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Pandemics and cryptocoins

Afees A. Salisu[a,b], **Ahamuefula E. Ogbonna**[a,c,*], **Tirimisiyu F. Oloko**[a,d]

[a] *Centre for Econometrics and Applied Research (CEAR), Ibadan, Nigeria*
[b] *Department of Economics, University of Pretoria, Hatfield, South Africa*
[c] *Department of Statistics, University of Ibadan, Ibadan, Nigeria*
[d] *Department of Economics, Fountain University, Osogbo, Nigeria*

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Abstract This study examines the effect of pandemic-induced uncertainty on cryptocoins (Bitcoin, Ethereum and Ripple). It employs the Westerlund and Narayan (2012, 2015) predictive model to examine the predictability of pandemic-induced uncertainty and our model's forecast performance. We examine the role of asymmetry in uncertainty and the sensitivity of our results to the recently-developed Salisu and Akanni (2020) Global Fear Index. Cryptocoins act as a hedge against uncertainty due to pandemics, albeit with reduced hedging effectiveness in the COVID-19 period. Accounting for asymmetry improves predictability and model forecast performance. Our results may be sensitive to the choice of measure of pandemic-induced uncertainty.

The motivation

Ideally, when the economic atmosphere is characterised by uncertainties, like in the case of pandemics, investors are usually on the lookout for an alternative way to invest, as well as a better platform to hedge[1] their funds against any form of risk/uncertainty associated with other assets. It is important to stress that cryptocoins, which have been seen as new investment opportunities, are driven by investor sentiment just like other assets (Chuen, Guo, & Wang, 2017) and cryptocoins market efficiency (see Yaya, Ogbonna, & Olubusoye, 2019; Yaya, Ogbonna, Mudida, & Nuruddeen, 2020). More importantly, it is driven by 'expectations' similar to that of the stock market. However, unlike the traditional asset markets, there is no central regulator for cryptocoins (Bouri, Shahzad, & Roubaud, 2019; Jabotinsky & Sarel, 2020), and their values - measured by prices, have largely appreciated (Bouri et al., 2019). This has therefore made a number of studies conclude that they could be used as a speculative investment rather than a medium for storage and transaction (see for example, Baek & Elbeck, 2015; Baur, Hong, & Lee, 2018; Bouoiyour, Selmi, & Tiwari, 2015; Cheah & Fry, 2015; Ciaian, Rajcaniova, & Kancs, 2016; Goodell & Goutte, 2020; Yermack, 2015).

Moreover, cryptocoins such as Bitcoin are made and designed to be limited in supply, with about twenty-one million of them to be mined (Chuen et al., 2017; Hayes, 2020). Thus, when it is expected that cryptocoins, for example,

*Corresponding author.
E-mail address: ogbonnaephraim@yahoo.com (A.E. Ogbonna).

[1] In a financial asset – uncertainty measure nexus, Bouri et al. (2018) defined the hedge (safe haven) potential of a financial asset as the existence of a significant positive relationship in a period of low (high) uncertainty. Further definitions of hedge and safe haven, with respect to a pair of financial assets, are provided by Bouri et al. (2017) and Shahzad, Bouri, Roubaud, and Kristoufek (2019), wherein the relationship is expected to be significantly negative during the period of low (high) uncertainty.

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Bitcoin, would become an alternative investment 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 the stock market that is characterised by higher volatility to cryptocoins[2] 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 & Lucey, 2010; Chuen et al., 2017; Goodell & Goutte, 2020; Wong, Saerbeck, & Silva, 2018). A quick look at the trend of the cryptocoins trade since the inception of the novel coronavirus, especially when information about it was on the rise, till May;[3] there was a massive rise in the Bitcoin trade volume, and the same could also be said for their returns.[4] Studies such as Jabotinsky and Sarel (2020) and Mnif, Jarboui, and Mouakhar (2020) find that COVID-19 has a positive impact on the cryptocoins market efficiency.

