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The Hidden Predictive Power of Cryptocurrencies: Evidence from US Stock Market

By

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Abstract

This paper is motivated by the news that the surge in cryptocurrencies is an important candidate to in explaining the plummeting stock markets. To validate this believe, we construct a predictive model in which cryptocurrencies are identified as the predictors of US stock returns. The inherent statistical properties of cryptocurrencies such as persistence, endogeneity, and conditional heteroscedasticity are being accounted for in the Westerlund and Narayan (2015) estimator. Three salient results emanated from our estimations. First, we validated the importance of cryptocurrencies in predicting US stock prices; second, the cryptocurrencies predictive model outperforms the conventional time-series models such as Autoregressive Integrated Moving Average (ARIMA) model and the Autoregressive Fractionally Integrated Moving Average (ARFIMA); third, our results are robust to different method of forecast performance evaluation measures and different sub-sample periods. These results have important policy implications for the investors and policymakers.

JEL Classifications: C52; C53; G11; G14; G17
Keywords: Stock Prices, Cryptocurrency, Digital Asset Prices, Predictive Model, Forecast Evaluation

1. Introduction

One of the burgeoning issues in international finance literature is the analysis of cryptocurrencies on varieties of macroeconomic and financial variables[1]. This sudden interest in virtual currencies can be attributed to their increasing influence and usage. For instance, between 2016 and 2017, the price of Bitcoin rose by more than 1300%, reaching a market capitalization of US$215 billion (Bouri et al. 2018). The importance of virtual currencies has also been recognized on the political scene. As a classical example, Chicago Mercantile Group and the Chicago Board Options Exchanges allowed future contracts to be based on the prices of Bitcoin in December, 2017. Also, several policy papers and reports have been written on digital currencies (see European Central Bank, 2012; European Banking Authority, 2014, Financial Action Task Force, 2015).

Although the literature is at its embryonic state, there are three distinct strands. The first set of studies examines the risk associated with the use and emergence of cryptocurrencies (European Central Bank, 2012; Financial Task Force, 2015 and European Banking Authority, 2014 to name a few). The second strand of the literature highlights the price mechanism and speculation bubbles of the cryptocurrency markets (Cheah and Fry, 2015; Fry and Cheah, 2016; Blau, 2017 and Bariviera et al. 2017). The third strand focused on the substitutability or interlinkages between cryptocurrencies and other traditional assets (commodity prices, equities, bonds, and stocks). This strand is further decomposed into two sub-strands. The first sub-group confirmed the close relationship between the cryptocurrency and traditional markets. These studies further argued that the two markets cannot be isolated from each other (see Dyhrberg, 2016 and Bouri et al. 2018). On the flip side, the second group concluded that not only is the

[1] Digital currencies, virtual currencies and crypto-currencies have the same meaning and as such, are used interchangeably in this study.

correlation in the two markets low, the attendant returns and volatility are somewhat different (Baur et al. 2017a and b; Corbet et al. 2017; Kurka, 2017).

The inconclusive nature in the third strand, explained above, arouse our interest. An overview of the extant literature shows that the interlinkages between cryptocurrency markets (CM) and stock returns has received less scientific investigation. What is common in the literature is to examine the relationship between CM and multifactorial traditional assets. This being the case, it is very difficult to isolate the effect of stock returns from other assets in relation to CM. In order to avoid a feedback mechanism inherent in the traditional assets, we single out stock returns. What's more, existing studies have shied away from some characteristics of CM to produce reliable out-of-sample forecast. The norm adopted by these studies is to limit their investigation to impact or effect analyses (in-sample), which has been criticized for its inability to also be used for out-of-sample forecasts.

The broad objective of this study is to examine the plausible out-of-sample predictive power of CM that might be inherent in stock returns. In essence, this study hypothesizes that CM have strong predictive power in forecasting stock returns based on out-of-sample characteristics. The plausible existence of the predictive power of the CM has strong implications for investors and policy makers. Thus, information could be used when making futuristic plans that aim to (i) minimize risks and uncertainties and (ii) increase the return on investments. Consequent upon the above, we built a model in which virtual currencies are used as the predictor for stock prices. There are two specific objectives this study seeks to achieve. First, we account for some peculiar characteristics which might feature in the virtual currencies: endogeneity, persistence and conditional variance. These characteristics are being accounted for because the predictor is a high frequencies series. A section of the literature has argued the need for such characteristics be accounted for in a forecasting model (Narayan and Gupta, 2015; Salisu and Isah, 2017 and Salisu et al. 2018). Also, another section of the literature show that the inability to account for these features when present could spell doom for the reliability of the forecast performance of the predictive model (Westerlund and Narayan, 2012 and 2015, herein after WN). The second specific objective is to develop a Frictionally Autoregressive Moving Averages (ARFIMA), which is then compared with the predictive model using the standard forecast performance measures. The reason for this comparison is attributable to the intuition that ARFIMA models outperform any other forecasting model on stock returns (Koopman et al., 2005; Degiannakis, 2008, He and Wang, 2017 among others).

