Pandemics and cryptocurrencies

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Abstract

This study examines the effect of a pandemic-induced uncertainty on cryptocurrencies (specifically, Bitcoin, Ethereum and Ripple). It employs a predictive model by Westerlund and Narayan (2012, 2015) to examine the predictability of a pandemic-induced uncertainty as a predictor, as well as the forecast performance of our predictive model for cryptocurrency returns. We examine the role of asymmetry in uncertainty and the sensitivity of our results to alternative measures of uncertainty due to pandemics, using the recently developed Global Fear Index (GFI) by Salisu and Akanni (2020). Our results indicate that cryptocurrencies could act as hedge against uncertainty due to pandemics, albeit with reduced hedging effectiveness in the COVID-19 period. Accounting for asymmetry is found to improve the predictability and forecast performance of the model, which indicates that failure to account for asymmetry in modeling the effect of a pandemic-induced uncertainty on cryptocurrency may lead to incorrect conclusion. The results seem to be sensitive to the choice of measure of pandemic-induced uncertainty.

Pandemics and Cryptocurrencies

1. The Motivation

Ideally, when the economic atmosphere is characterized by uncertainties, like in the case of pandemics, investors are usually on the look-out for an alternative way to invest, as well as a better platform to hedge their funds against any form of risk/uncertainty associated with other assets. It is important to stress that cryptocurrencies, which have been seen as new investment opportunities, are driven by investor sentiment just like other assets (Chuen, Guo and Wang, 2017) and cryptocurrency market efficiency (see Yaya, Ogbonna and Olubusoye, 2019 and Yaya, Ogbonna, Mudida and Nuruddeen, 2020). More importantly, it is driven by 'expectations' similar to that of stock market. However, unlike the traditional asset markets, there is no central regulator for cryptocurrencies (Bouri et al. 2019; Jabotinsky and Sarel, 2020), and their values – measured by prices, have largely appreciated (Bouri et al. 2019). This has therefore made a number of studies to conclude that they could be used as a speculative investment rather than a medium for storage and transaction (see for example, Baek and Elbeck, 2015; Bouoiyour et al., 2015; Cheah and Fry, 2015; Yermack, 2015; Ciaian et al., 2016; Baur et al., 2018; Goodell and Goutte, 2020).

Moreover, cryptocurrencies such as Bitcoin are made and designed to be limited in supply, with about twenty-one million of it to be mined (Chuen, Guo and Wang, 2017; Hayes, 2020). Thus, when it is expected that cryptocurrency, for example, Bitcoin, would become a deflationary asset that people could use to hedge their money just the way they do with gold, especially during crises such as those associated with pandemics; they could move their funds away from stock market that is characterized by higher volatility to cryptocurrencies[1] that are considered potentially better portfolio diversifier, as they provide additional utility and safe haven to investors when uncertainty reign supreme in an economy (Baur and Lucey, 2010; Chuen, Guo and Wang, 2017; Wong, Saerbeck and Delgado, 2018; Goodell and Goutte, 2020). A quick look at the trend of the cryptocurrencies' trade since the inception of the novel coronavirus, especially when information about it was on the rise, till May[2]; there was a massive rise in the Bitcoin trade volume and same could also be said for their returns.[3] Studies such as Minf, Jarboui and Mouakhar (2020) and

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[1] See Jabotinsky and Sarel (2020).

[2] Various countries started to ease the non-pharmaceutical restrictions imposed on their economies in order to stem the spread of the virus.

[3] This rise in the trade volume of Bitcoin has ceased due to the gradual recovery of the world's economies from the constraint imposed by COVID-19. This (fall in the investment) could also be associated with the United States government decision to stimulate the stock market (see aljazeera.com for review).

Jabotinsky and Sarel, (2020) find that COVID-19 has a positive impact on the cryptocurrency market efficiency.

Consequently, one may be tempted to assume that cryptocurrencies are not susceptible to pandemics. However, the hedge and safe haven advantage of crypotocurrencies during the periods clouded by uncertainties have been keenly contested in the literature; with some confirming it (for example, Baur and Lucey, 2010; Dyhrberg, 2016; Chuen et al. 2017; Liu and Tsyvinski, 2018; Wong et al., 2018; Fang et al., 2019; Stensås et al., 2019; Urquhart and Zhang, 2019; Salisu, Isah and Akanni, 2019; Minf, Jarboui and Mouakhar, 2020; Goodell and Goutte, 2020[4]), while others have established a contrary evidence (see for example, Bouri et al., 2017; Conlon and McGee, 2020; Klein et al., 2018; Smales, 2019; Baur and Hoang, 2020; Cheema, Szulczyk and Bouri, 2020). Although, the results of these studies (except for few such as Minf, Jarboui and Mouakhar, 2020; Goodell and Goutte, 2020) do not capture the vulnerability or otherwise of cryptocurrencies to uncertainties due to pandemics. Even for the two related studies mentioned, we differ in terms of the measure of uncertainties associated with pandemics and the choice of methodology. We utilize two new datasets on pandemics; one by Baker et al. (2020) dataset which captures all the pandemics including COVID-19 and the other, which is a complementary dataset on COVID-19 developed by Salisu & Akanni (2020) using an alternative approach. The availability of these datasets at a high frequency is a major attraction.[5]

In terms of methodology, we adopt an approach proposed by Westerlund and Narayan (2012, 2015), which accounts for the salient features typical of most financial series including cryptocurrencies such as persistence, endogeneity and conditional heteroscedasticity (see also, Bannigidadmath & Narayan, 2015; Narayan & Gupta, 2015; Phan et al., 2015; Narayan et al., 2016; Devpura et al., 2018; Salisu et al., 2018; Salisu et al., 2019a,b,c,d&e; among others). As an additional analysis, we also evaluate whether the inclusion of these new measures of pandemic-induced uncertainties in the predictive model of a cryptocurrency can produce better in-sample and out-of-sample forecast results. For completeness, we consider three data samples: full sample, pre-COVID-19 and COVID-19, and we cover the three most traded cryptocurrencies globally,

[4] This study finds on a general note that cryptocurrencies, but bitcoin and tether do not possess diversifier as well as safe havens benefits.

[5] Baker et al. (2020) dataset is available at https://fred.stlouisfed.org/series/INFECTDISEMVTRACKD while that of Salisu & Akanni (2020) is available at https://www.researchgate.net/publication/342550321_COVID-19_Global_Fear_Index_Dataset

namely; Bitcoin (BTC), Ethereum (ETH) and Ripple (XRP), to offer some level of generalization on the results.

