

We proceed to complement the in-sample forecast evaluation discussed in the last section, by evaluating the out-of-sample forecast performance. We evaluate the out-of-sample forecast performance at three different horizons for 10 period (*h=1*), 20 period (*h=2*) and 30 period (*h=3*). The out-of-sample forecast results are generated using the rolling window approach for both the 50% and 75% data sample and the results for the C-T and D-M tests are summarised in Table 9.

Similar to what was obtained for the in-sample results, while the result is mixed for the C-T test, the DM test largely confirms the preference of the proposed Bitcoin-based predictive model for exchange rate over the ARFIMA model over the forecast horizons and data samples. Thus, including the Bitcoin prices in the predictive model for exchange rate may enhance its forecast performance relative to the time series models.

Table 9: Out-of-sample forecast evaluation results

	h=1		*h=2*		*h=2*	
Campbell Thompson	**50%**	**75%**	**50%**	**75%**	**50%**	**75%**
AUD	0.0042	0.0576	0.0017	0.0680	-0.0020	0.0751
CAD	0.4847	0.5027	0.4938	0.5081	0.5005	0.5112
EUR	-0.0354	0.0025	-0.0275	0.0060	-0.0203	0.0093
GBP	0.0105	-0.0580	0.0119	-0.0558	0.0131	-0.0538
YUA	0.0036	0.0156	0.0035	0.0152	0.0033	0.0148
YEN	0.0020	-0.0046	0.0015	-0.0048	0.0010	-0.0050
Diebold & Mariano						
AUD	-1.5150	-2.4392**	-1.1519	-2.6552***	-0.4968	-3.1536***
CAD	-24.918***	-38.774***	-25.099***	-39.030***	-25.676***	-39.467***
EUR	-41.799***	-38.845***	-42.095***	-39.050***	-42.180***	-39.502***
GBP	-15.838***	-24.982***	-16.029***	-25.217***	-15.856***	-25.682***
YUA	-9.8131***	-38.388***	-10.119***	-38.558***	-10.703***	-38.882***
YEN	-29.105***	-3.1429***	-29.409***	-3.2271***	-29.982***	-3.4153***

Note: The way the C-T test is constructed here, the model that incorporates Bitcoin is the unrestricted model while the ARFIMA model is the restricted model. Thus, a positive value implies that the unrestricted model outperforms the alternative model; otherwise, it does not. However, the reverse is the case for the D-M test. That is, a statistically significant negative D-M statistic implies that the unrestricted model outperforms the restricted model; however, the two forecast models are relatively identical in terms of forecast accuracy if the D-M statistic is not statistically significant.

5.0 Conclusion

This study attempts to forecast exchange rates using Bitcoin which is the most traded crypotocurrency in the world. The increasing demand for the digital currency has continued to raise serious concerns among policy makers owing to its potential negative consequences on the conventional assets. Although some analysts have argued that the Bitcoin bubble will soon burst, we however demonstrate in this paper that its connection with the selected currency pairs can be exploited while it lasts. Thus, we construct a predictive model that allows for Bitcoin as a predictor while also controlling for its underlying statistical properties. Our analysis produces forecast results for the Bitcoin-based exchange rate model that compare favourably with the time series models and in fact outperform the time series model judging by the Diebold and Mariano test regardless of the data sample and forecast horizon. Therefore, the Bitcoin currency can be used as a complementary variable in the forecast model for exchange rate particularly when dealing with most tradable currency pairs.

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