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The return volatility of cryptocurrencies during the COVID-19 pandemic: Assessing the news effect

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ABSTRACT

In this paper, we test the role of news in the predictability of return volatility of digital currency market during the COVID-19 pandemic. We use hourly data for cryptocurrencies and daily data for the news indicator, thus, the GARCH MIDAS framework which allows for mixed data frequencies is adopted. We validate the presupposition that fear-induced news triggered by the COVID-19 pandemic increases the return volatilities of the cryptocurrencies compared with the period before the pandemic. We also establish that the predictive model that incorporates the news effects forecasts the return volatility better than the benchmark (historical average)model.

1. The motivation

The major contribution of the study lies in its comparative analysis of calm and crisis periods occasioned by the uncertainties from the announcement of COVID-19 as a pandemic. This announcement raised risk levels in major financial markets in Europe, America and Asia (Zhang, Hu, & Ji, 2020) and therefore, we expect volatility in the virtual currency market to be adversely affected. Previous experiences have shown that the return volatility of Bitcoins was found to increase during the global financial crisis (see Kumar & Anandarao, 2019). The study conducted by Flori (2019) on Bitcoin showed an upsurge in the ability of news to shape investors' views to drive the Bitcoin market dynamics during the 2007/2008 global financial crisis. In addition, recent literature on the financial crisis induced by the COVID-19 pandemic has shown that Bitcoin loses whatever hedging or safe haven roles it possesses in times of severe financial crises (see Conlon & McGee, 2020; Corbet, Larkin, & Lucey, 2020).

This study relies on the established linkage between financial news and speculative assets to study the predictability of cryptocurrencies return volatilities with G-trend data. There are a number of attractions to study the behaviour of cryptocurrencies. One, there is investment benefit for studying cryptocurrencies, given evidences of some potential diversification roles for cryptocurrencies in investment portfolios (see Bouri, Gupta, Tiwari, & Roubaud, 2017; Feng, Wang, & Zhang, 2018; Gil-Alana, Abakah, & Rojo, 2020; Omane-Adjepong & Alagidede, 2019; Tiwari, Jana, & Roubaud, 2019). Two, volatility persistence is a crucial feature of cryptocurrencies' markets and hence, the virtual currencies are by design volatile, in most cases, more than traditional financial assets like gold, fiat currencies, stocks, among others (see Chu, Stephen, Saralees, & Joerg, 2017; Fakhfekh & Jeribi, 2020; Kumar & Anandarao, 2019). The justification to study the return volatility of virtual currencies further lies in their distinctive feature of excess volatility,

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which endear them to function more like investment assets than currencies (see İçellioğlu & Öner, 2019; Yermack, 2013). This distinguishing characteristic of cryptocurrencies is not far-fetched. Unlike fiat money, cryptocurrencies are defenceless with no legal protection, no central authority nor regulatory framework to protect investors against investment risks (see Dibrova, 2016; Flori, 2019; İçellioğlu & Öner, 2019; Vasek & Moore, 2015).

Our resolve to undertake the predictability of return volatility of cryptocurrencies with G-trend data is informed by the extant findings showing that the distinct feature of excess volatility in the assets is influenced by news (see Bouoiyour & Selmi, 2015). In this vein, a growing body of literature seem to agree that investors' attention and trends measured by Google search volumes, Twitter tweets and other social media trends could possess predictive power for trading volume and volatility of cryptocurrencies, especially Bitcoins (see for example, Polasik, Piotrowska, Wisniewski, Kotkowski, & Lightfoot, 2015a, 2015b; Shen, Urquhart, & Wang, 2019; Dastgir, Demir, Downing, Gozgor, & Lau, 2019). More broadly, G-trends data, as an alternative indicator of investors' sentiments, has been employed for predicting financial assets (see for example, Bijl, Kringhaug, Molnár, & Sandvik, 2016; Da, Engelberg, & Gao, 2011; Nguyen, Schinckus, & Nguyen, 2019) based on the theoretical argument that Google search captures investors' attention and can be interpreted as a measure of investor's interest in a given asset (see Aouadi, Arouri, & Teulon, 2013; Bank, Larch, & Peter, 2011; Preis, Moat, & Stanley, 2013).