Foreshadowing our results, cryptocurrencies were found to act as hedge against uncertainty due to pandemics, although with reduction in the degree of safe haven potential in the COVID-19 period. Accounting for asymmetry was found to improve the predictability of the pandemic-induced uncertainty measure and the forecast performance of our model; which indicates that failure to account for asymmetry in modeling the effect of uncertainty due to pandemic on cryptocurrency may lead to incorrect conclusion. The results are found to be sensitive to the choice of measure of uncertainty due to pandemic.

Following the introductory section, Section 2 discusses data issues and also provides some preliminary analyses required for estimation; Section 3 deals with methodology; the discussion of results is rendered in Section 4, while Section 5 concludes.

2. Data and Preliminary analyses

We employ 7-day daily data from August 7, 2015 to June 27, 2020; generating 1,787 observations. The period covered by the study was mainly determined by Equity Market Volatility in Infectious Disease Index (EMV-IDI); an important variable in the model which only became available from August 7, 2015. Other variables considered are three cryptocurrencies, namely; Bitcoin, Ethereum and Ripple, and a novel Global Fear Index (GFI). The EMV-IDI was obtained from the Federal Reserve Bank of St. Louis (FRED), cryptocurrency data were from coinmarketcap.com, and GFI was obtained from Salisu and Akanni (2020). Cryptocurrencies are expressed in US dollar, while GFI and EMV-IDI are indexes.

The results presented here are descriptive statistics (as illustrated in Table 1), unit root test (Table 2), persistence and endogeneity test (Table 3) and graphical illustrations (see Figure 1). These results will serve as a precursor to the main result and a justification for the adoption of the estimator (Westerlund and Narayan 2012; 2015) used in its analysis, which can be seen in equation (1). The results are segmented into 3 separate periods, pre-COVID – representing the period before the announcement of COVID-19 pandemic, post-COVID – representing the period after the announcement of the pandemic and full sample – an amalgamation of both periods. The scope of the data ranged from 07/08/2015 to 27/06/2020.

The cryptocurrency market appears to be volatile as shown in Figure 1 with Ethereum being the most volatile across the three data samples, judging by the standard deviation value in Table 1. The results of descriptive statistics in Table 1 further reveal that uncertainty due to pandemics became higher (32.41) in the post COVID-19 pandemic announcement as compared to pre-COVID-19 period (0.468). This is in consonance with the findings of Baker et al., 2020; Salisu et al., 2020 and Zhang et al., 2020, which stated that pandemics raise financial market volatility higher than those experienced during the global final crisis (GFC). All the cryptocurrencies recorded negative returns and became more volatile, with the exception of Ethereum. This is evident from the standard deviation result. The full sample result also show high volatility in both EMV-IDI and price returns. Results from diagnostic tests suggest the presence of autocorrelation and heteroscedasticity in both the predictor and predicted variable, especially for the full and pre-COVID samples.

Table 1: Summary statistics and residual based tests

Sample Period	Statistics		EMV_IDI	Bitcoin	Ethereum	Ripple
	Mean		2.96	0.19	0.25	0.17
	Standard deviation		10.31	4.03	7.06	6.71
	Autocorrelation	$k=2$	122.35***	0.91	3.14	26.87***
		$k=4$	126.51***	1.10	5.74	30.22***
full sample		$k=6$	129.72***	5.90	5.90	36.51***
	Heteroscedasticity	$k=2$	121.80***	7.81***	51.85***	86.42***
		$k=4$	63.27***	6.24***	33.22***	43.62***
		$k=6$	49.23***	4.70***	18.86***	29.01***
	Observations		1786	1786	1786	1786
	Mean		0.47	0.24	0.27	0.21
	Standard deviation		0.85	3.56	7.08	6.83
	Autocorrelation	$k=2$	17.13***	0.28	1.89	25.36***
		$k=4$	77.35***	0.45	8.60*	29.30***
Pre-COVID		$k=6$	86.79***	7.97	8.62	35.41***
	Heteroscedasticity	$k=2$	48.43***	22.38***	97.59***	83.61***
		$k=4$	101.74***	10.96***	60.91***	42.24***
		$k=6$	70.51***	11.38***	33.28***	28.09***
	Observations		1477	1477	1646	1646
	Mean		32.41	-0.08	-0.34	-0.02
	Standard deviation		20.49	5.48	5.17	6.83
	Autocorrelation	$k=2$	1.99	0.91	0.06	0.31
		$k=4$	2.94	0.08	13.17***	12.19**
Post-COVID		$k=6$	3.19	6.73	13.23**	12.24*
	Heteroscedasticity	$k=2$	1.88	0.03	0.004	0.02
		$k=4$	1.57	0.08	0.52	0.50
		$k=6$	1.33	0.06	0.35	0.34
	Observations		139	139	139	139

Note: Std is standard deviation. The the ARCH-LM test F-statistics are reported for the heteroscedasticity tests while the Ljung-Box test Q-statistics for the serial correlation test. We consider three different lag lengths (k) of 2, 4, and 6 for robustness. The null hypothesis for the autocorrelation test is that there is no serial correlation, while the null for the ARCH-LM (F distributed) test is that there is no conditional heteroscedasticity. ***, ** & * imply the rejection of the null hypothesis in both cases at 1% , 5% & 10% levels of significance, respectively.

In Table 2, the results show that price returns are largely stationary at level, as revealed by the Augmented Dickey-Fuller stationarity test. Hence, non-stationarity may not be an issue in the estimation; although, the EMV-IDI is mixed order. Therefore, given the evidences of autocorrelation and heteroscedasticity established in Table 1, the results in Table 3 suggest that while persistence may be a source of concern in the modelling, the evidences for endogeneity bias are not compelling.

Table 2: Unit root tests' results

		EMV-IDI	Bitcoin	Ethereum	Ripple
full sample	Level	-	-43.402***	-45.490***	-26.667***
	FD	-24.379***	-	-	-
	$I(d)$	$I(1)$	$I(0)$	$I(0)$	$I(0)$
Pre-COVID	Level	-13.407***	-39.173***	-43.336***	-25.445***
	FD	-	-	-	-
	$I(d)$	$I(0)$	$I(0)$	$I(0)$	$I(0)$
Post- COVID	level		-13.988***	-14.145***	-14.1056***
	FD	-6.63201***	-	-	-
	$I(d)$	$I(1)$	$I(0)$	$I(0)$	$I(0)$

Note: ADF test is the Augmented Dickey Fuller test. While FD denotes First Difference, *** indicates the rejection of the null hypothesis of a unit root at 1% - the cases where $t_{cal} < t_{crit.}$ at 0.01 level of significance. The test regression for all the unit root tests includes intercept and trend; $I(d)$ implies the order of integration, where d is the number of differencing required for a series to become stationary; All the variables are in their log forms.