Our contributions to the literature are based on the objectives highlighted above. In addition, we improve on existing studies that had focused exclusively on Bitcoin as a proxy for CM. Of the various forms of digital currency available, it is acknowledged that Bitcoin accounts for over 80% of the share of market capitalization[2] (Bariviera et al. 2017). Hence, it is quite understandable why existing studies had limited their investigations to Bitcoin. However, focusing on just one product of CM might not give a holistic view of the inherent properties of CM. To circumvent this problem and for robustness check of the results, we examine the use of four currencies (Bitcoin, Ethereum, Lite Coin and Ripple).

Based on US stock prices, it was established that cryptocurrency based predictive model has an enhancing forecast accuracy and predictability of stock prices. Our results are robust to (i) the predictive model capturing some statistical properties of digital asset prices including persistence, endogeneity and conditional heteroscedasticity; (ii) different method of forecast performance evaluation measures; (iii) different sub-sample period and (iv) the four variants of the cryptocurrency prices considered.

[2] Among the commonly used cryptocurrencies are Bitcoin, Litecoin, Ethereum, Ripple, Bitcoin Cash, Stellar, cardano, Monero, Dash among others.

The rest of the paper is structured as follows: the model and estimation procedures are presented in the second section. Section three dwells on data description and preliminary analysis. Empirical results are discussed in section four. Conclusion and policy implications are presented in section 5.

2. Econometric methods and estimation procedure

2.1 The Model

In attempt to evaluate the predictive prowess of the variant cryptocurrency prices in stock return, we follow WN (2012, 2015) approach to specifying stock returns predictive model as given below.

$$s_t = \delta + \phi' z_{t-1} + \varphi\left(z_t - \rho' z_{t-1}\right) + \varepsilon_t \tag{1}$$

where s_t is the natural log of stock price; z_t is a vector denoting the natural log of each of the cryptocurrency price under consideration; and ρ is the first order autocorrelation coefficient. The first term of the model (ϕz_{t-1}) merely captures the bivariate representation of a predictive model, while the inclusion of the second term $\left(z_t - \rho z_{t-1}\right)$ captures any inherent persistent effect in the predictive model (Lewellen, 2004). Accounting for persistence effect is in particular valid when dealing with high frequency predictors as they tend to exhibit random walk, where the AR(1) coefficient approximates to one for instance$\left(\rho = 1\right)$. Thus, it is necessary to pre-test series for persistence and account for same if found significant. Following the WN (2015), the persistence equation can be given as below.

$$z_t = \varphi\left(1-\rho\right) + \rho z_{t-1} + v_t; \qquad v_t \sim N\left(0, \sigma_v^2\right) \tag{2}$$

In addition, the presence of statistically significant persistence effect may introduce endogeneity bias as a result of possible correlations between the predictor[s]$\left(z_t\right)$ and the model error $\left(\varepsilon_t\right)$ (Salisu and Isah, 2018). Therefore, we test for endogeneity using the equation below:

$$\varepsilon_t = \varphi v_t + \mu_t \tag{3}$$

where ε_t and v_t are the error terms from (1) and (2) respectively. The parameter φ captures the endogeneity effect. The statistical significance of this parameter implies the presence of endogeneity of the predictor(s). Therefore, estimating [1] using the OLS method corrects for possible endogeneity bias, and yields a bias-adjusted OLS estimator for ϕ (Lewellen, 2004). This is described as:

$$\hat{\phi}_{adj} = \hat{\phi} - \varphi\left(\hat{\rho} - \rho\right) \qquad (4)$$

To deal with potential conditional heteroscedasticity effect in a predictor series, WN (2012, 2015) suggests pre-weighting the data with $1/\hat{\sigma}_\varepsilon$ which is obtained from an ARCH structure given as $\hat{\sigma}^2_{\varepsilon,t} = \mu + \sum_{i=1}^{q} \vartheta_i \hat{\varepsilon}^2_{t-i}$ and estimating the resulting equation with OLS.

2.2 Forecast Evaluation

The forecast evaluation is carried out for both the in-sample and out-of-sample periods. For robustness purpose, we use the 50 percent and 75 percent observations of the full-sample for the forecast evaluation following the recursive window approach which accounts for the time-varying behaviour in the stock-Bitcoin relationship to produce the forecast results. We begin the forecast evaluation with the in-sample predictability of the model using the Root Mean Square Error (RMSE), which is computed as:

$$RMSE = \sqrt{1/T \sum_{t=1}^{T} \left(\hat{s}_t - s_t\right)^2} \qquad (5)$$

where $\hat{s}_t$ and s_t denote the fitted and actual values of stock price respectively. For pairwise forecast evaluation, we also consider the Campbell-Thompson statistic which compares the forecast performance of the unrestricted model with the restricted model. The test which is described as the out-of-sample R-squared $\left(OOS\_R^2\right)$ statistic is computed as $OOS\_R^2 = 1 - \left(\widehat{MSE}_1 / \widehat{MSE}_0\right)$, where $\widehat{MSE}_1$ and $\widehat{MSE}_0$ are the mean square errors (*MSE*) of the out-of-sample prediction from the unrestricted and restricted models, respectively.