We explore the afore-stated objective for four digital currencies; namely Bitcoin, Ethereum, Litecoin and Ripple. In this regard, we are backed by evidences of herding behaviour in the cryptocurrency market due to volatility spillover and return co-movements (see Sifat, Mohamad, & Shariff, 2019; Katsiampa, Corbet, & Lucey, 2019; Omane-Adjepong & Alagidede, 2019; Kumar & Anandarao, 2019). In the end, we confirm the a priori and show that market risk and fear occasioned by the COVID-19 pandemic increase the return volatilities of the four classes of cryptocurrencies. More significantly, we show that the magnitude of the nexus between fear-induced news and the return volatilities is higher during the pandemic than the period before it. Our findings contribute to the extant literature on cryptocurrencies in the following ways: (i) it provides evidence about the vulnerability of the digital currencies to the COVID-19 pandemic which has received limited attention during the pandemic compared to the conventional financial assets; and (ii) it further examines the in-sample and out-of-sample predictive power of the news about the pandemic in the return volatilities of cryptocurrencies which is crucial for future investment decisions. In sum, our findings have implications for portfolio diversification strategies, which we set aside for future research. Following this section, Section 2 presents the methodology, Section 3 describes the data, Section 4 discusses the result and Section 5 concludes.

2. Methodology

Our choice of the GARCH-MIDAS framework is motivated by the available data for the variables of interest with mixed frequencies. The model is adopted to examine the predictability of daily Google trend data for hourly cryptocurrency returns volatility. This circumvents the problem of information loss resulting from data aggregation or dis-aggregation, The GARCH-MIDAS model with conditional variances multiplicatively decomposed into high and low frequency components (see Engle, Ghysels, & Sohn, 2013 for technical details) is defined in Eqs. (1)–(4), which comprises the constant conditional mean and the conditional variance, as:

$$r_{i,t} = \mu + \sqrt{\tau_t \times h_{i,t}} \times \varepsilon_{i,t}, \forall \ i = 1, \ldots, N_t \tag{1}$$

$$h_{i,t} = (1 - \alpha - \beta) + \alpha \frac{\left(r_{i-1,t} - \mu\right)^2}{\tau_i} + \beta h_{i-1,t} \tag{2}$$

$$\tau_i^{(rw)} = m_i^{(rw)} + \theta_i^{(rw)} \sum_{k=1}^{K} \phi_k(\omega_1, \omega_2) X_{i-k}^{(rw)} \tag{3}$$

$$\phi_k(\omega_1, \omega_2) = \frac{[k/(K+1)]^{\omega_1 - 1} \times [1 - k/(K+1)]^{\omega_2 - 1}}{\sum_{j=1}^{K} [j/(K+1)]^{\omega_1 - 1} \times [1 - j/(K+1)]^{\omega_2 - 1}} \tag{4}$$

$$\varepsilon_{i,t} \middle| \Phi_{i-1,t} \sim N(0,1) \tag{5}$$

where $r_{i,\,t} = \ ln\ (P_{i,\,t}) - \ ln\ (P_{i-1,\,t})$ denotes the return series for cryptocurrency prices - $P_{i,\,t}$ covering four of them namely Bitcoin, Ethereum, Litecoin and Ripple; on the i^{th} hour of day t; N_t represents the number of hours in day t; μ denotes the unconditional mean of the cryptocurrency returns; $h_{i,\,t}$ and τ_i indicate the short- and long -run components of the conditional variance part of Eq. (1), with the former assuming a GARCH(1,1) process; α and β in Eq. (2) are respectively ARCH and GARCH terms, conditioned such that $\alpha > 0$, $\beta \geq 0$ and $\alpha + \beta < 1$; in Eq. (3), m is the long-run constant, θ is slope coefficient (the sum of weighted rolling window exogenous variable) that indicates predictability of daily G-trend for hourly cryptocurrency price returns, $\phi_k(\omega_1, \omega_2)$ is the beta polynomial weighing scheme,[1] with $\phi_k(\omega_1, \omega_2) \geq 0, \ \ k = 1, \ldots, K$ and summing up to unity for model identification, X_{i-k} denotes the predictor variable (G-trend), while the superscripted "rw" indicates that the rolling window framework was employed; and the random shock $\varepsilon_{i,\,t}$ conditional on $\Phi_{i-1,\,t}$ that indicates the information set that is available at $i-1$ hour of day t, is normally distributed.

[1] We adopted the one-parameter Beta polynomial weighing scheme on the basis of its flexibility and popularity (see Colacito et al., 2011).