Table 3: Persistence and Endogeneity test results

	Persistence test results		
	Full Sample	**Pre-COVID**	**Post-COVID**
EMV-IDI	0.870***	0.254***	0.585 ***
	Endogeneity test results		
Bitcoin	-0.020	-0.055	-0.014
Ethereum	-0.020	0.329	-0.007
Ripple	-0.017	-0.036	-0.028

Note: ***, **, & * indicate statistical significance of coefficients at 1%, 5%, and 10% levels, respectively

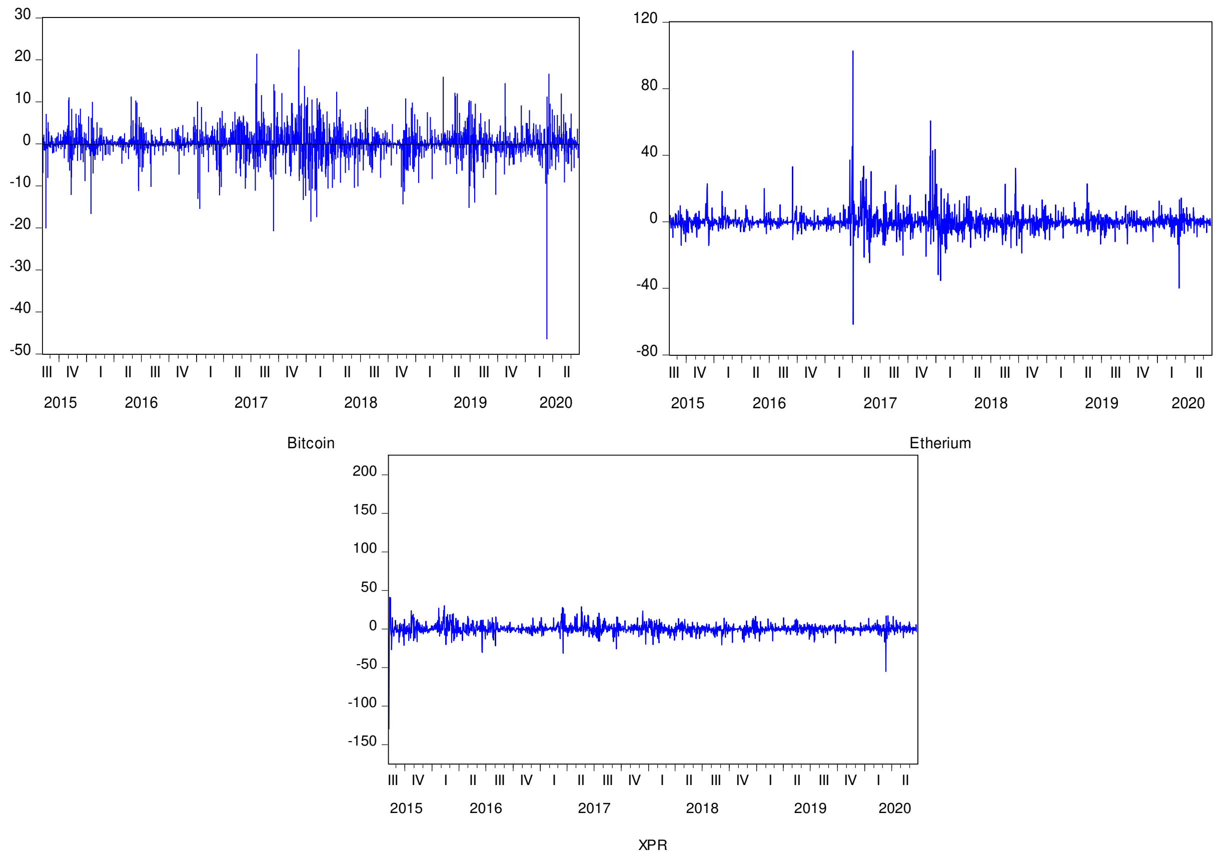

Fig. 1: Trends in price returns for the 3 top performing crypto currencies

3. Methodology

As noted earlier, the main objective of this study is to examine the vulnerability or hedging potential of cryptocurrency market in the face of uncertainties due to pandemics as measured using the new datasets by Baker et al. (2020) and a complementary dataset by Salisu and Akanni (2020). Thus, we construct a predictive model for this purpose while also accounting for the salient features of the series in question by following the approach of Westlerlund and Narayan (2012, 2015).[6] Essentially, our model estimation proceeds as follows: first, we test for the presence of endogeneity and conditional heteroscedasticity to ascertain the most appropriate structure for our predictive model (see also Bannigidadmath & Narayan, 2015; Narayan & Gupta, 2015; Phan et al., 2015; Narayan et al., 2016, Devpura et al., 2018; Narayan et al, 2018; Salisu et al., 2018; Salisu et al.,

[6] One of the attractions to this technique lies in its ability to isolate the predictor(s) of interest in the estimation and predictability analyses; thus, circumventing parameter proliferation. In essence, the technique helps to limit the predictability analyses to the predictor(s) of interest, while it also simultaneously resolves any inherent bias (see Westerlund and Narayan, 2012, 2015; for the theoretical expositions; and also Narayan and Gupta, 2015; Narayan, Phan, Sharma, 2018; Salisu et al., 2019; among others for recent applications).

2019a,b,c,d&e; among others); second, the predictive model is specified in a distributed lag model[7] accommodating up to five lags in order to account for day-of-the-week effect typical of most financial series available at high (daily) frequencies (see also Zhang et al., 2017; Yaya and Ogbonna, 2019; Salisu and Vo, 2020); third, the distributed lag model is pre-weighted with the inverse of the standard deviation of the residuals $\left(\hat{\sigma}_{\varepsilon}\right)$ in order to account for conditional heteroscedasticity effect, a prominent feature of most high frequency series. The $\hat{\sigma}_{\varepsilon}$ is obtained from an autoregressive conditional heteroscedastic (ARCH) structure - $\hat{\sigma}_{\varepsilon,t}^{2}=\varpi+\sum_{j=1}^{q}\hat{\varepsilon}_{t-j}^{2}$ in order to exploit additional information contained in the conditional heteroscedastic effect for improved predictability. The model is as given in equation (1)

$$r_t=\alpha+\sum_{i=1}^{k}\beta_i EMV_{t-i}+\gamma\left(EMV_t-EMV_{t-1}\right)+\varepsilon_t \tag{1}$$

where $r_t=\ln\left(P_t/P_{t-1}\right)$ is the returns on cryptocurrency prices P_t at time t; α is the model's constant term; EMV_{t-j} is the i^{th} lag of the model predictor variable - equity market volatility in infectious disease index, with $i=1,2,\ldots,k$ and $k=5$; and ε_t is the error term. The additional term $\gamma\left(EMV_t-EMV_{t-1}\right)$ corrects for any endogeneity bias resulting from the correlation between EMV and ε_t, as well as any inherent unit root problem in the predictor series.