For robustness and completeness purpose, we further complement equations (1) and (2), with relative forecast performance of time-series models namely, Autoregressive Integrated Moving Average (ARIMA) model and the Autoregressive Fractionally Integrated Moving Average (ARFIMA). The generalized specification for ARIMA (p,d,q) could be specified as follows:

$$\left(1-\sum_{i=1}^{p}\rho_i B^i\right)(1-B)^d\left(c_t-\psi\right)=\left(1+\sum_{i=1}^{q}\theta_i B^i\right)\varepsilon_t \qquad (6)$$

where ψ is the drift parameter, $(1-B)^d$ denotes the difference operator, p and q are the maximum lags for c_t and ε_t respectively. d is the order of integration, that is the number of times c_t is differenced to achieve stationarity. However, since c_t is integrated of order 1, a simple representation of equation (6) which is ARIMA (1,1,1) is considered and it is specified as:

$$\Delta c_t=\psi+\varepsilon_t+\theta_1\varepsilon_{t-1} \qquad (7)$$

In the case of the ARFIMA model, the $(1-B)^d$ can be defined as the fractional differencing operator described in a natural way by using binomial expansion for any real number d with Gamma function as:

$$(1-B)^d=\sum_{k=0}^{\infty}\binom{d}{k}(-B)^k=\sum_{k=0}^{\infty}\frac{\Gamma(d+1)(-B)^k}{\Gamma(k+1)\Gamma(d+1-k)} \qquad (8)$$

where $\Gamma(\cdot)$ denotes the generalized factorial function. The parameter $d\in(-0.5,0.5)$ and restricting d to integer values gives rise to the standard ARIMA model. Thus, the general for of the ARFIMA (*p,d,q)* process is defined as:

$$\Phi(B)(1-B)^d c_t=\Omega(B)\varepsilon_t \qquad (9)$$

The essence here, is to test our proposed cryptocurrency –based predictive model for stock returns will outperform a typical time series model which in this case are ARIMA and ARFIMA. To achieve this, we will compare the forecast performance of each of these conventional time series predictive models (i.e. ARIMA and ARFIMA) using their respective RMSE values as against that of a cryptocurrency –based predictive model using Campbell-Thompson (C-T) test. The C-T test is computed as: $\left[1-\left(\widehat{MSE}_1/\widehat{MSE}_0\right)\right]$

where the $M\widehat{S}E_1$ and $M\widehat{S}E_0$ are the mean square errors (MSE) of the prediction from an unrestricted and restricted models so define such that, a positive value of the statistic suggests that the unrestricted model outperforms the restricted model and vice-versa if otherwise.

3. Data and Preliminary Analysis

3.1 Data source and description

Dataset utilized in this study include USA daily stock price index mainly sourced from the Bloomberg terminal, while the variants measure of cryptocurrency asset prices namely; Bitcon (BTC), Ethereum (ETH), Lite Coin (LTC) and Ripple (XRP) are obtained from Coin Metrics at https://coinmetrics.io/datadownloads/. The choice of these digital assets among the other alternatives is mainly informed by their prominence as the most traded cryptocurrency prices in addition to their availability in sufficiently large daily frequency (see Dyhrberg, 2016; Corbet et al., 2018 and Phillip et al., 2018). While all the series have same end date, the start date however, differ across the series particularly for the digital asset prices. This might not be unconnected to the availability or otherwise of information on particular digital asset at a particular point in time. Table 1 gives more information about the data period and sample size. A snapshot of the table reveals that there is consistency in the start date for both in-sample and out-of-sample data. However, the end dates vary depending on the sub-sample period under consideration (i.e. the 50% and 75% sub-sample periods).

Table 1: Data Period and Sample Size

Date and sample description		*Stock Prices*	*BTC*	*ETH*	*LTC*	*XRP*
Full Sample	Start Date	4/29/2013	4/29/2013	08/07/2015	4/29/2013	08/05/2013
	End Date	2/21/2018	2/21/2018	2/21/2018	2/21/2018	2/21/2018
	Observation	1206	1206	635	1206	1138
50% -In-Sample	Start Date	4/29/2013	4/29/2013	08/07/2015	4/29/2013	08/05/2013
	End Date	9/22/2015	9/22/2015	11/10/2016	9/22/2015	11/10/2015
	Observation	603	603	318	603	569
75% -In-Sample	Start Date	4/29/2013	4/29/2013	08/07/2015	4/29/2013	08/05/2013
	End Date	12/06/2016	12/06/2016	6/30/2017	12/06/2016	12/30/2016
	Observation	905	905	476	905	854
50% Out-of-Sample (h=10)	Start Date	4/29/2013	4/29/2013	08/07/2015	4/29/2013	08/05/2013
	End Date	10/06/2015	10/06/2015	11/28/2016	10/06/2015	11/25/2015
	Observation	613	613	328	613	579
50% Out-of-Sample (h=20)	Start Date	4/29/2013	4/29/2013	08/07/2015	4/29/2013	08/05/2013
	End Date	10/21/2015	10/21/2015	12/12/2016	10/21/2015	12/10/2015
	Observation	623	623	338	623	589
50% Out-of-Sample (h=30)	Start Date	4/29/2013	4/29/2013	08/07/2015	4/29/2013	08/05/2013
	End Date	11/04/2015	11/04/2015	12/27/2016	11/04/2015	12/24/2015
	Observation	633	633	348	633	599
75% Out-of-Sample (h=10)	Start Date	4/29/2013	4/29/2013	08/07/2015	4/29/2013	08/05/2013
	End Date	12/20/2016	12/20/2016	7/17/2017	12/20/2016	1/17/2017
	Observation	915	915	486	915	864
75% Out-of-Sample (h=20)	Start Date	4/29/2013	4/29/2013	08/07/2015	4/29/2013	08/05/2013
	End Date	01/05/2017	01/05/2017	7/31/2017	01/05/2017	02/01/2017
	Observation	925	925	496	925	874
75% Out-of-Sample (h=30)	Start Date	4/29/2013	4/29/2013	08/07/2015	4/29/2013	08/05/2013
	End Date	1/23/2017	1/23/2017	8/14/2017	1/23/2017	2/15/2017
	Observation	935	935	506	935	884

Source: Authors' computation.