In addition to considering the full data sample, we also consider pre- and post-COVID announcement subsample periods. In a bid to ascertain the stability of the parameter estimates across the sub-sample periods, we employ a Chow-type test that assesses forecast performance using a modified F statistic (Chow, 1960; Fisher, 1970; Rea, 1978 and Wilson, 1978). In other words, the equality of the estimates of the model parameters in the subsamples are tested. The test is given by Eq. (6)

$$Chow-type = \frac{\left(RSS_{pre} + RSS_{post}\right)}{RSS_{full}} \times \frac{N_{post} - p + q}{N_{pre} - p} \tag{6}$$

where RSS_{full}, RSS_{pre} and RSS_{post} are the residual sum of squares from the full, pre and post sample periods, respectively; N_{pre} and N_{post} are the respective sample sizes associated with the pre- and post-COVID announcement periods; p is the number of parameters in the model; while q is the number of parameters being tested. It is based on a modified F-statistic and tests the null that parameter estimates in the subsamples do not differ markedly against the alternative that they do. Rejection of the null hypothesis will validate the sub-sampling by the COVID announcement as it would imply that estimates from both subsamples are not equal.

3. Data description and preliminary analysis

We employed hourly price data on four highly traded cryptocurrencies (Bitcoin, Ethereum, Litecoin and Ripple) and daily search volumes with keyword, “cryptocurrency”, spanning a period between the 2nd September 2019 and 29th September 2020. This chosen sample period is to include some months before and after the announcement of the COVID-19 pandemic. The data were respectively extracted from ForexTime (https://www.forextime.com/trading-instruments/cryptocurrency-cfds) and Google trends (trends (https://trends.google.com/trends/) and are summarized and preliminarily analyzed in Table 1. On a search scale of 1–100, the average G-trend relating to cryptocurrency for the period being considered is approximately 65.63 with standard deviation 15.64. Cryptocurrency price returns ranged, on the average, between −7.19E-05 and 4.94E-05, with Ripple having the least returns and being the most volatile among the cryptocurrencies considered. All the variables (Gtrend and cryptocurrency price returns) are negatively skewed, while all except Gtrend are leptokurtic, having excess kurtosis values that are higher than 3.

The preliminary analyses include conditional heteroscedasticity, autocorrelation and higher order autocorrelation tests at lags 6, 12 and 24. The formal tests employed herein are the Autoregressive Conditional Heteroscedasticity (ARCH) test, Q-statistics and Q^2-statistics, respectively (see results in the second pane of Table 1). While Gtrend does not exhibit ARCH effect and higher order autocorrelation at the three different lags considered, the returns on cryptocurrency prices exhibit ARCH effect and autocorrelation at all three specified lags. This is expected given the high frequency nature of the data and the characteristic of current prices being dependent on previous prices. Therefore, the confirmed significant ARCH effect cum the mixed data frequency of the data employed, the most appropriate model is the GARCH-MIDAS model framework.

4. Results and discussion

We present here the results in two phases: the predictability of Gtrend for cryptocurrency price returns and forecast performance of the GARCH-MIDAS model in comparison with a bench mark model - the historical average model. On the predictability, four different cryptocurrency (Bitcoin, Ethereum, Litecoin and Ripple) prices are considered for the purpose of ascertaining the sensitivity of the predictability result to the choice of the cryptocurrency price. Also, three different sample periods considered and they include the full

Table 1
Summary statistics and preliminary results.

	Gtrend	Bitcoin	Ethereum	Litecoin	Ripple
Summary Statistics					
Mean	59.59	1.30E-05	1.04E-04	−4.70E-06	−2.08E-05
Std. Dev.	15.53	8.89E-03	1.10E-02	1.19E-02	1.11E-02
Skewness	0.47	−2.56	−2.30	−2.18	−4.66
Kurtosis	2.43	114.72	72.63	58.52	110.95
N	282	6769	6769	5088	4679
Frequency	Daily	Hourly	Hourly	Hourly	Hourly
Start	Sep-2-2019	Sep-2-2019 0:00:00	Sep-2-2019 0:00:00	Dec-9-2019 3:00:00	Sep-2-2019 1:00:00
End	Sep-29-2020	Sep-29-2020 23:00:00	Sep-29-2020 23:00:00	Sep-29-2020 23:00:00	Sep-29-2020 23:00:00
Preliminary Analysis					
$ARCH(6)$	2.38**	116.03***	71.34***	47.07***	4.40***
$ARCH(24)$	1.27	59.63***	36.87***	24.94***	5.12***
$ARCH(12)$	1.20	67.69***	51.63***	30.83***	3.39***
$Q(6)$	27.38***	33.54***	16.56**	18.64***	17.37***
$Q(12)$	41.16***	50.85***	33.73***	48.51***	41.94***
$Q(24)$	69.41***	213.18***	128.48***	101.88***	92.40***
$Q^2(6)$	14.93***	815.47***	608.74***	404.63***	30.11***
$Q^2(12)$	17.74***	875.28***	668.29***	469.26***	71.41***
$Q^2(24)$	32.21***	2281.10***	1878.10***	1270.90***	112.32***