For the purpose of testing asymmetry effect, EMV_{t-j} is decomposed into positive and negative partial sums, which are respectively defined as $EMV_t^{+}=\sum_{j=1}^{t}\Delta EMV_j^{+}=\sum_{j=1}^{t}\max\left(\Delta EMV_j,0\right)$ and $EMV_t^{-}=\sum_{j=1}^{t}\Delta EMV_j^{-}=\sum_{j=1}^{t}\min\left(\Delta EMV_j,0\right)$ (see also, Narayan & Gupta, 2015; Salisu et al., a,b,c,d&e; Salisu, Ogbonna and Adewuyi, 2020). The model postulates the lags of the equity market volatility in infectious disease index as predictors of cryptocurrency returns. Consequently, while we examine the statistical significance of the individual lags, we consider the joint

[7] This model does not include an autoregressive part. The inclusion of the lagged dependent variable is likely to crowd out the effect of equity market volatility infectious disease index (EMV-IDI) in the prediction of cryptocurrency returns.

predictability of these lags, under the null hypothesis of no predictability using the Wald test statistic. Essentially, the joint significance to be tested is $\sum_{j=1}^{k}\beta_j = 0$, such that a rejection of the test statistic would imply no joint significance of the lags of EMV-IDI. We expect a positive relationship a priori between cryptocurrency returns and EMV-IDI, given that the former could serve as a safe haven for investors in the equity market.

Also, in a bid to account for plausible time-dependent parameters, we adopt the rolling window approach rather than the fixed window approach to forecast selected cryptocurreny returns. For the purpose of comparison, we also estimate a historical average model as a benchmark model, which regresses the cryptocurrency returns on constant only. Consequently, we compare the forecast performance of our predictive model with the benchmark historical average model using Clark and West [CW] (2007) test - a pairwise comparison test that is suitable when contending models are nested. Clark and West (2007) framework provides a basis for testing whether the difference between the forecast errors of two contending models is statistically different from zero. For a given pair of forecast errors from a corresponding pair of contending models, the CW estimation equation is given in (2):

$$\hat{f}_{t+h} = \left(r_{t+h} - \hat{r}_{1t,t+h}\right)^2 - \left[\left(r_{t+h} - \hat{r}_{2t,t+h}\right)^2 - \left(\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h}\right)^2\right] \tag{2}$$

where h is the forecast period; $\left(r_{t+h} - \hat{r}_{1t,t+h}\right)^2$ and $\left(r_{t+h} - \hat{r}_{2t,t+h}\right)^2$ are the squared errors for the restricted (historical average) and unrestricted (our distributed lag predictive) models, respectively; while $\left(\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h}\right)^2$ is the adjusted squared error that CW test incorporates as a corrective measure for any noise associated with the forecast of the larger model. The sample average of $\hat{f}_{t+h}$ is defined as $MSE_1 - \left(MSE_2 - adj.\right)$, where $MSE_1 = P^{-1}\sum\left(r_{t+h} - \hat{r}_{1t,t+h}\right)^2$, $MSE_2 = P^{-1}\sum\left(r_{t+h} - \hat{r}_{2t,t+h}\right)^2$, $adj. = P^{-1}\sum\left(\hat{r}_{1t,t+h} - \hat{r}_{2t,t+h}\right)^2$ and P indicates the number of forecasts that is to be averaged. Regressing $\hat{f}_{t+h}$ on a constant and comparing the obtained t-statistic with the conventional critical values gives an indication of the equality, or otherwise, of the forecast errors of the paired contending models. Significant t-statistic implies that the unrestricted model performs better than the restricted model. In the context of asymmetry, significance would implies the presence of asymmetry effect.

4. Results and Discussion

In this section, we present and discuss the empirical results from this study. Firstly, we discuss results about the relationship between financial uncertainties due to pandemics and the performance of crytocurrencies. Secondly, as earlier studies have identified possible asymmetry in the impact of financial (good and bad) news (see Salisu and Oloko, 2015), we examine the role of asymmetry in the relationship financial uncertainties due to pandemics and the performance of crytocurrencies. Thirdly, we present and discuss results about the role of financial uncertainty due to pandemics in forecasting the performance of crypocurrencies. Lastly, and for and sensitivity analysis, we discuss results for the behaviour and forecast performance of cryptocurrencies in the light of a recently developed measure of pandemic; the global fear index by Salisu and Akanni (2020).

4.1 Does uncertainty due to pandemics affect cryptocurrencies?

As evident from previous studies on the relationship between cryptocurrencies and uncertainties, the relationship between crytocurrencies and uncertainty due to pandemics can be defined in terms of the hedging and safe haven quality of cryptocurrencies (see Bouri et al., 2018; Wu et al. 2019). More explicitly, in the period of high uncertainties such as during COVID-19, cryptocurrencies are assessed based on their safe haven quality, and are assessed in terms of their hedging quality in the period of relative tranquility (see Stensås et al. 2019; Lahmiri and Bekiros, 2020). Thus, the relationship between cryptocurrencies and uncertainties due to pandemic would be interpreted in terms of hedging quality under the full sample and pre-COVID-19 period, and interpreted in terms of safe haven under the COVID-19 period. A positive and significant relationship between uncertainty and cryptocurrency implies that cryptocurrency is a good hedge or safe haven, as high uncertainty is correlated with high cryptocurrency returns.

Table 4 presents the results for the predictability of pandemic-induced uncertainties for cryptocurrencies. The optimal lags of 5 period (days) on the equity market volatility infectious disease in infectious disease index (EMV-IDI), used as the measure of pandemic-induced uncertainty, was determined using Akaike Information Criterion (AIC) and the difference between

EMV-IDI and its immediate lag period was included to capture the effect of persistence in the model. The summary responses of cryptocurrencies to pandemic-induced uncertainties are determined by the Wald statistic for joint test of statistical significance of the lagged explanatory variables. As evident from the joint significance statistics, the result overtly shows that equity market volatility in infectious disease index has positive and statistically significant impact on cryptocurrencies. In other words, cryptocurrencies respond positively and statistically significantly to changes in equity market volatility in infectious disease index. This suggests that cryptocurrencies act as hedge against uncertainty due to pandemics.

