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Predicting the stock prices of G7 countries with Bitcoin prices

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Abstract

This paper attempts to establish that some inherent features of the Bitcoin price can be exploited to produce better forecast results for stock prices. It does so by constructing predictive models for stock prices of G7 countries with symmetric and asymmetric prices of Bitcoin. The underlying statistical properties of Bitcoin prices such as persistence and conditional heteroscedasticity are captured in the estimation process using the Westerlund and Narayan (2015) estimator that allows for such effects in forecasting. There are two striking findings from the analysis. First, the results suggest that accounting for asymmetries is more likely to enhance the predictive power of Bitcoin in forecasting stock prices regardless of the data sample and forecast horizon. Secondly, the Bitcoin-based predictive model for stock prices, particularly the asymmetric variant, outperforms the Fractionally Integrated Autoregressive Moving Average (ARFIMA) model. While there are concerns as to whether the cryptocurrencies are veritable substitutes to the conventional financial assets, their close link with the developed stock exchanges such as those in the G7 countries suggests that they share some common characteristics such as news effects [asymmetries] which can be exploited when forecasting the behaviour of stock prices.

JEL Classification: C52; C53; G11; G14; G17

Keywords: Stock price, Bitcoin price, G7 countries, Forecast evaluation

Predicting the stock prices of G7 countries with Bitcoin prices

1. Introduction

Finance and economic literature recently is witnessing a tremendous interests on the possible linkage between cryptocurrencies and conventional assets, particularly its influence on stock prices and returns. The popular theme in the early literature before now is that the behaviour of cryptocurrency prices is detached from any economic fundamentals and as such may be irrational (see Katsiampa, 2017; Nadarajah and Chu, 2017; Pieters and Vivanco, 2017). However, the untold substitution by investors from conventional assets and currencies for cryptocurrencies and its increasing utilisation in transactions has attracted renewed interests and hence cannot be completely isolated from conventional assets (Koutmos, 2018). Besides, while taking into consideration that no virtual currency existed outside the online gaming communities, the disruptions cryptocurrencies have caused and could cause the monetary market further pose challenges as well as opportunities to policy makers (Dyhrberg, 2016).

Moreover, the dependence of the cryptocurrency markets, most especially Bitcoin, on self-fulfilling expectations and the lack of centralised regulatory body vis-à-vis its implication on the conventional asset markets has further renewed interest of economic and financial regulatory bodies, particularly central banks. Bitcoin has been extremely volatile with wild fluctuations in its market share and capitalisations. For example, a $1000 investment in Bitcoin between July, 2010 and July, 2017 would have returned about $81,000,000 (BNC, 2017). Despite the threats and actions from governments, policy makers and bankers to crush the Bitcoin, its resilience attribute has made its trajectory continue on an ascending pattern (Younis et al., 2018). Similarly, the financial markets are reflecting investors' sentiments as Bitcoin's correlation to broader markets, such as US Dow Jones index and S&P 500 index, continue to increase (Torpey, 2018).

Furthermore, growing number of academic papers have been devoted to evaluating the possible linkages, especially the correlation and impact analysis, between Bitcoin and conventional markets, particularly stocks and commodity markets. For example, Baur et al. (2017 a&b), Corbet et al. (2017) and Kurka (2017) among others all find low level of connectedness between Bitcoin and other financial assets. However, the striking contribution of our study is a relatively uninvestigated aspect in the literature that has to do with the characteristics of Bitcoin to generate out-of-sample forecast for conventional financial assets, particularly stocks. Information about the probable out-of-sample forecast abilities of Bitcoin may help in investment and policy decision purposes. For instance, if it truly holds that Bitcoin exhibits such predictive powers, investors and policy makers can exploit such information when making future decisions which may minimize risks and uncertainties associated with financial assets.

To achieve this, we construct a predictive model that captures Bitcoin as a predictor of stock prices after accounting for peculiar characteristics of the predictors such as persistence, endogeneity and conditional heteroscedasticity as evident in most financial series[1]. The approach of Westerlund and Narayan (2012, 2015) [henceforth; WN] is followed to implement the out-of-sample forecasts. This approach is an improvement on the traditional Ordinary Least Squares (OLS) which ignores the inherent features of predictors when forecasting and the Lewellen (2004) which ignores a prominent feature of high frequency predictors. Although, the latter seems to be the first empirical attempt to allow for the characteristics of predictors such as endogeneity and persistence effects in forecasting stock returns, it however fails to account for conditional heteroscedasticity which may matter when dealing with high frequency predictors. This is the contribution of WN (2012, 2015) and the estimator is described as Feasible Quasi Generalized Least Squares (FQGLS) estimator as it involves pre-weighting the data with the inverse of the standard deviation of the residuals obtained from a GARCH process. Recent applications of this approach to forecasting stock returns, although not from the perspective of cryptocurrencies, include Narayan and Bannigidadmath (2015); Narayan and Gupta (2015); Phan et al. (2015); Bannigidadmath and Narayan (2016); and Devpura et al. (2018).