Note: ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

sample, pre-COVID-19 pandemic announcement and post-COVID-19 pandemic announcement (see Table 2). We further check for model mis-specification and parameter estimate stability across subsamples (see Table 3). On the forecast performance, we consider both in-sample and out-of-sample forecast using the root mean square error (RMSE) and compare same to the historical average forecasts (see Table 4).

4.1. Predictability of Gtrend for cryptocurrency return volatility

Our main contributions to the literature are twofold. First, to provide evidence about the vulnerability of the digital currencies to the COVID−19 pandemic which has received limited attention during the pandemic compared to the conventional financial assets. Second, to examine the in-sample and out-of-sample predictive power of pandemic news in the return volatilities of cryptocurrencies which is crucial for future investment decisions. We present here the parameter estimates of our predictive model for all four cryptocurrency (Bitcoin, Ethereum, Litecoin and Ripple) prices (see Table 2), which include the unconditional mean cryptocurrency price returns (μ), the ARCH term (α), GARCH term (β), the slope coefficient (θ), the adjusted beta polynomial weight (w), and the long run constant term (m). On the full sample data and across the cryptocurrencies considered, we find statistically significant ARCH and GARCH terms, as well as the slope coefficient and the long-run constant. All four cryptocurrencies exhibit higher degree of volatility persistence in the range of 0.76 and 0.95, and mean reverting property as the sum of α and β are less than unity. Other previous studies have also established volatility persistence in cryptocurrencies with the two chief reasons being the lack of regulatory arrangements in the markets and its high response to news (see Chu et al., 2017; Dibrova, 2016; Fakhfekh & Jeribi, 2020; İçellioğlu & Öner, 2019; Kumar & Anandarao, 2019; Vasek & Moore, 2015). However, the results affirm that shocks to cryptocurrency prices may only take a longer time period to decay, it would not be permanent.

Except for the case of Bitcoin, the adjusted beta weights are greater than one and statistically significant, hence implying that larger weights are assigned to the most recent past observations. The statistically significant slope coefficients (θ) indicate the predictability

Table 2
Predictability of Gtrend for cryptocurrency.