Table 4: Results for the Predictability of Cryptocurrencies by Uncertainties due to Pandemics

Variable	Full	Pre-COVID-19	Post-COVID-19
		Bitcoin	
C	0.2097*** [0.0092]	0.1666*** [0.0026]	-0.5553*** [0.1692]
$EMV(-1)$	0.1252*** [0.0105]	0.0119 [0.0081]	0.0139*** [0.0029]
$EMV(-2)$	-0.0332*** [0.0017]	0.0925*** [0.0036]	-0.0241*** [0.0029]
$EMV(-3)$	-0.0119** [0.0049]	-0.0928*** [0.0032]	0.0056 [0.0039]
$EMV(-4)$	0.0006 [0.0014]	-0.1102*** [0.0052]	0.0507*** [0.0054]
$EMV(-5)$	-0.0530*** [0.0015]	0.1990*** [0.0036]	-0.0224*** [0.0032]
$EMV-EMV(-1)$	0.0290*** [0.0009]	0.0432*** [0.0025]	-0.0282*** [0.0021]
Joint Significance	0.0278*** [0.0037]	0.1003*** [0.0062]	0.0237*** [0.0051]
		Ethereum	
C	0.0942*** [0.0032]	-0.1273*** [0.0174]	0.1297 [0.1991]
$EMV(-1)$	0.0653*** [0.0035]	0.2362*** [0.0375]	0.0577*** [0.0063]
$EMV(-2)$	-0.0017 [0.0048]	0.3013*** [0.0231]	0.0038 [0.0071]
$EMV(-3)$	0.0040 [0.0037]	0.0317** [0.0146]	-0.0076 [0.0081]
$EMV(-4)$	-0.0009 [0.0024]	-0.0206 [0.0304]	-0.0104** [0.0044]
$EMV(-5)$	-0.0357*** [0.0016]	0.0830*** [0.0132]	-0.0253*** [0.0046]
$EMV-EMV(-1)$	-0.0362*** [0.0027]	0.1264*** [0.0239]	-0.0661*** [0.0040]
Joint Significance	0.0311*** [0.0021]	0.6316*** [0.0462]	0.0181*** [0.0051]
		Ripple	
C	-0.2517*** [0.0027]	-0.4133*** [0.0197]	-1.9545*** [0.0771]
$EMV(-1)$	0.0226*** [0.0030]	0.3039*** [0.0307]	0.0580*** [0.0061]
$EMV(-2)$	0.0097* [0.0052]	0.1066*** [0.0114]	0.0044 [0.0056]
$EMV(-3)$	-0.0106*** [0.0033]	-0.0535*** [0.0141]	0.0065 [0.0068]
$EMV(-4)$	0.0074*** [0.0028]	0.1217*** [0.0098]	-0.0032 [0.0073]
$EMV(-5)$	-0.0085** [0.0042]	0.0998*** [0.0127]	0.0029 [0.0022]
$EMV-EMV(-1)$	-0.0489*** [0.0017]	0.2551*** [0.0248]	-0.0200*** [0.0073]
Joint Significance	0.0205*** [0.0018]	0.5785*** [0.0428]	0.0685*** [0.0050]

Note: Under each panel, the last row labelled Joint significance is the summed coefficients of the lags of the independent variable and Wald statistic determined significance. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Figures in square brackets are the corresponding standard error of the estimated.

Specifically, Bitcon, Ethereum and Ripple provide a good hedge against uncertainty due to pandemics under the full sample, pre-COVID-19 and post-COVID-19 periods. Meanwhile, in the pre-COVID-19 period that is characterized by relatively low (tranquility) uncertainty effect of pandemic, Ethereum appears to have stronger hedging potential than Bitcon and Ripple. This partly supports the finding by Wu et al. (2019), who find that Bitcoin acts as weak hedge against economic policy uncertainty. For all the cryptocurrencies, the joint coefficients of the lags of EMV are positive and significant, which implies that crypocurrencies act as safe haven during the COVID-19 pandemic. However, the result shows that their degree of safe haven potential declined during the COVID-19 period relative to the pre-COVID-19 period; suggesting that the COVID-19 pandemic weakens the safe haven potential of crypocurrencies. This result is consistent with the finding by Ji et al. (2020) and Lahmiri and Bekiros (2020), which indicate that the safe haven roles of most assets including cryptocurrencies have become less effective. The result appears to place in-between the far right studies like Mnif et al. (2020) and Goodell and Goutte (2020), which concludes that COVID-19 has positive impact on the efficiency of the cryptocurrency market, and the far left studies like Conlon and McGee (2020) and Corbet et al. (2020), which find that cryptocurrency do not act as safe-haven during COVID-19.

4.2 Does asymmetry have a role to play in the nexus?

In examining the role of asymmetry, we investigate responses of crytocurrencies to positive and negative uncertainties due to pandemic. The objective is to determine whether cryptocurrencies respond symmetrically to same unit of good and bad uncertainties. Empirical result for this analysis is presented in Table 5. The result shows overly significant asymmetric responses of cryptocurrencies to uncertainty due to pandemic, under the full sample, pre-COVID-19 and post-COVID-19 periods. The exception only applies to Bitcoin in the post-COVID-19 period, where positive and negative uncertainties due to COVID-19 have symmetric effect on Bitcoin returns. More so, under the full sample period, cryptocurrencies respond positively to negative uncertainty due to pandemic, while it responds negatively to positive uncertainty due to pandemic. This implies that crypocurrencies act as a hedge against negative uncertainty due to pandemic, but reduce in returns in the face of positive uncertainty due to pandemic.

This result appears plausible as investors would mostly be expected to explore the hedging quality of cryptocurrencies in the face of negative uncertainty due to pandemic. In this case, pandemic leads to improvement in equity market performance as suggested by positive uncertainty due to pandemic, investors would have to take short position in crytocurrency market and long position in equity market; thus making cryptocurrency prices and returns to fall. The result in the pre-COVID-19 period is similar to that obtained under the full sample analysis for all considered cryptocurrencies except Ripple, which responds positively to positive uncertainty due to pandemic and negatively to negative uncertainty due to pandemic.

Table 5: Asymmetry and the Predictability of Cryptocurrencies by Uncertainties due to Pandemics