In addition, we account for the role of asymmetry in the Bitcoin-based predictive model for stock prices. This consideration is motivated by the fact that an asymmetric transmission of macroeconomic factors to stock market indices can occur if the distributions of the variables involved are non-elliptic or fat tailed, and this has been well-documented in the economics and finance literature (see Benkareim et al., 2018). Other studies that have investigated the question of asymmetry in stock indices include Koutmos and Martin (2007); Kilian (2008); Hsu et al. (2009); Dieci and Westerhoff (2013); Naifar and Al Dohaiman (2013); Wang et al.

[1] Ignoring these features when they are found to be significant have implications on the forecast performance of a predictive model (see Lewellen, 2004; Westerlund and Narayan, 2012, 2015; Nayaran and Gupta, 2015; Salisu and Isah, 2017; Salisu et al., 2018)

(2013); Ali et al. (2015); Salisu and Oloko (2015); Bahmani-Oskooee and Saha (2016) and Salisu and Isah (2017a). Thus, we formulate a non-linear predictor framework which allows for positive and negative changes in Bitcoin prices using the Shin et al. (2014) approach (see also, Salisu and Isah, 2017b).

The comparative forecast evaluation is thus partitioned into two phases. The first phase involves comparing the Bitcoin-based linear predictive model for stock prices with the non-linear variant that captures positive and negative changes in Bitcoin price. Thereafter, in the second phase, the preferred model between the two in the first phase is compared with a time series model such as the Fractionally Integrated Autoregressive Moving Average (ARFIMA) model. The forecast evaluation is conducted for both in-sample and out-of-sample forecasts under different forecast horizons and data samples.

The remainder of this study is organized as follows: Section 2 provides a detailed discussion on the econometric methods and estimation procedure; Section 3 describes the data used and also offers some preliminary analyses; Section 4 presents and discusses the main results while Section 5 concludes the paper.

2. Econometric methods and estimation procedure

The empirical analyses in this paper are structured into three stages. The first stage involves the pre-test of variables of interest for endogeneity, persistence and conditional heteroscedasticity effects. This is detailed in the next section. The next stage involves the in-sample predictability and forecast evaluation based on the outcome in the first stage. The last stage involves the out-of-sample forecast evaluation under different forecast horizons.

2.1 The model

To evaluate the predictive nexus between stock price and Bitcoin price, we specify a predictive model that follows the approach of WN (2012, 2015) as given below:

$$s_t = \delta + \phi b_{t-1} + \varphi\left(b_t - \rho b_{t-1}\right) + \varepsilon_t \quad [1]$$

where s_t is the natural log of stock price; b_t is the natural log of Bitcoin price; and ρ is the first order autocorrelation coefficient. The first term of the model (ϕb_{t-1}) ordinarily captures the bivariate representation of a predictive model. However, the inclusion of the second term

$\left(b_t - \rho b_{t-1}\right)$ captures any inherent persistent effect in the predictive model (see LW, 2004). Accounting for persistence effect may be valid when dealing with high frequency predictors as they tend to exhibit random walk, where the AR(1) coefficient approximates to one $\left(\rho = 1\right)$. Hence, it is necessary to pre-test series for persistence and account for same if found significant. Following the WN (2015), the persistence equation is given as

$$b_t = \varphi\left(1-\rho\right) + \rho b_{t-1} + v_t \qquad [2]$$

where $v_t \sim N\left(0, \sigma_v^2\right)$. In addition, the presence of statistically significant persistence effect may introduce endogeneity bias as a result of possible correlations between the predictor $\left(b_t\right)$ and the regression error $\left(\varepsilon_t\right)$. Therefore, we test for endogeneity using the equation (see also Salisu and Isah, 2017b):

$$\varepsilon_t = \varphi v_t + \mu_t \qquad [3]$$

where ε_t and v_t are the error terms from [1] and [2] respectively. The parameter φ captures the endogeneity effect and if found to be statistically significant, then, there is presence of endogeneity effect (i.e. the predictor is endogenous). Therefore, estimating [1] using the OLS method corrects for possible endogeneity bias, and yields a bias-adjusted OLS estimator for ϕ (LW, 2004). This is described as:

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

To account for conditional heteroscedasticity effect, WN (2012, 2015) suggesting 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.

