Economics Bulletin

Volume 41, Issue 3

Fear of the Coronavirus and Cryptocurrencies' returns

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Abstract

Do Cryptocurrencies fear Coronavirus? This paper answers this question by examining the predictive power of the Covid-19 global fear index of Salisu and Akanni (2020) on major cryptocurrencies' returns during the period from 07/02/2020 to 05/03/2021. First, we formulate a predictive model of major cryptocurrencies' returns based on the Covid-19 global fear index. Second, we combine the global fear of the pandemic with other fear proxies and we present a multiple-factor fear-based predictive model that captures the effects of other economic and financial fear variables. Finally, we examine whether accounting for asymmetries would improve the predictability of returns. The empirical findings show that the global fear index contains information that help predict major cryptocurrencies and that the multiple-factor model is a better predictive model for cryptocurrencies' returns. Specifically, global fear related to health risks exhibits a significantly negative impact on the majority of the sampled cryptocurrencies' returns. Consistent with in-sample results, global fear provides a statistically significant out-of-sample forecast outcome. Our results suggest that, in the period of the pandemic, cryptocurrencies are not very different from other assets and that they exhibit a significant reaction to the fear environment.

Funding sources: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.
Declaration of interest: none.
Citation: Sinda Hadhri, (2021) "Fear of the Coronavirus and Cryptocurrencies' returns", *Economics Bulletin*, Vol. 41 No. 3 pp. 2041-2054
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Submitted: May 29, 2021. **Published:** September 18, 2021.

1. Introduction

The new Covid-19 pandemic outbreak has led to the emergence of studies that had examined its economic and financial impacts. This strand of literature has examined the impact of Covid-19 on financial stock markets (e.g., Aggarwal et al., 2020; Just and Echaust, 2020; Okorie and Lin, 2020; Contessi and DePace, 2021), commodity markets (e.g., Salisu et al., 2020; Sharif et al., 2020; Wang et al., 2020) and cryptocurrencies (e.g., Caferra, 2020; Corbet et al., 2020; Umar and Gubareva, 2020; Goodell and Goutte, 2021).
As Covid-19 is becoming one of the major concerns of both investors and policymakers, the importance of accurate prediction of the different asset classes in times of crisis is more than needed. Cryptocurrencies are considered as a core asset class mainly used for diversification purposes and driven by increased speculative activities (Shahzad et al., 2019; Urquhart and Zhang, 2019 among others). Hence, the ability to accurately predict them might help investors in making decisions of portfolio adjustments and asset pricing, and academics in developing forecasting models.
Based on this rationality, and as economic and financial series forecasting during stress and high uncertainty periods is important for both investors and market regulators, we aim to complement the existing literature on financial and economic series predictability as we formulate a predictive model for cryptocurrencies that uses the global fear of Covid-19 pandemic as a predictor of cryptocurrencies' returns.
The rest of the paper is organized as follows: Section 2 presents the theoretical background. Section 3 describes the data used. Section 4 presents the method. Section 5 discusses the results, and, Section 6 concludes the paper.

2. Theoretical background

Recently, the focus of the research on Bitcoin and other cryptocurrencies has exceeded their technical aspects and stylized facts (e.g., Dweyer, 2015; Swan, 2015; Feng et al., 2018) to speculative properties (Glaser et al., 2014; Cheah and Fry, 2015; Baur et al., 2018; Corbet et al., 2018) and hedging effectiveness (e.g., Dyhrberg, 2016; Bouri et al., 2017a; Bouri et al., 2017b; Demir et al., 2018).
As Cryptocurrencies are considered as similar to other financial markets (Urquhart, 2017), the emergence of studies in relation to their efficiency is not surprising. Specifically, the Efficient Market Hypothesis (EMH) introduced by Fama (1965) is one of the main assumptions in the financial theory. It stipulates that stock prices include all available information, and as a main consequence, investors could not earn profit since stock prices are unpredictable and follow a random walk. Several studies have attempted to model Cryptocurrencies' pricing mechanism and examine whether these assets are predictable (e.g., Urquhart, 2016; Nadarajah and Chu, 2017; Tiwari et al., 2018; Kjuntia and Pattanayak, 2018, among others). The focus has been, primarily, on Bitcoin. Mixed results characterize this literature stream, as some studies showed that Bitcoin is an efficient market (e.g., Nadarajah and Chu, 2017; Tiwari et al., 2017), while others found the opposite (e.g., Briviera, 2017; Jiang et al., 2017). Lately, Brauneis and Mestel (2018) extended the efficiency analysis to other cryptocurrencies and found heterogeneous results.