Consequently, one may be tempted to assume that cryptocoins are not susceptible to pandemics. However, the hedge and safe haven advantage of cryptocoins during the periods clouded by uncertainties have been keenly contested in the literature; with some confirming it (for example, Baur & Lucey, 2010; Chuen et al., 2017; Dyhrberg, 2016; Fang, Bouri, Gupta, & Roubaud, 2019; Goodell & Goutte, 2020; Liu & Tsyvinski, 2018; Mnif, Jarboui, & Mouakhar, 2020; Salisu, Isah, & Akanni, 2019a; Stensås, Nygaard, Kyaw, & Treepongkaruna, 2019; Urquhart & Zhang, 2019; Wong et al., 2018,[5]), while others have established contrary evidence (for example, Baur & Hoang, 2021; Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017; Cheema, Szulczyk, & Bouri, 2020; Conlon & McGee, 2020; Klein, Thu, & Walther, 2018; Smales, 2019). Although, the results of these studies (except for a few such as Goodell & Goutte, 2020; Mnif, Jarboui, & Mouakhar, 2020) do not capture the vulnerability or otherwise of cryptocoins 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 utilise two new datasets on pandemics; one by Baker, Bloom, Davis, and Terry (2020) dataset which captures all the pandemics including COVID-19 and the other, which is a complementary dataset on COVID-19 developed by Salisu and Akanni (2020) using an alternative approach. The availability of these datasets at a high frequency is a major attraction.[6]

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 cryptocoins such as persistence, endogeneity and conditional heteroscedasticity (see also, Bannigidadmath & Narayan, 2016; Devpura, Narayan, & Sharma, 2018; Narayan & Gupta, 2015; Narayan, Phan, Sharma, & Westerlund, 2016; Phan, Sharma, & Narayan, 2015; Salisu, Ogbonna, & Omosebi, 2018; Salisu et al., 2019a; Salisu et al., 2019b; Salisu et al., 2019c; Salisu et al., 2019d; Salisu et al., 2019e; 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 cryptocoin 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 cryptocoins globally, namely,; Bitcoin (BTC), Ethereum (ETH) and Ripple (XRP), to offer some level of generalisation on the results. It is noteworthy to highlight some of the peculiarities of cryptocoins. Bitcoin is a digital currency and an alternative to fiat money that is based on blockchain technology and used for payment for goods and services. Ethereum, on the other hand, is also based on blockchain technology that only provides an alternative virtual currency, but does not coexist alongside extant fiat money. Ripple is another blockchain technology-based cryptocoin that uses a distributed consensus ledger comprising a network of validating servers and crypto tokens; and serves as a payment settling, currency exchange and remittance system intended for banks and payment networks. Essentially, while Bitcoin and Ethereum are mostly used for transactions with vendors that are willing to accept them, Ripple is used to facilitate money transfers between different currencies, in a similitude to the extant general use of the US dollars as a base currency for converting between other currencies.

Foreshadowing our results, cryptocoins were found to act as a hedge against uncertainty due to pandemics, although with a 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 modelling the effect of uncertainty due to pandemics on cryptocoins may lead to an incorrect conclusion. The results are found to be sensitive to the choice of measure of uncertainty due to pandemics.

Following the introductory section, the next section discusses data issues and also provides some preliminary analyses required for estimation; the third section deals with methodology; the fourth section deals with the discussion of results, while the final section concludes the paper.

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 on August 7, 2015. Other variables considered are three cryptocoins, 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), cryptocoin data were from coinmarketcap.com, and GFI was obtained from Salisu and

[2] See Jabotinsky and Sarel (2020).

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

[4] 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 investment) could also be associated with the United States government's decision to stimulate the stock market (see aljazeera.com for review).

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

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

Akanni (2020). Cryptocoins are expressed in the US dollar, while GFI and EMV-IDI are indexed.