As previously mentioned, we account for asymmetries in the predictor in equation [1] by partitioning Bitcoin price into two to account for the positive and negative changes. The resulting equation from [1] is given as:

$$s_t = \delta + \phi^+ b^+_{t-1} + \phi^- b^-_{t-1} + \varphi^+\left(b^+_t - \rho b^+_{t-1}\right) + \varphi^-\left(b^-_t - \rho b^-_{t-1}\right) + \varepsilon_t \qquad [5]$$

Following Shin et al., (2014), the computational procedure for b_t^+ and b_t^- involves partial sum decompositions of positive and negative Bitcoin price changes and it is given below as:

$$b_t^+ = \sum_{k=1}^{t} \Delta b^+_{ik} = \sum_{k=1}^{t} \max(\Delta b_{ik}, 0) \qquad [6a]$$

$$b_t^- = \sum_{k=1}^{t} \Delta b_{ik}^- = \sum_{k=1}^{t} \min(\Delta b_{ik}, 0) \qquad [6b]$$

There is evidence of asymmetric effect of Bitcoin prices on stock returns, if the coefficients of b_t^+ and b_t^- are statistically significant and the reverse indicates symmetric effects.

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:

$$RMSE = \sqrt{1/T \sum_{t=1}^{T} \left(\hat{s}_t - s_t\right)^2} \qquad [7]$$

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 $OOS\_R^2 = 1 - \left(M\widehat{S}E_1 / M\widehat{S}E_0\right)$, 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.

In addition to equations [1] and [2], for completeness, we also consider the relative forecast performance of time-series models with reference to the Autoregressive Fractionally Integrated Moving Average (ARFIMA) model. This enables us to test if the Bitcoin-based model for stock prices will outperform a typical time series model.

3. Data and preliminary analyses

3.1 Data source and description

The daily dataset utilized in this study include stock price indexes of the G7 countries and Bitcoin prices being the single largest cryptocurrency asset with more than one billion worth of market value. The choice of G7 countries is underscored by the fact that they constitute major stock exchanges in the world and coupled with their high volume of Bitcoin transactions; they are more likely to be influenced by the dynamics of Bitcoin activities. For instance, the U.S. has the highest number of Bitcoin users, ATMs and trading volumes globally. Similarly, other G7 countries although continue to monitor the dynamics of Bitcoin trading, most of them have classified it as private money and in fact as a legal tender in Japan and have been subject to capital gains and income taxes in Germany, Italy and UK. This partly explains why in 2013 the G7's Financial Action Task Force issued the following statement in guidelines which may be applicable to companies involved in transmitting bitcoin and other currencies, "Internet-based payment services that allow third party funding from anonymous sources may face an increased risk of [money laundering/terrorist financing]." They concluded that this may "pose challenges to countries in [anti-money laundering/counter terrorist financing] regulation and supervision" (Financial Action Task Force, 2013).

Although there are other variants of cryptocurrency, the choice of Bitcoin among the alternatives is mainly informed by its prominence as the most traded cryptocurrency and coupled with the fact that it also has sufficiently large daily datasets when compared to other cryptocurrencies (see Dyhrberg, 2016; Corbet et al., 2018 and Phillip et al., 2018). The data scope for both series range from the 29th of April 2013 to 16th of February 2016, the stock prices for each of the G7 countries namely, Canada, France, Germany, Italy, Japan, UK and US are mainly sourced from Bloomberg terminal, while the Bitcoin prices on the other hand were obtained from Coin Metrics (https://coinmetrics.io/datadownloads/).

3.2 Preliminary analysis results

In line with the standard practice in the literature when dealing with variables that have time series properties, we consider the individual statistical features of the series and across countries under consideration (see Table 1A). Starting with the mean statistics for example, the average daily price for Bitcoin over the period under consideration is $1452.43. As expected, countries with the least and highest values of mean stock prices, Japan and Italy respectively, equally record the least and highest standard deviation values in that order. Given its mean value relative to those of stock prices, the standard deviation value at 2889.49 seems quiet alarming for Bitcoin price thus reaffirming the highly volatile nature of the variable. With respect to the statistical distribution of the series, the skewness reveals that the Bitcoin and virtually all the stock prices for the G7 countries as non-zero and they are mainly positively skewed with the exception of Canada and Italy. Also, the leptokurtic distribution is evident for Bitcoin and three stock prices involving Canada, Germany and Japan, although it is more pronounced for the former relative to the stock prices. Other stock prices for France, Italy, UK and US seem otherwise.