Note: The 50% and 75% represent part of the full observations used for the in-sample predictability and out-of-sample forecast evaluation. The start-date denotes the beginning of the period while the end-date is the last period of the data. The h=10, h=20 and h=30 are the forecast horizons for the out-of-sample forecast for 10 days, 20 day and 30 days ahead periods.

3.2 *Preliminary analysis results*

Table 2 gives a detailed representation of the potential statistical features of the series in the model. Starting with the mean statistics for example, the average daily digital asset prices was \$1,469.79, \$146.35, \$20.21 and \$0.10 for BTC, ETH, LTC and XRP, respectively, while the average US stock prices index (SP) for the period under consideration was $2,089.54. However, the standard deviation statistic for Bitcoin at 2925.18 makes it the most volatile of all the four variants of the cryptocurrencies while Ripple the least volatile. With the exception of BTC, it could be deduced that there is relative stability in the prices of the assets in CM as compared to the stock price index. With respect to the statistical distribution of the series, the skewness reveals virtually all digital asset prices as non-zero and positively skewed. The Kurtosis statistic also showed the digital assets as mainly leptokurtic while the distribution is otherwise for the stock prices.

Table 2: Preliminary Test Results

Var.	Descriptive Statistics				Unit Root Test		Persistence & Endogeneity Tests	
	Mean	*Standard Deviation*	*Skewness*	*Kurtosis*	*Level*	*First Difference*	*Persistence*	*Endogeneity*
stk_t	2089.5420	271.5771	0.5035	2.9098	-2.0646[a]	-23.5652***[b]		
btc_t	1469.7980	2925.1870	3.5741	16.2866	-1.3846[a]	-25.9819***[b]	0.9948	-0.0648
eth_t	146.3456	259.4371	2.3316	8.1353	-2.6516[b]	-29.3649***[b]	1.0003	-0.0322**
ltc_t	20.2083	46.5170	4.2460	22.6177	-0.4549[b]	-33.3672***[b]	1.0010	0.0107
xrp_t	0.0952	0.3061	5.8472	44.1031	-1.3073[n]	-29.6595***[b]	1.0012	-0.0037

Serial Correlation and Conditional Heteroscedasticity Tests

	$Q-Stat$			Q^2-Stat			*ARCH LM*		
	$k=10$	$k=20$	$k=30$	$k=10$	$k=20$	$k=30$	$k=10$	$k=20$	$k=30$
btc_t	5665.***	7681.9***	12079.***	4873.***	8110.***	10841.***	1686.6***	870.0***	565.8***
eth_t	6107.***	11695.***	16675.***	5890.***	10880.***	14763.***	8979.2***	4619.9***	3098.1***
ltc_t	11372.***	21448.***	30126.***	10483.***	18730.***	24933.***	13561.***	6868.8***	4612.9***
xrp_t	10663.***	19939.***	27781.***	9983.***	17358.***	22357.***	13207.***	1109.8***	1100.4***

Source: Authors' computation

Note: (i) The unit root test is performed using Augmented Dickey-Fuller (ADF) approach; (ii) The persistence test is done by regressing the first order autoregressive process for the predictors individually, for example: $z_t = \omega + \rho z_{t-1} + \upsilon_t$ using OLS estimator, where the first order autocorrelation coefficient (ρ) captures the persistence effect. The null hypothesis is that $H_0 : \rho = 0$ while the alternative is given as $H_1 : \rho \neq 0$; (iii) For the endogeneity test, we run a predictive regression model of the form $s_t = \alpha + \beta b_{t-1} + \varepsilon_t$, where s_t denotes log of stock prices and b_{t-1} is log of digital asset prices using WN (2015) estimator such that $b_t = \mu(1-\rho) + \rho b_{t-1} + v_t$ and finally capture the relationship between the two error terms using the following regression: $\varepsilon_t = \lambda v_t + \eta_t$. If the coefficient λ is statistically different from zero at any of the conventional levels of significance such as ***, ** and * for 1%, 5% and 10%, respectively; then, the predictor variable is endogenous; if otherwise, it is not; (iv) The reported values for the serial correlation are the Ljung-Box Q-statistics and ARCH-LM test F-statistics for the heteroscedasticity. We consider three different lag lengths (k) of 10, 20 and 30 for robustness.