	μ	α	β	θ	w	m	$e^{\theta \cdot \varphi_1(\omega)} - 1$
Full Sample							
Bitcoin	3.64E-05	1.46E-01***	8.36E-01***	5.40E-03***	1.00E+00***	-1.96E-04***	0.541
	[6.75E-05]	[3.11E-03]	[2.98E-03]	[4.69E-04]	[7.86E-02]	[2.24E-05]	
Ethereum	1.12E-04	9.67E-02***	8.62E-01***	5.56E-03***	1.00E+00***	−2.53E-04***	0.558
	[1.04E-04]	[2.96E-03]	[4.06E-03]	[2.25E-04]	[6.59E-02]	[1.45E-05]	
Litecoin	−2.92E-05	5.04E-02***	9.00E-01***	9.63E-02***	5.01E+00***	−3.56E-03***	62.01
	[2.86E-04]	[3.24E-03]	[6.31E-03]	[4.88E-04]	[2.92E-03]	[1.80E-05]	
Ripple	3.86E-04***	2.34E-01***	7.06E-01***	−7.23E-03***	4.70E+01***	7.91E-04***	−28.809
	[1.09E-04]	[1.08E-02]	[1.02E-02]	[5.08E-04]	[1.36E+01]	[5.35E-05]	
Pre-COVID-19 Pandemic Announcement							
Bitcoin	−2.32E-04*	1.01E-01*** [8.77E-03]	7.84E-01***	−2.80E-04***	2.87E+00	8.43E-05***	−0.080
	[1.31E-04]		[1.71E-02]	[5.31E-05]	[2.54E+00]	[3.96E-06]	
Ethereum	−1.18E-04	1.23E-01***	8.03E-01***	3.05E-03***	6.85E+00***	−1.02E-04***	2.111
	[1.34E-04]	[6.66E-03]	[1.42E-02]	[2.33E-04]	[2.41E+00]	[1.45E-05]	
Litecoin	2.11E-04	1.25E-02	1.80E-01	−4.88E-03***	1.29E+00***	5.18E-04***	−0.63
	[3.87E-04]	[1.76E-02]	[9.48E-01]	[2.31E-04]	[1.62E-01]	[1.88E-05]	
Ripple	−1.29E-04	8.67E-03	9.40E-02	−4.94E-03***	4.49E+01***	4.86E-04***	−19.893
	[4.72E-04]	[7.81E-03]	[2.36E+00]	[1.58E-04]	[1.20E+01]	[1.30E-05]	
Post-COVID-19 Pandemic Announcement (Covering period of the first wave: 11th Mar. – 8th May 2020)							
Bitcoin	7.68E-04***	9.26E-02***	9.03E-01***	4.28E-02***	3.55E+00***	−2.18E-03***	16.42
	[1.65E-04]	[4.67E-03]	[4.92E-03]	[7.42E-05]	[3.38E-02]	[1.45E-06]	
Ethereum	5.79E-04*	8.66E-02***	8.49E-01***	5.23E-03***	4.75E+01**	−1.43E-04***	28.21
	[3.15E-04]	[8.96E-03]	[1.58E-02]	[3.92E-04]	[2.20E+01]	[2.89E-05]	
Litecoin	2.83E-04	9.82E-02***	8.08E-01***	6.14E-03***	4.93E+01***	−2.06E-04***	35.32
	[3.46E-04]	[1.17E-02]	[2.13E-02]	[3.06E-04]	[1.32E+01]	[1.86E-05]	
Ripple	−1.58E-04	5.00E-02***	9.00E-01***	9.94E-02***	5.00E+00***	−3.77E-03***	64.40
	[4.29E-04]	[5.81E-03]	[1.82E-02]	[9.41E-03]	[8.24E-01]	[3.52E-04]	
Post-COVID − 19 Pandemic Announcement (Covering period of the first and second waves: 11th Mar. – 29th Sept., 2020)							
Bitcoin	6.23E-05	6.17E-02***	9.38E-01***	4.66E-02***	2.33E+00***	−1.75E-03***	11.469
	[6.98E-05]	[8.48E-04]	[8.39E-04]	[1.83E-03]	[1.35E-01]	[6.80E-05]	
Ethereum	2.18E-04	1.03E-02***	9.88E-01***	-1.82E-04*	5.91E+00	1.47E-04***	−0.108
	[1.73E-04]	[3.70E-04]	[4.12E-04]	[1.08E-04]	[1.43E+01]	[1.58E-05]	
Litecoin	1.75E-04	1.58E-01***	7.47E-01***	7.23E-04***	4.59E+00	7.50E-05***	0.332
	[1.17E-04]	[1.21E-02]	[1.38E-02]	[1.77E-04]	[6.07E+00]	[6.32E-06]	
Ripple	7.25E-05	1.75E-01***	7.30E-01***	1.71E-03***	5.05E+00	2.48E-05***	0.867
	[1.34E-04]	[9.68E-03]	[1.72E-02]	[2.04E-04]	[3.37E+00]	[8.37E-06]	

Note: μ - unconditional mean of cryptocurrency price returns, α- ARCH term, β - GARCH term, θ - slope coefficient, w - the adjusted beta polynomial weight, and m - long run constant term. The figures in square brackets are the standard errors of the parameter estimates, while the ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

Table 3
Mis-specification and parameter stability check.

Cryptocurrency	Likelihood ratio test			Chow-type Test
	Full sample	Pre-COVID announcement	Post-COVID announcement	Modified F-Stat
Bitcoin	-303.96	−28.39	−40.87	2.4355***
Ethereum	−22.74	13.41***	4.69**	3.8493***
Litecoin	−6870.00	56.14***	−30.45	1.9532***
Ripple	127.97***	56.71***	−1.74	1.6153***

Note: ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

Table 4
RMSE result.