Table 1A: Preliminary test results

	Descriptive Statistics				Unit Root Test		Persistence & Endogeneity Tests	
Variable	***Mean***	***Standard Deviation***	***Skewness***	***Kurtosis***	***Level***	***First Difference***	***Persistence***	***Endogeneity***
Bitcoin	1452.43	2889.49	3.62	16.72	-0.6541[b]	-35.2552***		
Canada	11885.30	1161.22	-0.41	3.27	-1.7494[a]	-31.8472***	1.0008	-0.0254
France	5492.14	500.13	0.34	2.31	-1.7194[a]	-34.1277[a]***	1.0008	0.0087
Germany	12485.31	1381.45	0.77	3.14	-1.6348[b]	-34.4294[b]***	1.0008	-0.0206
Italy	25709.13	3362.38	-0.05	2.13	-1.4729[b]	-35.3646[b]***	1.0008	-0.0208
Japan	159.18	16.98	1.18	4.24	-3.0688[b]	-41.7584[b]***	1.0008	-0.0043
UK	1186.23	140.63	0.39	2.12	-1.0404[b]	-27.7259[b]***	1.0008	-0.0077
US	2088.32	271.27	0.50	2.91	-2.8724[b]	-34.6346[b]***	1.0008	-0.0462

Note: The listing of countries in the first column is to help identify the stock price variable of each of the G7 countries under consideration. The persistence test is done by regressing a first order autoregressive process for the predictor, for example: $z_t = \omega + \rho z_{t-1} + \upsilon_t$ using OLS estimator. The first order autocorrelation coefficient (ρ) captures the persistence effect and is reported in Table 1A. The null hypothesis is that $H_0 : \rho = 0$ while the alternative is given as $H_1 : \rho \neq 0$. For the endogeneity test, it involves three-step procedures: First, we run the following predictive regression model: $s_t = \alpha + \beta b_{t-1} + \varepsilon_t$, where s_t denotes natural log of stock prices and b_{t-1} is the natural log of Bitcoin price. In the second step, we follow WN (2015) and model the predictor variable as follows: $b_t = \mu(1-\rho) + \rho b_{t-1} + v_t$ and in the final step, the relationship between the two error terms is captured 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; otherwise, it is not.

As a formal precondition for analysing with time series variables, we further explore the stochastic properties of the relevant variables using the Augmented Dickey Fuller (ADF) test. Thus, the ADF test results in Table 1A seem to reveal both the predictor and the predicting variables as non-stationary series. Consequently, we test for endogeneity and persistence effects to see the extent to which these parameters matter in the predictive model. The persistence test suggests a high degree of persistence in the predictor series while there is no evidence of serious endogeneity bias in the predictive model. However, the presence of both persistence and hereroscedasticity effects justifies the relevance of the predictive model in equation [1] as well as the chosen WN estimator for the analysis of the relationship between Bitcoin and stock prices.

Table 1B: Preliminary test results

Variable	Serial Correlation and Conditional Heteroscedasticity Tests								
	$Q-Stat$			Q^2-Stat			$ARCH\ LM$		
	$k=10$	$k=20$	$k=30$	$k=10$	$k=20$	$k=30$	$k=10$	$k=20$	$k=30$
Bitcoin	11360.***	21682.***	30859.***	11140.***	20765.***	28490.***	25981.***	2419.***	9241.***
Canada	11302.***	21683.***	31204.***	10120.***	17791.***	23143.***	4618.***	942.***	1636.***
France	10880.***	20306.***	28420.***	8849.8***	14295.***	17504.***	1906.***	2428.***	627.***
Germany	10953.***	20465.***	28606.***	10180.***	17717.***	23148.***	4849.***	1209.***	1609.***
Italy	11186.***	21192.***	30113.***	9466.4***	15709.***	20081.***	2444.***	2274.***	796.***
Japan	10919.***	20418.***	28499.***	10255.***	17614.***	22559.***	4197.***	2090.***	1616.***
UK	11337.***	21588.***	30715.***	9567.4***	15614.***	19263.***	14817.***	7318.***	1368.***
US	11279.***	21560.***	30850.***	10809.***	19838.***	27274.***	13543.***	9241.***	4907.***

Note: The reported values for the serial correlation are the Ljung-Box Q-statistics while for heteroscedasticity test, we use the ARCH-LM test F-statistics. We consider three different lag lengths (k) of 10, 20 and 30 for robustness. The null hypothesis for the autocorrelation test is that there is no serial correlation, while the null for the ARCH-LM test is that there is no conditional heteroscedasticity. *** indicates significance at 1%.

In Table 1B, we check for autocorrelation and conditional heteroscedasticity in the predictor and the predicted series and we find the presence of serial dependence and conditional heteroscedasticity in both series judging by the Ljung-Box and the Engle (1982) ARCH-LM tests respectively. We further extend our preliminary analyses to include visual inspection of trends in daily Bitcoin and stock prices movement. To achieve this, we plot the Bitcoin price against each of the selected stock price indexes (see Figure 1). The evidence of possible interaction between Bitcoin and stock prices seems obvious for all the countries considered. The figure depicts some co-movements between the two series except for few instances involving Japan and US, where their respective stock prices seem to be moving in opposite directions with Bitcoin, particularly in the period between 2013 and 2014. The reason for this, might be that investors in crypto and stocks do overlap, with both usually attracting a higher level of risk takers trying to earn higher returns.