From a portfolio management perspective, some studies found that Bitcoin and other Cryptocurrencies can be used as a diversifier (e.g., Dyhrberg, 2016; Bouri et al., 2017a; Bouri et al., 2017b), while others showed that these digital assets can only be used as a speculative asset (e.g., Cheah and Fry, 2015; Baur et al., 2018). During periods of crisis and high uncertainty, it is natural that the main objective of investors is the search for safe assets. During the early stages of the Covid-19 pandemic outbreak, Bitcoin and other cryptocurrencies have performed as a hedge but soon later, they fell in value as many other assets (Iqbal et al., 2021). With the growing use and importance of these digital currencies, it is important that the literature on these assets is enriched in order to enhance the understanding of their dynamics and forecasting. The recent Covid-19 pandemic provides an opportunity to evaluate the behavior of cryptocurrencies in periods of extreme stress.

Excessive fear in periods of uncertainty could have significant implications on investment decision-making and, hence, affect asset prices. More particularly, Covid-19 could, theoretically, influence investment choices and portfolio allocations by driving investors to swift their trading and risk-taking behavior. We, hence, hypothesize a heterogeneity in their risk perceptions according to their risk profile and investment preferences.

The impact of fear on financial stock markets has been studied by a number of previous studies. The measures used are mainly related to the implied volatility that has been widely considered as a proxy of the fear in the market (e.g., Baker and Wurgler, 2006; Bouri et al., 2018; Shaikh and Padhi, 2015) and to media and news-generated fear (e.g., Badshah et al., 2018; Gradinaru, 2014; Narayan, 2019; Westerhoff, 2004). Information related to Covid-19 number of confirmed cases and deaths can also imply fear and panic at all levels (government, household, business) which may, by extension, have a possible impact on any relevant macroeconomic fundamental or market (Salisu and Akanni, 2020). Therefore, we apply a newly-developed Covid-19 induced panic index that captures fear in the period of the pandemic and uses Covid-19 parameters which makes it more efficient index than other usually used fear proxies that either, by construction, do not capture Covid-19 source of fear or are only related to uncertainty in the market (e.g., the CBEO's VIX index). Relevant studies on the predictability of stock and commodity markets using fear index (e.g., Bouri et al., 2018; Zhu et al., 2019; Salisu and Akanni, 2020; Salisu et al., 2020) found that the fear index is a good predictor of stock markets and commodity markets' performance. We assess the predictive power of fear in the forecast of cryptocurrencies' activity.

In examining this, there are two alternative hypotheses that can be tested. First, as highly speculative assets, cryptocurrencies can be influenced by investors' sentiment and fear as a result of changes in their risk perceptions and expectations. Alternatively, due to their speculative nature, unique decentralized peer-to-peer cash system and the relatively isolated nature of this market (Baur et al., 2016), they may exhibit a weak response to the fear environment.

3. Data

We use data for major cryptocurrencies from the Binance exchange. The period spans 07/02/2020-05/03/2021. Data includes the daily close prices as well as the daily trading volumes. Cryptocurrencies returns (R_t) are computed as the log of change in daily settlement prices.

The control variables that we use are the growth of the daily trading volume (TV) calculated as the ratio of the difference between daily settlements on previous day's trading volume, the Economic Policy Uncertainty (*EPU*) index of Baker et al., (2016) to control for the uncertainty related to policy measures, the investors' fear gauge index which consists of the stock market's volatility index based on S&P500 index options *(VIX),* and the crude oil volatility index *(OVX)* of the *Chicago Board Options Exchange (CBEO).* More specifically, the trading volume is argued to gauge asset liquidity and a number of previous studies concluded that trading volume