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 Fig. 1). These results will serve as a precursor to the main result and a justification for the adoption of the estimator (Westerlund & Narayan, 2012; 2015) used in its analysis, which can be seen in Eq. (1). The results are segmented into 3 separate periods, pre-COVID – representing the period before the announcement of the COVID-19 pandemic, post-COVID – representing the period after the announcement of the pandemic and a full sample – an amalgamation of both periods. The scope of the data ranged from 07/08/2015 to 27/06/2020.

The cryptocoins market appears to be volatile as shown in Fig. 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 the pre-COVID-19 period (0.468). This is in consonance with the findings of Baker et al. (2020), Salisu, Ogbonna, and Adewuyi, (2020) and Zhang, Hu, and Ji, (2020), which stated that pandemics raise financial market volatility higher than those experienced during the global final crisis (GFC). All the cryptocoins 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 shows 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.

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 in mixed order. Therefore, given the evidence 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 evidence for endogeneity bias are not compelling.

Methodology

As noted earlier, the main objective of this study is to examine the vulnerability or hedging potential of the cryptocoins market in the face of uncertainties due to pandemics as measured

Table 1 Summary statistics and residual-based tests.

Sample Period	Statistics		EMV-IDI	Bitcoin	Ethereum	Ripple
Full sample	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***
		$k = 6$	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
Pre-COVID	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***
		$k = 6$	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
Post-COVID	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**
		$k = 6$	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 the standard deviation. 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. ***, ** and * imply the rejection of the null hypothesis in both cases at 1%, 5% and 10% levels of significance, respectively.

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.

	Full sample	Pre-COVID	Post-COVID
Persistence test results 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. ***, ** and * indicate statistical significance of coefficients at 1%, 5%, and 10% levels, respectively.

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).[7] 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, 2016; Devpura et al., 2018; Narayan & Gupta, 2015; Narayan et al., 2016, Narayan, Phan, & Sharma, 2019; Phan, Sharma, & Narayan, 2015; Salisu et al., 2018; Salisu et al., 2019a; Salisu et al., 2019b; Salisu et al., 2019c; Salisu et al., 2019d; Salisu et al., 2019e; among others); second, the predictive model is specified in a distributed lag model[8] accommodating up to five lags in order to account for the day-of-the-week effect typical of most financial series available at high (daily) frequencies (see also Salisu & Vo, 2020; Yaya & Ogbonna, 2019; Zhang, Lai, & Lin, 2017); third, the distributed lag model is pre-weighted with the inverse of the standard deviation of the residuals in order to account for conditional heteroscedasticity effect, a prominent feature of most high-frequency series. The $\widehat{\sigma}_{\varepsilon}$ is obtained from an autoregressive conditional heteroscedastic (ARCH) structure,

$$\widehat{\sigma}^2_{\varepsilon,t} = \varpi + \sum_{j=1}^{q} \widehat{\varepsilon}^2_{t-j}$$

in order to exploit additional information contained in the conditional heteroscedastic effect for improved predictability. The model is as given in Eq. (1)

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

where $r_t = \ln(P_t/P_{t-1})$ is the returns on cryptocoin 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 - EMV-IDI, with $i = 1, 2, \ldots, k$ and $k = 5$; and ε_t is the error term. The additional term $\gamma(EMV_t - EMV_{t-1})$ 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.

To test the asymmetry effect, EMV_{t-j} is decomposed into positive and negative partial sums, which are respectively defined as

$$EMV_t^+ = \sum_{j=1}^{t} \Delta EMV_j^+ = \sum_{j=1}^{t} \max(\Delta EMV_j, 0)$$

and

$$EMV_t^- = \sum_{j=1}^{t} \Delta EMV_j^- = \sum_{j=1}^{t} \min(\Delta EMV_j, 0)$$

(see also, Narayan & Gupta, 2015; Salisu et al., 2019a; Salisu et al., 2019b; Salisu et al., 2019c; Salisu et al., 2019d; Salisu et al., 2019e; Salisu, Ogbonna, & Adewuyi, 2020). The model postulates the lags of the EMV-IDI as predictors of cryptocoin returns. Consequently, while we examine the statistical

[7] One of the attractions of 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 & Narayan, 2012, 2015; for the theoretical expositions; and also Narayan & Gupta, 2015; Narayan, Phan, & Sharma, 2018; Salisu et al., 2019; among others for recent applications).