Figure 1: Trends in Bitcoin and Stock Prices of the G7 Countries

Fig. 1.1: Trends in Canadian Stock Prices and Bitcon

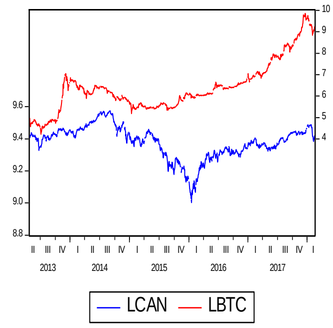


Fig. 1.2: Trends in France Stock Prices and Bitcon

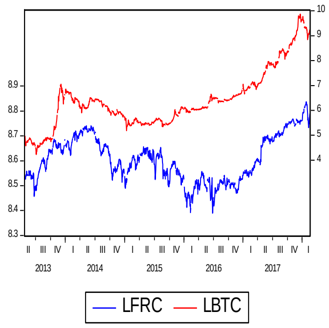


Fig. 1.3: Trends in Italian Stock Prices and Bitcon

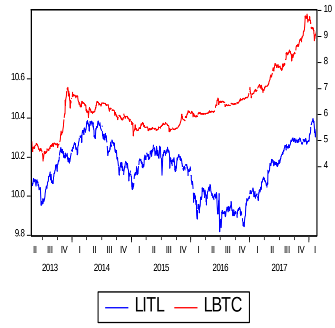


Fig. 1.4: Trends in Japanese Stock Prices and Bitcon

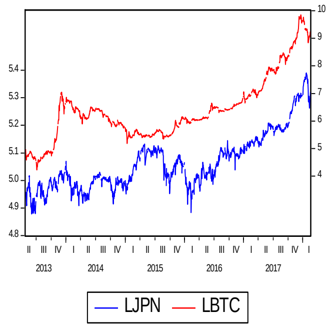


Fig. 1.5: Trends in Germany Stock Prices and Bitcon

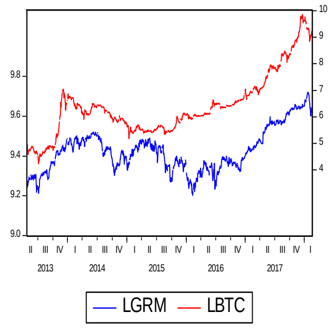


Fig. 1.6: Trends in UK Stock Prices and Bitcon

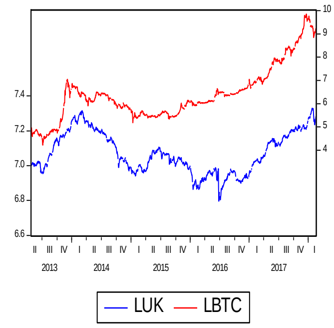
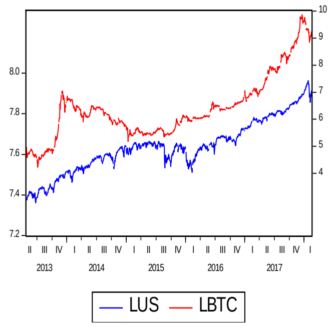


Fig. 1.7: Trends in US Stock Prices and Bitcon



4. Results and discussion

4.1 In-sample forecast evaluation

Here, we first demonstrate the extent to which the Bitcoin–based predictive model (as in equation [1]) and its proposed asymmetric version (as in equation [5]) are able to track the actual data (see Figures 2 and 3). We also extend same to the ARFIMA model (see Figure 4). A closer look at these figures suggests that the ARFIMA model performs worse than the predictive models that include Bitcoin price. Meanwhile, both the symmetric and the asymmetric forecast models seem to share similar predictive powers and are able to track the actual data reasonably well. This implies that the information contained in the Bitcoin prices can be exploited to forecast behaviour of stock prices in G7 countries. Nonetheless, a formal forecast evaluation is necessary to identify the model with better forecast results. As previously noted, we employ both the RMSE and the Campbell and Thomson (2008) [C-T] statistics for this purpose and the results are reported in Tables 3 and 4 respectively.

Starting with the in-sample forecast performance evaluation results when only 50% of the total observation is utilized, the RMSE as reported in Table 3a seems relatively lower for the asymmetric predictive model for four out of seven countries. Also, for the out-of-sample forecast of the 50% scenario, the asymmetric predictive model produces better forecast results for five of the G7 countries irrespective of the forecast horizon. Turning to the 75% scenario as presented in Table 3b, the predictive power of the asymmetric variant over the symmetric model is further as the former outperforms the latter in virtually all the countries considered with the exception of Japan.