We explore the stochastic properties of the concern variables using the Augmented Dickey Fuller (ADF) unit root test. The unit root test results are also in Table 2 and reveal that all the variables in the model are non-stationary series. We further test for endogeneity and persistence in the predictors and our finding suggests a high degree of persistence in all the predictor series while there is no evidence of serious endogeneity bias in the predictive model expect for model with EHT as the predictor. The results for autocorrelation and conditional heteroscedasticity indicate presence of serial dependence and conditional heteroscedasticity in both the predicting and the predictor series irrespective of the lag orders. The decision to use WN as the most appropriate estimator, in the digital assets predictability of US stock returns, is being further validated by the presence of persistence, autocorrelation and hereroscedasticity effects.

Figure 1: Trends in Stock Prices and Cryptocurrencies

Fig. 1.1: Trends in Daily Stock Prices and BTC (2013-2018)

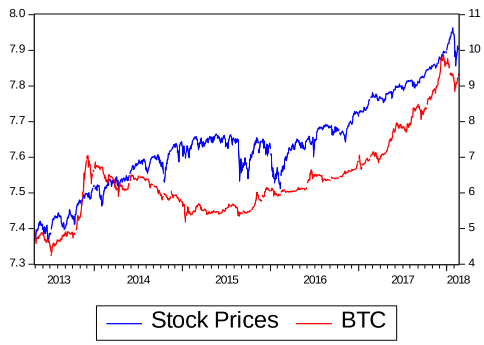


Fig. 1.2: Trends in Daily Stock Prices and ETH (2015-2018)

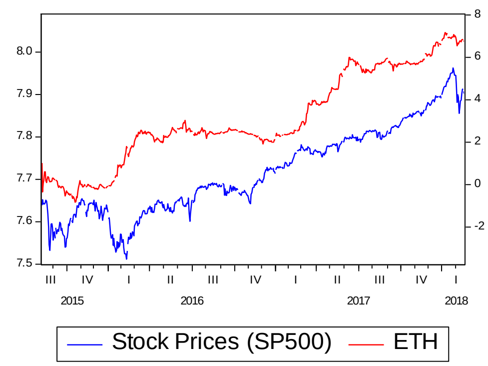


Fig. 1.3: Trends in Daily Stock Prices and LTC (2013-2018)

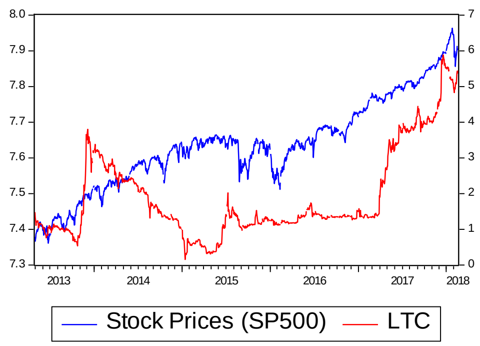
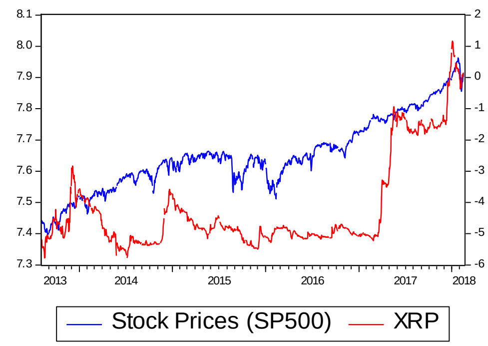


Fig. 1.4: Trends in Daily Stock Prices and XRP (2013-2018)



The Figure 1 above further extends our preliminary analyses to include visual inspection of trends in the US stock prices and the respective digital asset prices. From the figure evidence of possible interaction between stock prices and the selected cryptocurrencies seems obvious.

4. Empirical Results and Discussions

Consequent to the indicating the potential correlation between US stock prices and digital currencies, as depicted in figure 1, we proceed to test the predictability of the latter as potential predictor of former by plotting their respective fitted values against the actual data (see Figures 2&3) using 50% and 75% of the total sample period, respectively. The manner in which the fitted values mirror the actual data serves as a pointer to the fact that the digital currencies have a strong predictive prowess on US stock prices. This points to the fact that information contained in the cryptocurrency prices can be exploited to forecast the behaviour of stock prices. What's more, we used RMSE and the Campbell and Thomson (2008) [C-T] statistics of forecast performance evaluation in order to identify the model with better forecast results. The results are presented in Tables 3 and 4, respectively.

The results of the in-sample forecast performance of RMSE is reported in Table 3(a and b). The RMSE is considerably lower when we use the WN-based predictive model as compared to the RMSE obtained for the OLS-based predictive model. The implication of this further reinforces the strength of WN, as the more accurate estimator for the in-sample forecasts of US stock prices. It is also instructive to note that this estimator corrects for potential bias that might arise as a result of heteroscedasticity, persistency and/or endogeneity that might feature in the predictors. This stance holds for the various sub-sample periods considered and for the variants of digital currencies used. However, it is quite instructive to point out the fact that the existence of in-sample is no sufficient condition to assume out-of-sample forecast gain. To this end, we now turn to the out-of-sample forecast performance results also presented in Table 3for the 50% and 75% sub-sample period, respectively. Here, we specifically explore the rolling window approach and therefore, report results for forecast horizon (h) such that; h=10 is for 10 days period ahead forecast, h=20 is for 20 days period ahead forecast and h=30 is for 30 days period ahead forecast. Similar to the in-sample forecast performance evaluation results, we also compare the out-of-sample forecast performance of the WN predictive model relative to the traditional OLS based predictive model, and yet find the former as the more accurate for forecasting the US stock prices irrespective of the different sub-sample period the variants of the cryptocurrencies that is under consideration.