[8] This model does not include an autoregressive part. The inclusion of the lagged dependent variable is likely to crowd out the effect of EMV-IDI in the prediction of cryptocoin returns.

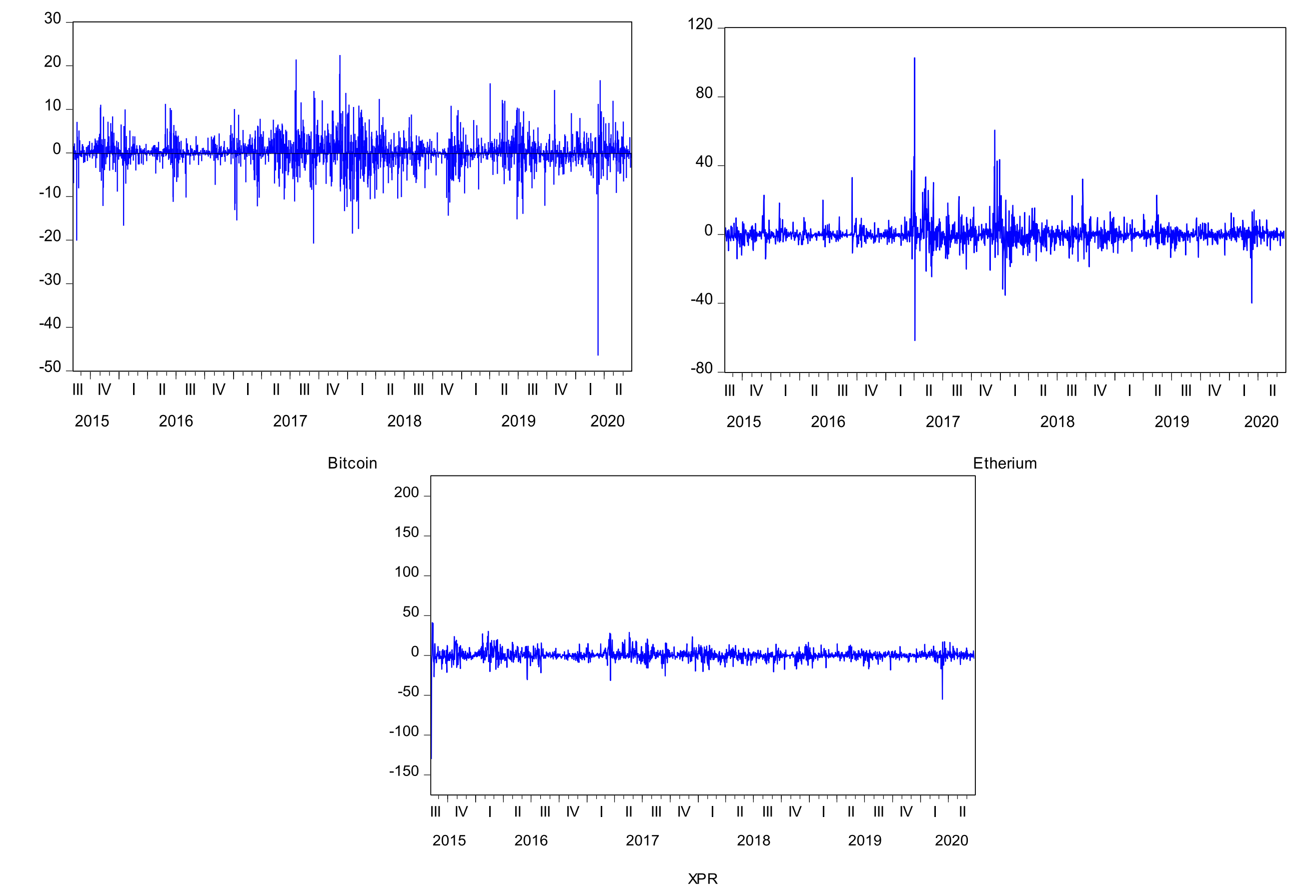

Fig. 1 Trends in price returns for the 3 top performing cryptocoins.