Figure 2: Symmetric Bitcoin predictability of G7 stock prices

Fig. 2.1: Symmetry_Bitcon predictability of Canadian stock prices

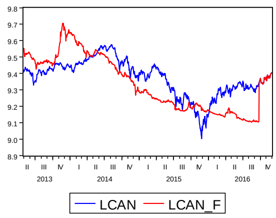


Fig. 2.2: Symmetry Bitcon predictability of France stock prices

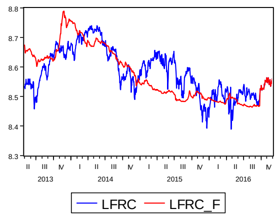


Fig. 2.3: Symmetry_Bitcon predictability of Germany stock prices

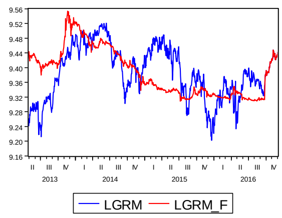


Fig. 2.4: Symmetry_Bitcon predictability of Italy stock prices

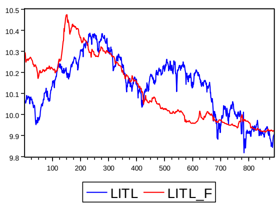


Fig. 2.5: Symmetry_Bitcon predictability of Japanese stock prices

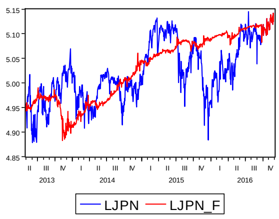


Fig. 2.6: Symmetry_Bitcon predictability of UK stock prices

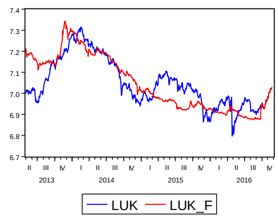


Fig. 2.7: Symmetry_Bitcon predictability of US stock prices

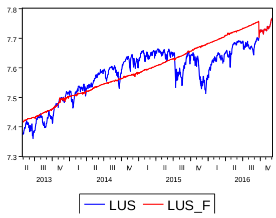


Figure 3: Asymmetric Bitcoin predictability of G7 stock prices

Fig. 3.1: Asymmetry_Bitcon predictability of Canadian stock prices

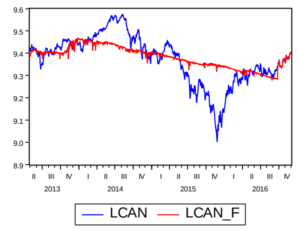


Fig. 3.2: Asymmetry Bitcon predictability of France stock prices

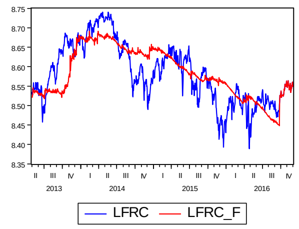


Fig. 3.3: Asymmetry_Bitcon predictability of Germanystock prices

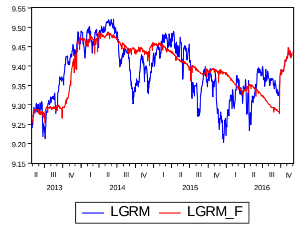


Fig. 3.4: Asymmetry_Bitcon predictability of Italy stock prices

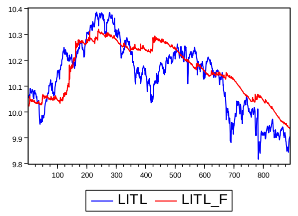


Fig. 3.5: Asymmetry_Bitcon predictability of Japanese stock prices

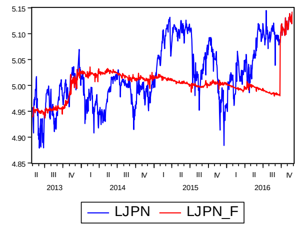


Fig. 3.6: Asymmetry_Bitcon predictability of UK stock prices

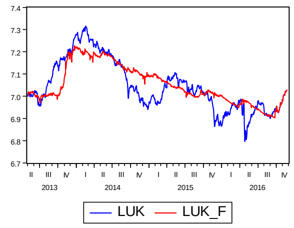


Fig. 3.7: Asymmetry_Bitcon predictability of US stock prices

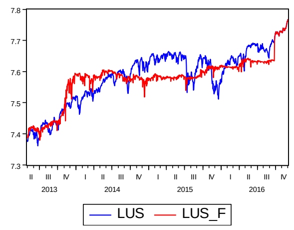


Figure 4: ARFIMA Predictability of G7 stock prices

Fig. 4.1: ARFIMA predictability of Canadian stock prices

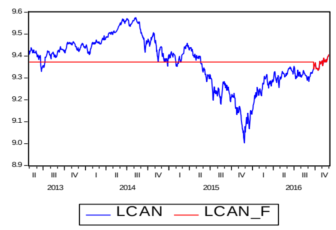


Fig. 4.2: ARFIMA predictability of France stock prices

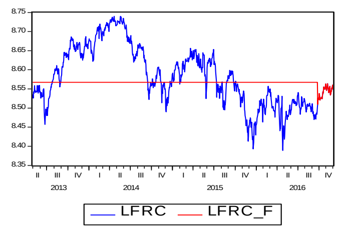


Fig. 4.3: ARFIMA predictability of Germany stock prices

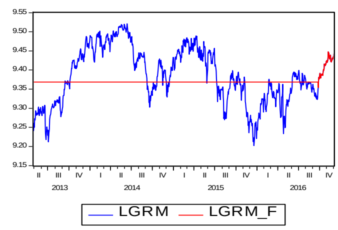


Fig. 4.4: ARFIMA predictability of Italy stock prices

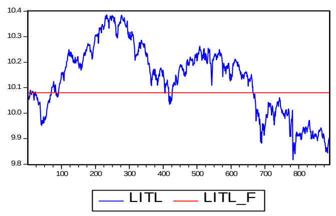


Fig. 4.5: ARFIMA predictability of Japanese stock prices

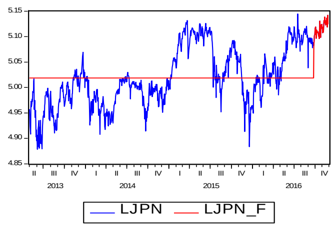


Fig. 4.6: ARFIMA predictability of UK stock prices

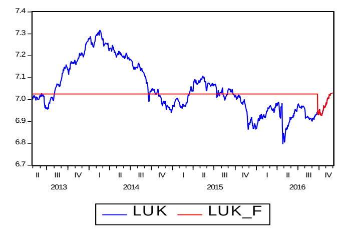


Fig. 4.7: ARFIMA predictability of US stock prices

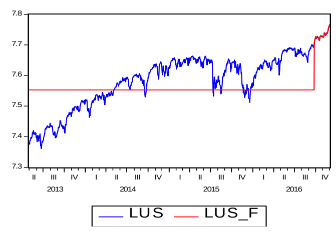