Cryptocurrency	Historical Average				GARCH-MIDAS			
	In-Sample	Out-of-Sample			In-Sample	Out-of-Sample		
		$h = 6$	$h = 12$	$h = 24$		$h = 6$	$h = 12$	$h = 24$
Full Sample								
Bitcoin	8.94E-03	8.94E-03	8.94E-03	8.93E-03	8.32E-04	9.56E-05	7.40E-05	5.68E-05
Ethereum	1.10E-02	1.10E-02	1.10E-02	1.10E-02	9.98E-04	1.58E-04	1.25E-04	1.00E-04
Litecoin	1.19E-02	1.19E-02	1.19E-02	1.19E-02	1.79E-03	1.58E-04	1.56E-04	1.54E-04
Ripple	1.12E-02	1.12E-02	1.12E-02	1.11E-02	1.35E-03	2.08E-04	1.66E-04	1.30E-04
Pre-COVID-19 Pandemic Announcement								
Bitcoin	7.13E-03	7.12E-03	7.12E-03	7.15E-03	3.77E-04	3.30E-05	3.55E-05	2.32E-04
Ethereum	9.24E-03	9.25E-03	9.24E-03	9.27E-03	5.70E-04	1.18E-04	1.02E-04	2.43E-04
Litecoin	1.21E-02	1.21E-02	1.21E-02	1.21E-02	9.69E-04	1.86E-04	1.59E-04	2.34E-04
Ripple	1.19E-02	1.19E-02	1.19E-02	1.19E-02	2.10E-03	1.14E-04	1.17E-04	2.10E-04
Post-COVID-19 Pandemic Announcement (Covering period of the first wave of the spread)								
Bitcoin	1.30E-02	1.30E-02	1.30E-02	1.30E-02	1.49E-03	2.08E-04	1.56E-04	1.39E-04
Ethereum	1.54E-02	1.54E-02	1.54E-02	1.54E-02	1.72E-03	4.95E-04	3.68E-04	2.79E-04
Litecoin	1.56E-02	1.56E-02	1.56E-02	1.55E-02	1.61E-03	5.42E-04	4.07E-04	3.19E-04
Ripple	1.51E-02	1.51E-02	1.50E-02	1.50E-02	2.57E-03	4.70E-05	6.33E-05	8.81E-05
Post-COVID-19 Pandemic Announcement (Covering period of the first and second waves of the spread)								
Bitcoin	1.04E-02	1.04E-02	1.03E-02	1.03E-02	1.12E-03	9.74E-05	7.01E-05	5.03E-05
Ethereum	1.25E-02	1.25E-02	1.24E-02	1.24E-02	1.33E-03	1.55E-04	1.17E-04	9.18E-05
Litecoin	1.18E-02	1.18E-02	1.18E-02	1.18E-02	1.13E-03	1.46E-04	1.12E-04	8.47E-05
Ripple	1.09E-02	1.09E-02	1.09E-02	1.09E-02	8.34E-04	1.98E-04	1.48E-04	1.08E-04

of Gtrend for cryptocurrency price returns with a positive impact on the volatility of all but one cryptocurrency – Ripple. This suggests that the higher the volume of information available to investors, the higher the return volatility of the cryptocurrency, on average. This further validates the role of information in the valuation of cryptocurrencies as widely reported in emerging studies (for example, Bouoiyour & Selmi, 2015; Dastgir et al., 2019; Polasik et al., 2015a, 2015b; Shen et al., 2019). Since these currencies are digital in nature, it is not unexpected why the role of information is considered crucial.

The results of the pre-COVID-19 pandemic announcement are slightly different from those of the full sample data points. Significant ARCH and GARCH terms were only found for Bitcoin, Ethereum and Litcoin, while the degree of volatility persistence was lower than what was obtained using the full sample data. The beta polynomial weights were still greater than one and the slope coefficients of all four cryptocurrencies were significantly negative (Bitcoin, Litecoin and Ripple) and positive (Ethereum). Consequently, the impact of an increase in the Gtrend would be negative on the long-term volatility of all the crypto currencies except Ethereum.