significance of the individual lags, we consider the joint 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 cryptocoin 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 cryptocoin returns. For the purpose of comparison, we also estimate a historical average model as a benchmark model, which regresses the cryptocoin returns on constant only. Consequently, we compare the forecast performance of our predictive model with the benchmark historical average model using the Clark and West (CW) (2007) test — a pairwise comparison test that is suitable when contending models are nested. The 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 Eq. (2):

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

where h is the forecast period; $\left(r_{t+h} - \widehat{r}_{1t,t+h}\right)^2$ and $\left(r_{t+h} - \widehat{r}_{2t,t+h}\right)^2$ are the squared errors for the restricted (historical average) and unrestricted (our distributed lag predictive) models, respectively; while $\left(\widehat{r}_{1t,t+h} - \widehat{r}_{2t,t+h}\right)^2$ is the adjusted squared error that the CW test incorporates as a corrective measure for any noise associated with the forecast of the larger model. The sample average of $\widehat{f}_{t+h}$ is defined as $MSE_1 - (MSE_2 - adj.)$, where $MSE_1 = P^{-1}\sum\left(r_{t+h} - \hat{r}_{1t,t+h}\right)^2$, $MSE_2 = P^{-1}\sum\left(r_{t+h} - \widehat{r}_{2t,t+h}\right)^2$, $adj. = P^{-1}\sum\left(\widehat{r}_{1t,t+h} - \widehat{r}_{2t,t+h}\right)^2$ and P indicates the number of forecasts that is to be averaged. Regressing $\widehat{f}_{t+h}$ 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, the significance would imply the presence of an asymmetry effect.

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 cryptocoins. Secondly, as earlier studies have identified possible asymmetry in the impact of financial (good and bad) news (see Salisu & Oloko, 2015), we examine the role of asymmetry in the relationship between financial uncertainties due to pandemics and the performance of cryptocoins. Thirdly, we present and discuss results about the role of financial uncertainty due to pandemics in forecasting the performance of cryptocoins. Lastly, and for sensitivity analysis, we discuss results for the behaviour and forecast performance of cryptocoins in the light of a recently developed measure of a pandemic; the GFI by Salisu and Akanni (2020).

Does uncertainty due to pandemics affect cryptocoins?

As evident from previous studies on the relationship between cryptocoins and uncertainties, the relationship between cryptocoins and uncertainty due to pandemics can be defined in terms of the hedging and safe haven quality of cryptocoins (see Bouri, Gupta, Lau, 2018; Wu, Tong, Yang, & Derbali, 2019). More explicitly, in the period of high uncertainties such as during COVID-19, cryptocoins are assessed based on their safe haven quality and are assessed in terms of their hedging quality in the period of relative tranquility (see Lahmiri & Bekiros, 2020; Stensås et al., 2019). Thus, the relationship between cryptocoins and uncertainties due to pandemics 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 cryptocoin implies that cryptocoin is a good hedge or safe haven, as high uncertainty is correlated with high cryptocoin returns.

Table 4 presents the results for the predictability of pandemic-induced uncertainties for cryptocoins. The optimal lags of 5 periods (days) on the 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 cryptocoins to pandemic-induced uncertainties are determined by the Wald statistic for the joint test of statistical significance of the lagged explanatory variables. As evident from the joint significance statistics, the result overtly shows that EMV-IDI has a positive and statistically significant impact on cryptocoins. In other words, cryptocoins respond positively and statistically significantly to changes in EMV-IDI. This suggests that cryptocoins act as a hedge against uncertainty due to pandemics.