Variable	Full		Pre-COVID-19		Post-COVID-19	
	Positive	Negative	Positive	Negative	Positive	Negative
			Bitcoin			
C	0.4712*** [0.0183]	0.3146*** [0.0039]	0.3507*** [0.0131]	0.2847*** [0.0094]	-1.3221*** [0.2795]	-1.6567*** [0.1148]
$EMV(-1)$	0.1696*** [0.0163]	0.0711*** [0.0008]	0.0272 [0.0189]	-0.0960*** [0.0127]	0.0343*** [0.0055]	0.0387*** [0.0049]
$EMV(-2)$	-0.1161*** [0.0171]	-0.0855*** [0.0015]	0.1139*** [0.0235]	0.1965*** [0.0188]	-0.0208*** [0.0048]	-0.0845*** [0.0018]
$EMV(-3)$	0.0043 [0.0082]	-0.0246*** [0.0015]	-0.1444*** [0.0097]	-0.1402*** [0.0267]	0.0184** [0.0078]	-0.0195*** [0.0033]
$EMV(-4)$	0.0012 [0.0067]	0.0645*** [0.0016]	-0.1607*** [0.0071]	-0.1894*** [0.0251]	0.0551*** [0.0060]	0.0640*** [0.0049]
$EMV(-5)$	-0.0606*** [0.0052]	-0.0250*** [0.0002]	0.1634*** [0.0065]	0.2296*** [0.0086]	-0.0860*** [0.0057]	-0.0006 [0.0011]
$EMV-EMV(-1)$	0.0646*** [0.0083]	-0.1410*** [0.0003]	-0.0155* [0.0093]	0.0428*** [0.0126]	0.0178*** [0.0046]	-0.0956*** [0.0118]
Joint Significance	-0.0016*** [0.0001]	0.0006*** [0.0000]	-0.0005*** [0.0000]	0.0005*** [0.0000]	0.0009*** [0.0002]	0.0009*** [0.0002]
			Ethereum			
C	0.3562*** [0.0126]	0.3136*** [0.0147]	0.1042*** [0.0177]	0.1014*** [0.0086]	1.0619*** [0.2463]	0.4316** [0.1736]
$EMV(-1)$	0.1085*** [0.0127]	0.0140*** [0.0027]	0.3660*** [0.0312]	-0.4977*** [0.0374]	0.1371*** [0.0064]	0.0164*** [0.0036]
$EMV(-2)$	-0.0110 [0.0179]	-0.0841*** [0.0147]	0.0606* [0.0317]	0.3433*** [0.0396]	-0.1244*** [0.0207]	-0.0076 [0.0047]
$EMV(-3)$	0.0271 [0.0196]	0.0424*** [0.0152]	-0.1837*** [0.0114]	0.0651*** [0.0115]	0.0862*** [0.0269]	0.0168*** [0.0041]
$EMV(-4)$	-0.0980*** [0.0141]	0.0112 [0.0147]	-0.3686*** [0.0106]	-0.1307* [0.0765]	-0.0831*** [0.0188]	-0.0970*** [0.0105]
$EMV(-5)$	-0.0278*** [0.0059]	0.0174 [0.0124]	0.1248*** [0.0076]	0.2210*** [0.0763]	-0.0185 [0.0145]	0.0723*** [0.0108]
$EMV-EMV(-1)$	-0.0038 [0.0058]	-0.1439*** [0.0079]	0.0144 [0.0122]	-0.1910*** [0.0136]	-0.0170 [0.0126]	-0.1354*** [0.0070]
Joint Significance	-0.0012*** [0.0001]	0.0008*** [0.0001]	-0.0008*** [0.0000]	0.0009*** [0.0000]	-0.0027*** [0.0002]	0.0010*** [0.0003]
			Ripple			
C	-0.2167*** [0.0072]	-0.1790*** [0.0126]	-0.3842*** [0.0278]	-0.3528*** [0.0272]	1.3951*** [0.0434]	-1.9068*** [0.2833]
$EMV(-1)$	0.0521*** [0.0102]	0.0155*** [0.0035]	0.0464*** [0.0155]	-0.1143*** [0.0225]	0.0659*** [0.0074]	-0.0176** [0.0087]
$EMV(-2)$	0.0152 [0.0172]	-0.0106*** [0.0024]	0.1925*** [0.0411]	0.0690*** [0.0230]	-0.0362*** [0.0111]	0.0098 [0.0077]
$EMV(-3)$	-0.0467*** [0.0138]	-0.0279*** [0.0024]	-0.2314*** [0.0408]	-0.1048*** [0.0247]	0.0101 [0.0110]	-0.0195*** [0.0050]
$EMV(-4)$	-0.0122 [0.0082]	0.0242*** [0.0012]	0.1153*** [0.0294]	-0.1004** [0.0400]	-0.0386*** [0.0119]	-0.0034 [0.0064]
$EMV(-5)$	-0.0084 [0.0067]	-0.0010 [0.0015]	-0.1224*** [0.0272]	0.2501*** [0.0397]	-0.0043 [0.0089]	0.0296*** [0.0051]
$EMV-EMV(-1)$	-0.0103 [0.0096]	-0.1042*** [0.0076]	0.0527*** [0.0036]	0.0173 [0.0142]	-0.0056 [0.0034]	-0.1550*** [0.0178]
Joint Significance	-0.0001*** [0.0000]	0.0003*** [0.0001]	0.0004*** [0.0001]	-0.0003*** [0.0001]	-0.0031*** [0.0001]	-0.0010*** [0.0004]

Note: Under each panel, the last row labelled Joint significance is the summed coefficients of the lags of the independent variable and Wald statistic determined significance. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Figures in square brackets are the corresponding standard error of the estimated.

In the COVID-19 era however, the responses of the three crypocurrencies considered are different. Specifically, Bitcoin responds symmetrically to changes in positive and negative uncertainties due to pandemic. This happens as the coefficients of the responses of Bitcoin to positive and negative uncertainty due to pandemic are the same. This implies that Bitcoin unconditionally provides weak safe haven against uncertainties during pandemic. This partly supports the finding by Goodell and Goutte (2020), which stated that COVID-19 causes a rise in Bitcoin prices. Meanwhile, the response of Ethereum during COVID-19 is consistent with its response under the full sample and the pre-COVID-19 periods; concluding that Ethereum acts as hedge against negative uncertainty due to pandemic, but may respond with lower returns to positive uncertainty due to pandemic. This suggests Ethereum may not act as a good hedge against uncertainty in the period of pandemic where equity market improves during pandemic. For Ripple in the COVID-19 era, the result shows that it does not provide a good hedge against uncertainty in the period of relatively high uncertainty due to pandemic. As some distinct results are obtained after accounting for the role of asymmetry, it indicates that failure to account for the role of asymmetry would lead to incorrect conclusion.

4.3 Does uncertainty due to pandemics improve cryptocurrencies forecasts?

Relying on our predictability model, we examine the in-sample and out-of-sample forecast performance of the cryptocurrency model using Clark and West (2007) approach. The Clark and West [CW] model was considered appropriate as our predictability model for crypocurrencies and the historical average model (considered as the baseline forecast model) are nested models (see also, Salisu et al. 2019a,b,c,d&e). Table 6a and 6b present the in-sample and out-of-sample Clark and West statistics for forecast evaluation of the linear and asymmetric model, respectively. As evident from the tables, the 5-day, 10-day and 20-day forecast horizons were considered for the out-of-sample forecasts. Considering the linear model in Table 6a, the result shows that equity market volatility pandemic index is not a good predictor of cryptocurrencies returns. This result is apparent in the pre-COVID-19 and post-COVID-19 period. But under the full sample, Ethereum was weakly predicted by pandemic-induced uncertainty in the in-sample and out-of-sample forecasts.