Table 3(a): Forecast performance results using RMSE for 50% of the data sample

Predictor	**OLS predictive model**				**WN predictive model**			
		Out-of-sample				***Out-of-sample***		
	In-sample	***h=10***	***h=20***	***h=30***	***In-sample***	***h=10***	***h=20***	***h=30***
BTC	0.0790	0.0785	0.0783	0.0785	0.0280	0.0322	0.0319	0.0317

ETH	0.0365	0.0369	0.0380	0.0401	0.0391	0.0385	0.0379	0.0374
LTC	0.0834	0.0827	0.0823	0.0824	0.0326	0.0367	0.0364	0.0362
XPR	0.0701	0.0699	0.0697	0.0694	0.0403	0.0407	0.0403	0.0400

Table 3(b): Forecast performance results using RMSE for 75% of the data sample

Predictor	OLS predictive model				WN predictive model			
	In-sample	*Out-of-sample*			*In-sample*	*Out-of-sample*		
		h=10	***h=20***	***h=30***		***h=10***	***h=20***	***h=30***
BTC	0.0728	0.0729	0.0730	0.0731	0.0501	0.0500	0.0497	0.0495
ETH	0.0448	0.0444	0.0441	0.0438	0.0353	0.0354	0.0350	0.0347
LTC	0.0823	0.0832	0.0841	0.0850	0.0529	0.0526	0.0523	0.0520
XPR	0.0711	0.0720	0.0730	0.0743	0.0486	0.0483	0.0481	0.0478

Source: Authors' computation

Note: the smaller the RMSE value, the better the forecast accuracy of the predictive model in question.

For consistence and robustness sake, we further compliment the RMSE approach to forecasting performance evaluation with the C-T method to determine, in relative term, the forecast performance of two or more alternatives or competing predictive models. The C-T test in particular was developed to make decisions on the predictability of an unrestricted model against a restricted model (see WN, 2015). However, having already established the WN–based predictive as the more accurate and the preferred model relative to the traditional OLS method, we herein extend the forecast performance evaluation to some of the conventional time series based predictive models namely, ARMA and ARFIMA. Hence, we rely on the forecast performance evaluation, which unlike the RMSE involves a pairwise comparison of forecast models to compare the forecast performance of each of these alternative time-series predictive models define as the restricted models as against our preferred model (WN digital asset –based predictive model) define as the unrestricted model.

Hence, a positive C-T test statistic implies that a so define unrestricted predictive model is superior to those define as a restricted model while the reverse is the case if it is negative. Thus, the C-T results as depicted in Table 4(a&b) show that the WN based predictive model resoundingly outperforms the ARMA and ARFIMA models regardless of the data sample and/or choice of the digital asset or cryptocurrency prices. For instance, the C-T statistics are consistently positive for all the four variants of the cryptocurrency prices utilized and across the different sub-sample period considered. Saying it differently, accounting for some of the inherent features of the cryptocurrencies the basis for our choice of WN as the preferred predictive model seems essential for enhancing the predictability of stock prices in the US.

Table 4(a): Campbell –Thompson (C-T) test results using 50% of the data sample

	ARMA vs WN				**ARFIMA vs WN**			
		Out-of-sample				***Out-of-sample RMSE***		
Predictor	***In-sample***	***h=10***	***h=20***	***h=30***	***In-sample***	***h=10***	***h=20***	***h=30***
BTC	0.6661	0.6132	1.6136	2.6153	0.7041	0.6583	1.6614	2..6668
ETH	0.3159	0.3155	1.3161	2.3185	0.0986	0.1219	1.1556	2.2017
LTC	0.6118	0.5594	1.5598	2.5617	0.6559	0.6107	1.6143	2.6204
XPR	0.1869	0.1724	1.1727	2.1727	0.4435	0.4397	1.4461	2.4500

Table 4(b): Campbell –Thompson (C-T) test results using 75% of the data sample

	ARMA vs WN				**ARFIMA vs WN**			
		Out-of-sample				***Out-of-sample***		
Predictor	***In-sample***	***h=10***	***h=20***	***h=30***	***In-sample***	***h=10***	***h=20***	***h=30***
BTC	0.2039	0.2018	1.2021	2.2023	0.4277	0.4374	1.4482	2.4590
ETH	0.4893	0.4835	1.4835	2.4836	0.5269	0.5313	1.5432	2.5537
LTC	0.1605	0.1607	1.1609	2.1611	0.3965	0.4084	1.4197	2.4311
XPR	0.0106	0.0106	1.0110	2.0126	0.3316	0.3455	1.3599	2.3764

Note: The C-T test results are based on the forecast performance comparison of our preferred [WN (digital asset based predictive model] the ARMA and ARFIMA predictive models. Hypothetically, a positive C-T statistic or value implies that the WN digital based predictive model outperforms the ARMA and ARFIMA time series based predictive models and the reverse holds if the statistic is negative.