Table 3(a): Forecast performance results using 50% of the data sample

	Symmetric predictive model				**Asymmetric predictive model**			
	In-sample	***Out-of-sample***			***In-sample***	***Out-of-sample***		
		h=10	***h=20***	***h=30***		***h=10***	***h=20***	***h=30***
Canada	0.0754	0.0751	0.0746	0.0741	0.0624	0.0666	0.0683	0.0701
France	0.0582	0.0578	0.0577	0.0576	0.0509	0.0517	0.0515	0.0511
Germany	0.0494	0.0531	0.0551	0.0558	0.0514	0.0514	0.0510	0.0511
Italy	0.0667	0.0663	0.0657	0.0653	0.0760	0.0766	0.0791	0.0817
Japan	0.0537	0.0562	0.0578	0.0586	0.0536	0.0533	0.0528	0.0525
UK	0.0923	0.0938	0.0954	0.0969	0.0700	0.0695	0.0690	0.0684
US	0.0271	0.0316	0.0337	0.0347	0.0379	0.0376	0.0377	0.0390

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

	Symmetric predictive model				**Asymmetric predictive model**			
	In-sample	***Out-of-sample***			***In-sample***	***Out-of-sample***		
		h=10	***h=20***	***h=30***		***h=10***	***h=20***	***h=30***
Canada	0.0728	0.0729	0.0730	0.0731	0.0501	0.0500	0.0497	0.0495
France	0.0448	0.0444	0.0441	0.0438	0.0353	0.0354	0.0350	0.0347
Germany	0.0711	0.0710	0.0710	0.0714	0.0531	0.0539	0.0551	0.0566
Italy	0.1271	0.1265	0.1260	0.1257	0.0825	0.0822	0.0821	0.0821
Japan	0.0563	0.0560	0.0557	0.0554	0.0608	0.0618	0.0629	0.0641
UK	0.0764	0.0763	0.0761	0.0763	0.0669	0.0666	0.0664	0.0664
US	0.0502	0.0501	0.0500	0.0499	0.0455	0.0461	0.0467	0.0473

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

We further compliment the RMSE method of evaluating forecast performance with the C-T method to further confirm the superiority of the asymmetric model. The C-T test as explored in Narayan and Gupta (2015), makes decisions on the predictability of an unrestricted model (which is the asymmetric model in this case) as against the restricted version which is the symmetric version. Unlike the RMSE, it is easier to verify the performance of two competing models using the C-T statistic as it involves a pairwise comparison of forecast models. A positive C-T statistic is an indication that the asymmetric model is superior to the symmetric model while the reverse is the case if it is negative. At a glance, we can easily evaluate the extent to which the asymmetric model is able to outperform the symmetric model and vice versa. Although, it reiterates the conclusion drawn from using the RMSE statistic; it however offers a cursory evaluation of the forecast performance of the considered models.