For the post-COVID-19 pandemic announcement period (covering first wave of the coronavirus spread) however, the ARCH term, GARCH term, slope coefficient, beta polynomial weights and the long-term constant are all statistically significant across the cryptocurrency price returns. Also, the degree of volatility persistence appears to be quite higher than the case of the full sample and pre-COVID-19 pandemic announcement periods, except for the case of Litecoin, where the degree of persistence was lower. This finding is not surprising as the a priori specifies that return volatility of cryptocurrencies be higher with increased fear and market risks during periods of financial crisis like the one induced by the COVID-19 announcement (see Conlon & McGee, 2020; Corbet et al., 2020; Flori, 2019; Kumar & Anandarao, 2019; Zhang et al., 2020). Interestingly again, the beta weights are greater than one but this time all the slope coefficients are positive, such that 1% increase in the volume of Google searches with keyword, “cryptocurrency” could lead to double digits increase in the long-term volatility of the cryptocurrency price returns. Within this sample period, the predictability of Gtrend for crypto currency price returns are similar across cryptocurrency choices, however, the stance here differs markedly from those of the full sample and the pre-COVID-19 pandemic announcement sample periods. Consequently, predictability of Gtrend for cryptocurrency price returns may be sensitive to the choice of data sample as well as cryptocurrency, but most importantly, the former. In sum, the COVID-19 pandemic has raised the return volatility of cryptocurrencies thus making it risky to invest in them during the pandemic period.

For the post-COVID-19 pandemic announcement period (covering both first and second waves of the coronavirus spread), the results are similar except with respect to the insignificant unconditional mean across the cryptocurrencies, the negatively signed slope coefficient of G-trends in the case of Ethereum and the insignificant beta weights in the cases of Ethereum, Litecoin and Ripple. Although G-trends are again shown to have positive and significant impact on the long-term volatility of cryptocurrency returns, it appears that the impact is greatly reduced as the COVID-19 pandemic enters the second wave. As such the impact, in comparison with the case of the first wave only period, is lower.

The results from the foregoing shows some support for the inclusion of G-trends as a predictor in the GARCH-MIDAS model framework, especially with respect to Ethereum, Litecoin and Ripple (see the Likelihood ratio test result in Table 3). Only in the case of Bitcoin, is the GARCH-MIDAS model framework with realized volatility sufficient for the prediction of the long-term volatility of the cryptocurrency, which implies that the inclusion of G-trends may not provide more information than already contained in the realized volatility of the cryptocurrency. However, on the stability of the parameter estimates, we find these to be unequal, given the statistically significant modified F-statistic of the Chow-type test (see the last column of Table 3).

4.2. Forecast evaluation

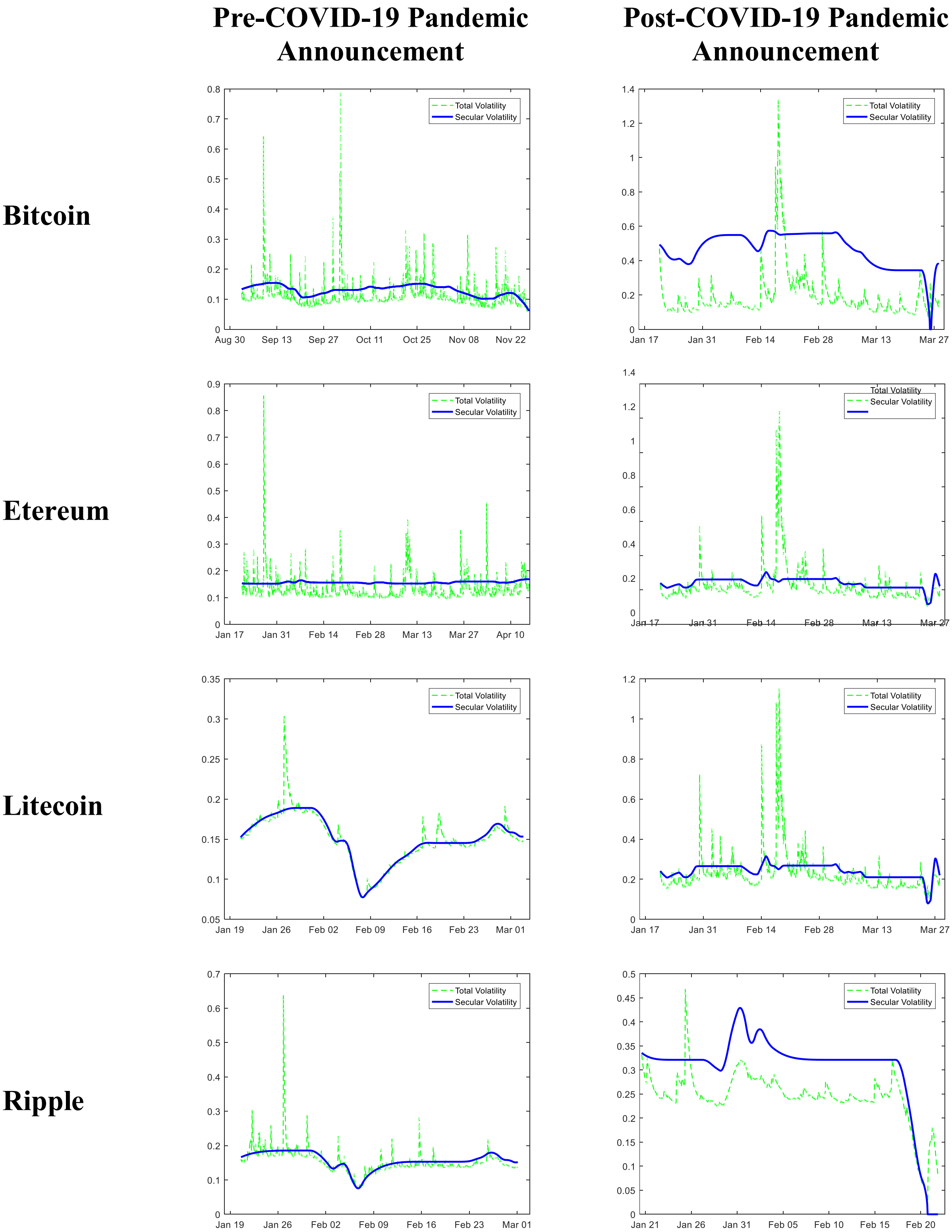
Here, we examine the forecast performance of our predictive model against the historical average (the conventional GARCH(1,1)) model over the three specified sample periods. Specifically, we considered the in-sample forecast performance as well as the out-of-sample performance using the conventional RMSE statistic that is a model adequacy measure, based on forecast errors. The adoption of the RMSE to ascertain model performance is in line with the design framework of the method employed in this study (see Engle et al., 2013). Comparatively, the smaller the RMSE, the better the forecast. We find consistent out-performance of the GARCH-MIDAS model over the historical average model across the data sample and cryptocurrency prices both in the in-sample and all three out-of-sample forecast horizons ($h = 6$, 12, 24). Clearly, the GARCH-MIDAS would be preferred over the historical average as the incorporation of Gtrend prove to improve forecast of the volatility in cryptocurrency price returns better than the historical average that ignore incorporating same.