However, the forecast evaluation result from the asymmetric model presented in Table 6b shows clear improvement in the forecast performance of the predictive capacity of our proposed crypocurrency model. Although, it corroborates the linear model in explaining that pandemic-induced uncertainty does not predict cryptocurrency returns in COVID-19 period, it shows that uncertainty due to pandemic strongly predicts Ripple under the full sample, and more strongly in the pre-COVID-19 period. This result appears to conform to the finding by Salisu et al. (2017), which noted that oil price volatility impacts more on mid cap and small cap than large cap, Bitcoin and Ethereum have larger market capitalization than Ripple. It also suggests that Ripple is more exposed to uncertainty due to pandemic than Bitcoin and Ethereum.

Table 6a: In-sample and out-of-sample forecast evaluation from linear model

Cryptocurrency	$in-sample$	$h=5$	$h=10$	$h=20$
		Full		
Bitcoin	0.1378 [0.0894]	0.1388 [0.0892]	0.1325 [0.0888]	0.1432 [0.0902]
Ethereum	0.4007* [0.2242]	0.3904* [0.2235]	0.3815* [0.2224]	0.3927* [0.2210]
Ripple	0.4745 [0.5255]	0.4708 [0.5267]	0.4944 [0.5181]	0.5649 [0.5181]
		Pre-COVID-19		
Bitcoin	0.0977 [0.0832]	0.1023 [0.0829]	0.0977 [0.0824]	0.0938 [0.0815]
Ethereum	0.5066 [0.3080]	0.5076* [0.3063]	0.5002 [0.3045]	0.4218 [0.2765]
Ripple	0.2733 [0.3823]	0.2858 [0.3805]	0.2604 [0.3785]	0.2438 [0.3741]
		Post-COVID-19		
Bitcoin	2.2220 [5.6757]	2.1093 [5.3084]	2.3801 [4.9671]	2.4709 [4.3892]
Ethereum	3.1348 [7.3437]	2.7880 [6.8415]	2.6163 [6.3833]	2.2972 [5.6819]
Ripple	6.5760 [4.2064]	6.2213 [3.9309]	5.5113 [3.6979]	4.2341 [3.4105]

Note: ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Figures in square brackets are the corresponding standard error of the estimate.

Table 6b: In-sample and out-of-sample forecast evaluation from asymmetric model

Cryptocurrency	$in-sample$	$h=5$	$h=10$	$h=20$
		Full		
Bitcoin	0.0880 [0.0594]	0.0885 [0.0593]	0.0970 [0.0594]	0.0883 [0.0591]
Ethereum	0.0799 [0.2342]	0.1061 [0.2335]	0.1273 [0.2328]	0.1295 [0.2311]
Ripple	0.8763*** [0.2251]	0.8665*** [0.2246]	0.8516*** [0.2235]	0.8359*** [0.2240]
		Pre-COVID-19		
Bitcoin	0.1067 [0.0684]	0.1047 [0.0680]	0.1004 [0.0676]	0.0973 [0.0670]
Ethereum	-0.0165 [0.1621]	-0.0148 [0.1612]	-0.0138 [0.1602]	-0.0171 [0.1584]
Ripple	0.7147*** [0.1949]	0.7074*** [0.1937]	0.7018*** [0.1926]	0.6990*** [0.1903]
		Post-COVID-19		
Bitcoin	4.4236 [3.4771]	4.0634 [3.2405]	4.0250 [3.0244]	3.0112 [2.7627]
Ethereum	15.3044 [10.6452]	14.0465 [9.8983]	14.1414 [9.2751]	14.1592* [8.2265]
Ripple	8.3211 [6.0036]	7.8966 [5.5814]	7.4311 [5.2058]	6.2573 [4.6194]

Note: Significant statistics indicate that the negative asymmetry results are markedly different from the positive asymmetry. Figures in square brackets are the corresponding standard error of the estimated statistic, while ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively.

4.4 Are the results sensitive to alternative measures of uncertainty?

We examine the sensitive of the results of this study by considering an alternative measure of pandemic-induced uncertainty. The recently developed global fear index (GFI) by Salisu and Akanni (2020) was considered in this case. The GFI was constructed in respect of the COVID-19 pandemic; hence, the models comparison are focused on the post-COVID-19 period. Tables 7a and 7b present the cryptocurrencies predictability results with Global Fear Index under the linear and asymmetric uncertainty assumptions. Whereas, the in-sample and out-of-sample forecast evaluation results under the linear and asymmetric uncertainty assumptions are presented in Tables 8a and 8b.

From Table 7a, it can be observed that the signs of the lagged coefficients of GFI are mixture of positive and negative, but the joint coefficient for all the crytocurrencies are negative. This suggests that none of the selected crypocurrencies act as safe haven in the COVID-19 period. This result is different from the one obtained using EMV-IDI as the proxy for pandemic-induced uncertainty, where Bitcon, Ethereum and Ripple were found to act as hedge against uncertainty due to pandemics even in the COVID-19 periods. This suggests that the result is sensitive to the choice of the measure of uncertainty due to pandemics.

Table 7a: Cryptocurrencies Predictability Results with Global Fear Index (Linear)

Variable	Bitcoin	Ethereum	Ripple
C	1.4469 [1.0545]	5.1864*** [1.2195]	0.0936 [1.5482]
$GFI(-1)$	0.9353 [0.8763]	7.0790*** [1.3912]	-2.8667 [1.7537]
$GFI(-2)$	-1.9352 [1.2747]	-4.7352*** [0.9617]	-0.1819 [1.9732]
$GFI(-3)$	-1.9993 [1.3741]	-17.6112*** [0.8044]	-11.8478*** [1.0656]
$GFI(-4)$	-1.7267** [0.7422]	8.6425*** [1.4801]	7.0659*** [0.8646]
$GFI(-5)$	4.3730*** [1.3823]	5.4982*** [0.6202]	7.8250*** [1.4900]
$GFI-GFI(-1)$	-0.3376 [0.6729]	-2.0192*** [0.5643]	1.0197 [1.3256]
Joint Significance	-0.3529 [0.2631]	-1.1268*** [0.2818]	-0.0055 [0.3856]

Note: The last row labelled Joint significance is the summed coefficients of the lags of the independent variable and Wald statistic determined significance. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Figures in square brackets are the corresponding standard error of the estimated.