5. Conclusions

This study is motivated by the linkage between uncertainty in stock prices and the surge in the digital currency prices. This present study therefore, examines the plausible predictive powers of the cryptocurrencies that might be inherent in stock prices. In essence, we hypothesized that relative to the traditional OLS method to forecasting stock prices behaviour, a cryptocurrency based predictive model whose estimation process has the potential to capture some of the underlying statistical properties of digital asset prices such as, persistence, endogeneity and conditional heteroscedasticity is likely to prove the more accurate for forecasting stock prices. Using the Westerlund and Narayan (2015) estimator that allows for such effects in the forecasting process of stock prices, we explored four variants of cryptocurrencies to consistently validate our hypothesis that digital asset prices have strong predictive powers in forecasting stock returns. More so, when we compare our WN digital asset –based predictive model with traditional time series forecasting models (ARMA and ARFIMA), there is evidence to uphold the WN digital asset –based predictive model as the more accurate for forecasting stock prices behavior in US.

Our results have important policy implications for investors. There is evidence to prove that investing in digital markets could be an important plausible diversification approach that could be explored. To policy makers, there is the need to come up with means through which digital markets could be regularized as being the case for the traditional asset markets. Caution must be exercised here, it is rather too early to consider our results as generic. Hence, future studies could expand on the frontier of knowledge by mimicking our empirical strategies to other stock markets. Also, the importance of asymmetry in the predictive power of stock returns appears to be an interesting venture future studies could consider.

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Appendix: Cryptocurrency Predictability of US Stock Prices

Figure 2: Cryptocurrency in-sample predictability of stock return (50% sample period)