5. Conclusion

This study undertakes a comparative analysis of the nexus between fear-induced news (measured with G-trend data during COVID-19 announcement) and return volatility of four cryptocurrencies (Bitcoin, Ethereum, Litecoin and Ripple). The research objective is informed by the established linkage between financial news and speculative assets and more specifically, the connection between excess volatility in Bitcoins and news. The stfudy employs G-trends data obtained before and after the announcement of COVID-19 as a pandemic to examine whether return volatilities of cryptocurrencies behave differently during financial crisis. With GARCH MIDAS technique, the study validates this supposition with the finding of positive impact of news on return volatility of the digital currencies being higher during the COVID-19 pandemic than the period before it. In other words, we show that the return volatility of cryptocurrencies is riskier during the coronavirus pandemic as obtained during previous financial crises like the global financial crisis. This finding alings with the extant literature examining the volatility of crypocurrencies although without considering the COVID-19 effect which is one of the main contributions of this study (see Chu, Stephen, Saralees, & Joerg, 2017; Fakhfekh & Jeribi, 2020; Kumar & Anandarao, 2019).

Overall, our findings contribute to the extant literature on cryptocurrencies in the following ways: (i) it provides evidence about the vulnerability of the digital currencies to the COVID-19 pandemic which has received limited attention during the pandemic compared to the conventional financial assets; and (ii) it further examines the in-sample and out-of-sample predictive power of the pandemic news in the return volatilities of cryptocurrencies which is crucial for future investment decisions. We however set aside for future research the portfolio diversification strategies for the digital currencies during the pandemic.

Appendix A


Pre-COVID-19 Pandemic Announcement
Post-COVID-19 Pandemic Announcement
Bitcoin
Etereum
Litecoin
Ripple
Total Volatility
Secular Volatility
Aug 30 Sep 13 Sep 27 Oct 11 Oct 25 Nov 08 Nov 22
Jan 17 Jan 31 Feb 14 Feb 28 Mar 13 Mar 27
Jan 17 Jan 31 Feb 14 Feb 28 Mar 13 Mar 27 Apr 10
Jan 19 Jan 26 Feb 02 Feb 09 Feb 16 Feb 23 Mar 01
Jan 21 Jan 26 Jan 31 Feb 05 Feb 10 Feb 15 Feb 20

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