Specifically, Bitcoin, 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 characterised by the relatively low (tranquility) uncertainty effect of the pandemic, Ethereum appears to have stronger hedging potential than Bitcoin and Ripple. This partly supports the finding by Wu et al. (2019), who find that Bitcoin acts as a weak hedge

Table 4 Results for the predictability of cryptocoins 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. Fig.s in square brackets are the corresponding standard error of the estimate.

against economic policy uncertainty. For all the cryptocoins, the joint coefficients of the lags of EMV are positive and significant, which implies that cryptocoins act as a 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 cryptocoins. This result is consistent with the findings by Ji, Zhang, and Zhao (2020) and Lahmiri and Bekiros (2020), which indicate that the safe haven roles of most assets including cryptocoins have become less effective. The result appears to place in between the far right studies like Mnif, Jarboui, and Mouakhar (2020) and Goodell and Goutte (2020), which concludes that COVID-19 has a positive impact on the efficiency of the cryptocoins market, and the far left studies like Conlon and McGee (2020) and Corbet, Larkin, and Lucey (2020), which find that cryptocoins do not act as safe-haven during COVID-19.

Does asymmetry have a role to play in the nexus?

In examining the role of asymmetry, we investigate the responses of cryptocoins to positive and negative uncertainties due to pandemics. The objective is to determine whether cryptocoins respond symmetrically to the same unit of good and bad uncertainties. The empirical result of this analysis is presented in Table 5. The result shows overly significant asymmetric responses of cryptocoins to uncertainty due to pandemics, 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 a symmetric effect on Bitcoin returns. More so, under the full sample period, cryptocoins respond positively to negative uncertainty due to pandemics, while it responds negatively to positive uncertainty due to pandemics. This implies that cryptocoins act as a hedge against negative uncertainty due to pandemics, but reduce returns in the face of positive uncertainty due to pandemics.

This result appears plausible as investors would mostly be expected to explore the hedging quality of cryptocoins in the face of negative uncertainty due to pandemics. In this case, the pandemic leads to improvement in equity market performance as suggested by positive uncertainty due to the pandemic, investors would have to take a short position in the cryptocoins market and a long position in the equity market; thus making cryptocoins 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 cryptocoins except Ripple, which responds positively to positive uncertainty due to the pandemic and negatively to negative uncertainty due to the pandemic.

In the COVID-19 era, however, the responses of the three cryptocoins considered are different. Specifically, Bitcoin responds symmetrically to changes in positive and negative uncertainties due to the pandemic. This happens as the coefficients of the responses of Bitcoin to positive and negative uncertainty due to the pandemic are the same. This implies that Bitcoin unconditionally provides a weak safe haven against uncertainties during the 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 a hedge against negative uncertainty due to the pandemic, but may respond with lower returns to positive uncertainty due to the pandemic. This suggests Ethereum may not act as a good hedge against uncertainty in the period of the pandemic when the equity market improves during a pandemic. For Ripple in the COVID-19 era, the result shows that it does not provide a good hedge against uncertainty in a period of relatively high uncertainty due to the 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 conclusions.

Does uncertainty due to pandemics improve cryptocoin forecasts?

Relying on our predictability model, we examine the in-sample and out-of-sample forecast performance of the cryptocoin model using Clark and West (2007) approach. The CW model was considered appropriate as our predictability model for cryptocoins and the historical average model (considered as the baseline forecast model) are nested models (see also, Salisu et al., 2019a; Salisu et al., 2019b; Salisu et al., 2019c; Salisu et al., 2019d; Salisu et al., 2019e). Table 6a and 6b present the in-sample and out-of-sample CW 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 the equity market volatility pandemic index is not a good predictor of cryptocoins returns. This result is apparent in the pre-COVID-19 and post-COVID-19 periods. However, under the full sample, Ethereum was weakly predicted by pandemic-induced uncertainty in the in-sample and out-of-sample forecasts.