Fig. 2.1: BTC predictability of stock prices

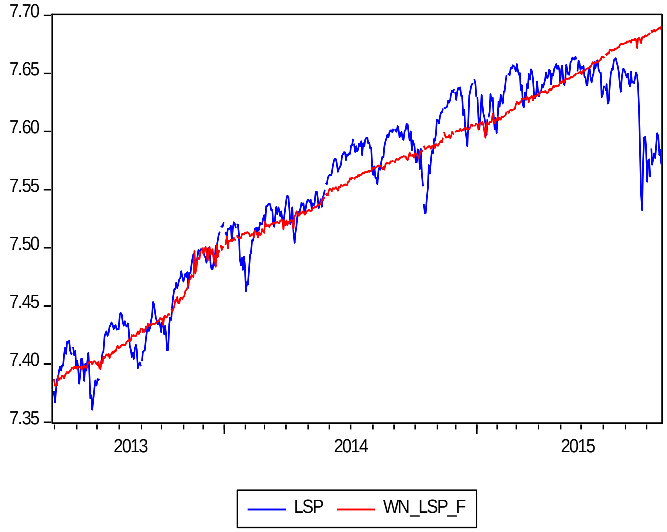

Fig. 2.2: ETH predictability of stock prices

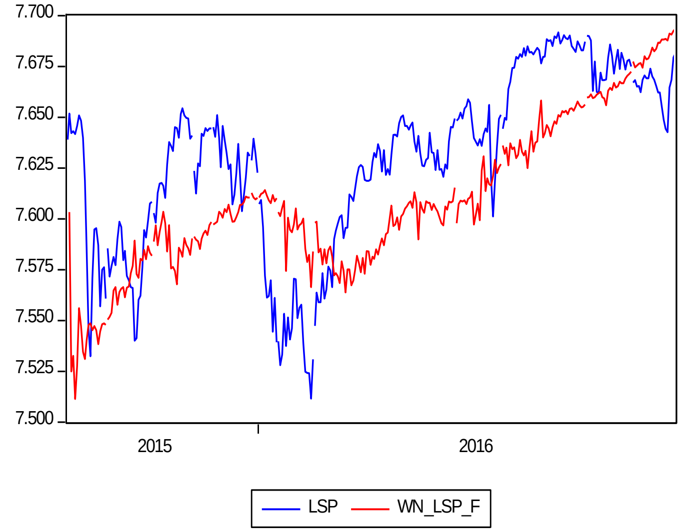

Fig 2.3: LTC predictability of stock prices

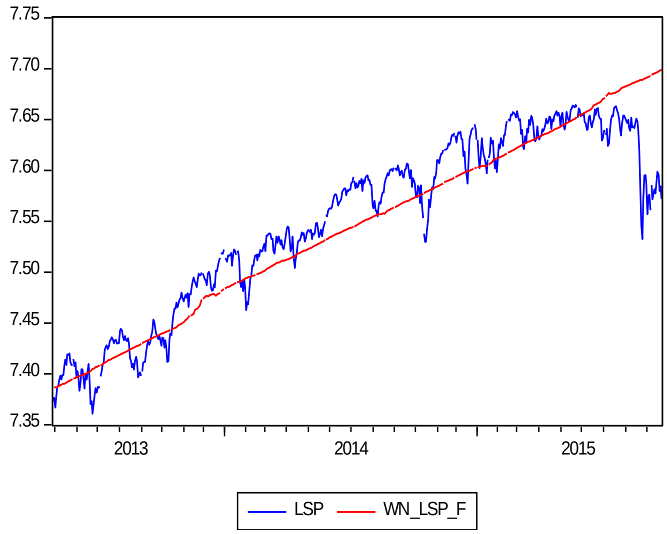

Fig. 2.4: XRP predictability of stock prices

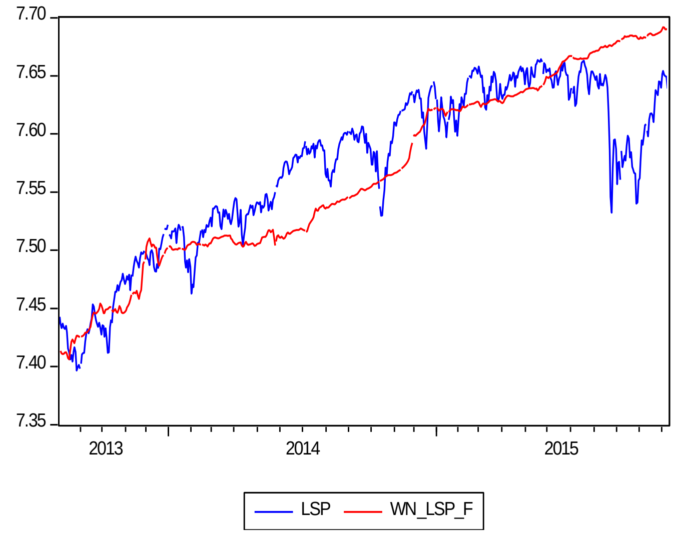

Figure 3: Cryptocurrency in-sample predictability of stock return (75% sample period)

Fig. 3.1: BTC predictability of stock prices

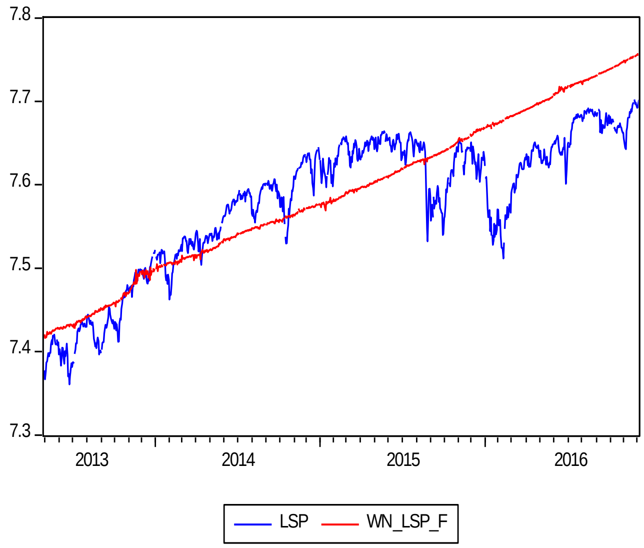

Fig. 3.2: ETH predictability of stock prices

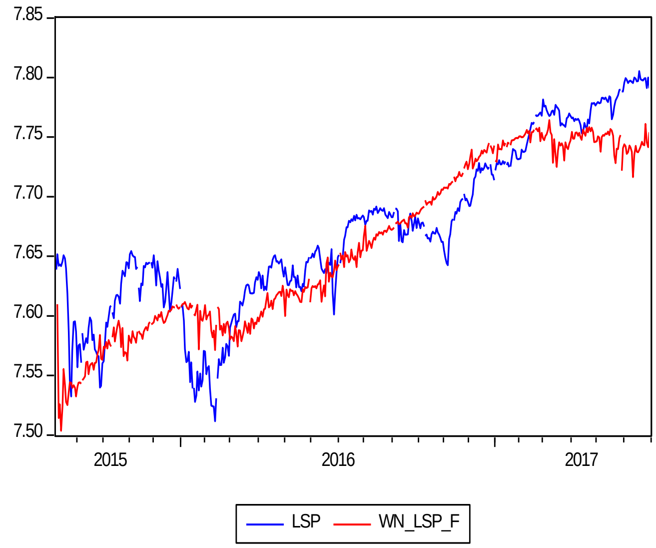

Fig. 3.3: LTC predictability of stock prices

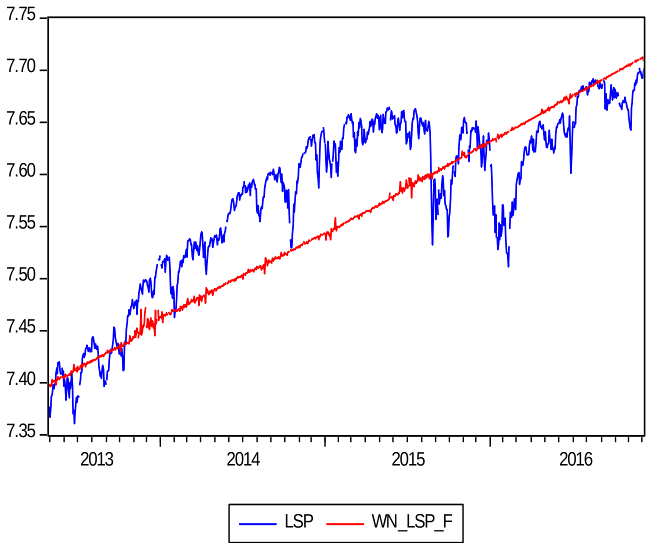

Fig. 3.4: XRP predictability of stock prices