As customary when forecasting with time series, we extend the forecast evaluation to the ARFIMA model both for the in-sample and out-of-sample forecasts. Since, the asymmetric model seems to dominate the symmetric model in terms of predictive powers; the former is therefore compared with the ARFIMA model. The C-T test results are presented in Table 4. The asymmetric model resoundingly outperforms the ARFIMA model regardless of data sample and forecast horizon as the C-T test statistics are consistently positive for all the G7 countries, with the exception of Japan under 75% scenario. In other words, there seems to be some inherent characteristic features of the Bitcoin prices which may help forecast the stock prices of G7 countries better than the ARFIMA model.

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

	Symmetric vs Asymmetric				Asymmetric vs ARFIMA			
	In-sample	*Out-of-sample*			*In-sample*	*Out-of-sample*		
		h=10	*h=20*	*h=30*		*h=10*	*h=20*	*h=30*
Canada	0.1726	0.1134	0.0836	0.0532	0.2017	0.1804	0.1720	0.1640
France	0.1259	0.1054	0.1075	0.1139	0.1970	0.1931	0.1935	0.1937
Germany	-0.0411	0.0328	0.0729	0.0832	0.3293	0.3325	0.3343	0.3278
Italy	-0.1405	-0.1562	-0.2025	-0.2516	0.2315	0.2201	0.1888	0.1550
Japan	0.0536	0.0533	0.0528	0.0525	0.0663	0.0653	0.0660	0.0693
UK	0.2417	0.2587	0.2769	0.2937	0.3287	0.3297	0.3306	0.3309
US	-0.3965	-0.1912	-0.1184	-0.1241	0.5926	0.5930	0.5923	0.5808

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

	Symmetric vs Asymmetric				Asymmetric vs ARFIMA			
	In-sample	*Out-of-sample*			*In-sample*	*Out-of-sample*		
		h=10	*h=20*	*h=30*		*h=10*	*h=20*	*h=30*
Canada	0.3085	0.3214	0.3310	0.3423	0.2521	0.2495	0.2468	0.2421
France	0.1817	0.1799	0.1704	0.1622	0.3393	0.3315	0.3217	0.3088
Germany	0.2528	0.2404	0.2235	0.2072	0.2901	0.2748	0.2553	0.2329
Italy	0.3707	0.3502	0.3479	0.3466	0.2343	0.4333	0.4316	0.4291
Japan	-0.0801	-0.1049	-0.1298	-0.1566	-0.0628	-0.0740	-0.0836	-0.0927
UK	0.1246	0.1262	0.1271	0.1301	0.4298	0.4303	0.4311	0.4287
US	0.0932	0.0799	0.0662	0.0518	0.4816	0.4826	0.4832	0.4840

Note: The C-T test results are based on the forecast performance comparison of our preferred [the asymmetric model] against the symmetric model as well as the ARFIMA model. Between the symmetric and the asymmetric models, the former is treated as the restricted model while the latter is the unrestricted. For ARFIMA and the asymmetric model, we treat the former as the restricted and the latter as the unrestricted. Hypothetically, a positive C-T statistic or value implies that an unrestricted model outperforms the restricted model and the reverse holds if the statistic is negative.

5. Concluding remarks

Building on the news making round that the plunge in the stock markets is traceable to the surge in cryptocurrency; we explore an evidence-based approach where Bitcoin is hypothesized as a good predictor of variations in stock prices of G7 countries. Consequently, we construct two predictive models [symmetric and asymmetric models] that include Bitcoin as a predictor in the predictive model of stock price. The symmetric model assumes identical impact of both positive and negative changes in Bitcoin price on stock price while the asymmetric variant considers it to be nonidentical. Their forecast performance is evaluated for both in-sample and out-of-sample forecasts under multiple data samples and forecast horizons. The results suggest that accounting for asymmetries is more likely to enhance the predictive power of Bitcoin in forecasting stock prices regardless of the data sample and forecast horizon. Thereafter, the preferred model is compared with the ARFIMA model and the superiority of the asymmetric model is still upheld. Although, there are concerns as to whether the cryptocurrencies are veritable substitutes to the conventional financial assets, their close link with the developed stock exchanges such as those in the G7 countries suggests that they share some common characteristics such as news effects [asymmetries] which can be exploited when forecasting the behaviour of stock prices.

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