The forecast evaluation result from the asymmetric model presented in Table 6b shows a clear improvement in the forecast performance of the predictive capacity of our proposed cryptocoin model. Although it corroborates the linear model in explaining that pandemic-induced uncertainty does not predict cryptocoin returns in the COVID-19 period, it shows that uncertainty due to the 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, Swaray, and Oloko (2017), which noted that oil price volatility impacts more on mid-cap and small-cap than large-cap, Bitcoin and Ethereum have larger market capitalisation than Ripple. It also suggests that Ripple is more exposed to uncertainty due to the pandemic than Bitcoin and Ethereum.

Are the results sensitive to alternative measures of uncertainty?

We examine the sensitivity of the results of this study by considering an alternative measure of pandemic-induced uncertainty. The recently developed GFI by Salisu and

Table 5 Asymmetry and the predictability of cryptocoins 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. Fig.s in square brackets are the corresponding standard error of the estimate.

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

Cryptocoin	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. Fig.s in square brackets are the corresponding standard error of the estimate.

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

Cryptocoin	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. Fig.s in square brackets are the corresponding standard error of the estimated statistic, while ***, ** and * denote statistical significance at 1%, 5% and 10%, respectively.

Akanni (2020) was considered in this case. The GFI was constructed in respect of the COVID-19 pandemic; hence, the model comparison is focused on the post-COVID-19 period. Table 7a and 7b present the cryptocoins predictability results with GFI 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 Table 8a and 8b.

From Table 7a, it can be observed that the signs of the lagged coefficients of GFI are a mixture of positive and negative, but the joint coefficient for all the cryptocoins are negative. This suggests that none of the selected cryptocoins act as a 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 Bitcoin, Ethereum and Ripple were found to act as a 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.

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 a proxy for the uncertainty during the 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 summarises that cryptocoins respond asymmetrically to changes in uncertainty due to the pandemic (measured with GFI). While this is consistent with the conclusion obtained when EMV was used as a proxy for pandemic-induced uncertainty in respect of Ethereum and Ripple, it varies for Bitcoin, which exhibits a symmetric relationship with uncertainty due to the pandemic (measured with EMV). This further suggests that the result is sensitive to the choice of the measure of uncertainty due to pandemics.

Furthermore, we evaluate the in-sample and out-of-sample forecast performance of the cryptocoins predictability

Table 7a Cryptocoins predictability results with GFI (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 estimate.

Table 7b (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 Significance	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 estimate.

model using GFI as a proxy for pandemic-induced uncertainty. The results for the linear model and the asymmetric model are presented in Table 8a and 8b, respectively. Apparently, Table 8a reveals that uncertainty due to pandemics (measured with GFI) is not a good predictor of cryptocoins. 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

Table 8a Cryptocoins forecast evaluation result with GFI (Linear).

Cryptocoin	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 estimate.

Table 8b Cryptocoins forecast evaluation result with GFI (Asymmetry).

Cryptocoin	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 GFI is compared with the positive variant under the null of no marked difference in the prediction of cryptocoin returns. Significance implies evidence of asymmetry.

after accounting for the role of asymmetry. Notably, the forecast evaluation results for cryptocoins using EMV-IDI as a predictor suggest that uncertainty due to pandemics does not predict any of the selected cryptocoins return in the COVID-19 period, which is at variance with the conclusion here (where GFI is used as a 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.

Conclusion

In this study, we examined the effect of pandemic-induced uncertainty on cryptocoins (specifically, Bitcoin, Ethereum and Ripple) over the period from August 7, 2015 to June 27, 2020. Our analysis is partitioned into the full sample, pre-COVID-19 period and post-COVID-19 period. We employed the predictability model by Westerlund and Narayan (2012, 2015), and thus examined the predictability of pandemic-induced uncertainty measure for three well-traded cryptocoins and the 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 GFI by Salisu and Akanni (2020). Our results indicate that cryptocoins act as a hedge against uncertainty due to pandemics, although with a 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 modelling the effect of uncertainty due to the pandemic on cryptocoin may lead to incorrect conclusions. The results are found to be sensitive to the choice of measure of uncertainty due to the pandemic.

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