Meanwhile, accounting for the role of asymmetry (see Table 7b), the safe haven property of Bitcoin was restored, as it responds positively to positive (high) fear in the post-COVID-19 era, which is consistent with its result using EMV-IDI as proxy for uncertainty during pandemic. The result however suggests that Ethereum and Ripple would tend to act as safe havens when there is negative fear (high market confidence) in the post-COVID-19 period. Nonetheless, Table 7b summarizes that cryptocurrencies respond asymmetrically to changes in uncertainty due to pandemic (measured with GFI). While this is consistent with the conclusion obtained when EMV was used as proxy for pandemic-induced uncertainty in respect of Ethereum and Ripple, it varies for Bitcoin, which exhibits symmetric relationship with uncertainty due to pandemic (measured with EMV). This further suggests that the result is sensitive to the choice of the measure of uncertainty due to pandemics.

Table 7b: Cryptocurrencies Predictability Results with Global Fear Index (Asymmetry)

Variable	Bitcoin		Ethereum		Ripple	
	Positive	Negative	Positive	Negative	Positive	Negative
c	-0.9498^{***} [0.1881]	-1.7853^{***} [0.1580]	1.6615^{***} [0.4261]	0.4535^{*} [0.2394]	2.3517^{***} [0.2285]	2.1206^{***} [0.1719]
$GFI(-1)$	-0.8080^{*} [0.4659]	-1.5888 [1.1710]	10.8782^{***} [2.4774]	7.7552^{***} [1.6931]	-2.4572^{***} [0.1482]	0.1584 [1.4888]
$GFI(-2)$	0.9564 [0.6941]	-1.1775 [1.2567]	5.4359^{*} [2.8862]	2.4892^{*} [1.4689]	4.4674^{***} [0.2149]	3.7978^{**} [1.4751]
$GFI(-3)$	3.3515^{***} [0.7748]	3.8041^{***} [0.9130]	-24.4820^{***} [3.5432]	-24.3242^{***} [2.2864]	-4.1635^{***} [0.8518]	-6.9232^{***} [0.6684]
$GFI(-4)$	-3.3307^{***} [0.6490]	-5.3142^{***} [1.0356]	33.2960^{***} [4.4880]	-8.7247 [6.4881]	8.3380^{***} [1.4691]	-1.1594 [0.8478]
$GFI(-5)$	0.0941 [0.2106]	3.8951^{***} [1.4222]	-25.5061^{***} [3.0539]	22.8740^{***} [6.8892]	-6.6679^{***} [1.2355]	4.5562^{***} [0.6480]
$GFI-GFI(-1)$	-0.6672^{**} [0.2767]	-2.5292^{***} [0.3865]	-5.2575^{**} [2.1345]	7.2986^{***} [1.9231]	-0.7820^{*} [0.4083]	0.0997 [1.0944]
Joint Significanc e	0.2633^{***} [0.0489]	-0.3812^{***} [0.0271]	-0.3781^{***} [0.1089]	0.0695^{***} [0.0430]	-0.4831^{***} [0.0402]	0.4298^{***} [0.0324]

Note: Under each panel, the last row labelled Joint significance is the summed coefficients of the lags of the independent variable and Wald statistic determined significance. ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Figures in square brackets are the corresponding standard error of the estimated.

Furthermore, we evaluate the in-sample and out-of-sample forecast performance of the cryptocurrencies predictability model using GFI as proxy for pandemic-induced uncertainty. The results for the linear model and the asymmetric model are presented in Tables 8a and 8b, respectively. Apparently, Table 8a reveals that uncertainty due to pandemic (measure with GFI) is not a good predictor of cryptocurrencies. The result however improved after accounting for the role of asymmetry, as Table 8b shows that pandemic-induced uncertainty (measured with GFI) is not a good predictor of Ethereum both in the in-sample and out-of-sample. The non-predictability for Bitcoin and Ripple remained even after accounting for the role of asymmetry. Notably, the forecast evaluation results for cryptocurrencies using EMV-IDI as predictor suggests that uncertainty due to pandemic does not predict any of the selected cryptocurrencies return in COVID-19 period, which is at variance with the conclusion here (where GFI is used as proxy for uncertainty due to pandemic). This also indicates that the result is sensitive to the choice of the measure of uncertainty due to pandemics.

Table 8a: Cryptocurrencies Forecast Evaluation Result with Global Fear Index (Linear)

Cryptocurrency	$in-sample$	$h=5$	$h=10$	$h=20$
Bitcoin	0.8400 [1.2837]	0.8740 [1.1928]	0.8468 [1.1131]	0.9364 [0.9903]
Ethereum	1.3243 [4.1143]	1.2793 [3.8380]	1.5602 [3.5844]	1.6433 [3.1989]
Ripple	0.8449 [1.3040]	0.8024 [1.2157]	0.9197 [1.1373]	0.9282 [1.0104]

Note: ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. Figures in square brackets are the corresponding standard error of the estimated.

Table 8b: Cryptocurrencies Forecast Evaluation Result with Global Fear Index (Asymmetry)

Cryptocurrency	$in-sample$	$h=5$	$h=10$	$h=20$
Bitcoin	7.8019 [12.6768]	7.4640 [11.7618]	6.9383 [10.9689]	6.9580 [9.6900]
Ethereum	8.2753** [3.5323]	7.9939** [3.2818]	7.4332** [3.0684]	6.5768** [2.7200]
Ripple	1.9894 [2.1297]	1.8908 [1.9752]	2.0333 [1.8569]	1.5222 [1.6504]

Note: Significant statistics indicate that the negative asymmetry results are markedly different from the positive asymmetry. Figures in square brackets are the corresponding standard error of the estimated statistic, while ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively. The negative global fear index is compared with the positive variant under the null of no marked difference in the prediction of cryptocurrency returns. Significance implies evidence of asymmetry.

5. Conclusion

In this study, we examined the effect of pandemic-induced uncertainty on cryptocurrencies (specifically, Bitcoin, Ethereum and Ripple) over the period from August 7, 2015 to June 27, 2020. Our analysis is partitioned into full sample, pre-COVID-19 period and post-COVID-19 period. We employed predictability model by Westerlund and Narayan (2012, 2015), and thus examined the predictability of pandemic-induced uncertainty measure for three well traded cryptocurrencies and forecast performance of our predictive model. We examined the role of asymmetry in uncertainty and the sensitivity of the results to alternative measures of uncertainty due to pandemics using a recently developed Global Fear Index (GFI) by Salisu and Akanni (2020). Our results indicate that cryptocurrencies act as hedge against uncertainty due to pandemics, although with reduced degree of safe haven potential in the COVID-19 period. Accounting for asymmetry was found to improve the predictability and forecast performance of the model, which indicates that failure to account for asymmetry in modeling the effect of uncertainty due to pandemic on cryptocurrency may lead to incorrect conclusion. The results are found to be sensitive to the choice of measure of uncertainty due to pandemic.

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