has a positive effect on Bitcoin returns (e.g., Ciaian et al., 2016; Ciaian et al., 2017; Kristoufek, 2015). We use this measure to gauge for the asset-based sentiment (Baker and Stein, 2004). Some other studies found a significant effect of *EPU* (e.g., Demir et al., 2018; Shaikh, 2020; Wang et al., 2020). *VIX* and *OVX* are, also, included to control for the effect of the equity and oil markets on Cryptocurrencies' returns.
The Global Fear index (*GFI*) that we use is the Salisu and Akanni (2020) index that captures fear and concerns associated with the spread and the severity of the pandemic. Unlike other Covid-19 fear proxies used in the literature (Ashraf, 2020; Umar and Gubareva, 2020, among others) that capture the news-driven panic, this index measures uncertainties related to the fear of Covid-19 health risks as it captures how far people's expectations on reported cases (deaths) on the preceding incubation period veered from today's reported numbers.[1] On a scale of 0 to 100, the higher the value of GFI, the higher the global fear of Covid-19. A value of 50 is considered neutral and any higher index value refers to higher fear or panic than usual.

A summary of all Cryptocurrencies' returns, GFI as well as all used control variables in the full sample is reported in Table I. The mean return of the cryptocurrencies for the sample goes from -4.36e-05 for Dash to 0.003 for Chainlink, which is the most volatile cryptocurrency (0.041) followed by NEM and Tezos. The mean GFI is 56.551 with a volatility of 9.252. The maximum/minimum values and standard deviations indicate a high volatility of all the used variables during the entire sample period.

Table I. Summary statistics of used variables.

	Mean	St. dev	Minimum	Maximum	Mean	St. dev	Minimum	Maximum
Cryptocurrencies								
	R				TV (%)			
Bitcoin	0.002	0.018	-0.202	0.073	0.016	1.227	-5.686	4.783
Altcoin								
Ethereum	0.002	0.025	-0.239	0.100	0.023	1.320	-4.565	4.932
Tether	1.03e-05	0.002	-0.017	0.022	0.021	1.102	-3.912	3.097
Cardano	0.003	0.028	-0.219	0.109	0.105	2.264	-9.286	9.463
Binance coin	0.001	0.023	-0.236	0.084	0.034	1.533	-6.057	6.823
XRP	0.0005	0.030	-0.238	0.193	0.041	1.755	-7.526	7.116
Litecoin	0.001	0.024	-0.195	0.082	0.015	1.304	-5.284	4.859
Bitcoin cash	9.82e-06	0.026	-0.244	0.114	0.014	1.748	-6.172	10.436
Bitcoin SV	-0.0005	0.027	-0.243	0.198	-0.001	1.911	-4.885	11.108
Stellar	0.002	0.030	-0.178	0.243	0.054	2.289	-6.675	10.719
EOS	-0.0004	0.024	-0.218	0.069	0.015	1.663	-5.886	7.079
Tezos	0.0006	0.028	-0.263	0.112	0.067	2.203	-8.311	7.284
NEM	0.002	0.026	-0.134	0.127	0.174	5.625	-39.831	57.230
Exchange Token								
Chainlink	0.003	0.032	-0.268	0.106	0.064	1.934	-7.082	8.553
Tron	0.005	0.024	-0.227	0.076	0.013	1.699	-5.824	13.575
Huobi Token	0.001	0.019	-0.216	0.081	0.043	3.067	-8.346	11.610
Privacy coin								
Monero	0.0007	0.022	-0.214	0.098	0.120	3.943	-27.306	40.563
Dash	-4.36e-05	0.025	-0.199	0.129	0.033	2.645	-19.744	34.556
Zcash	0.0004	0.026	-0.179	0.092	0.046	2.859	-21.198	30.503
Global fear index and other control variables								
GFI	56.551	9.252	9.886	97.579	-	-	-	-
EPU	296.822	139.021	56.470	807.660	-	-	-	-
VIX	30.396	11.532	13.680	82.690	-	-	-	-
OVX	65.577	45.021	31.700	325.150	-	-	-	-

[1] For more details about the construction of GFI, please see https://data.mendeley.com/datasets/yhs329pd7d/1
We use data from Johns Hopkins Coronavirus Resource Center.

Note: this table reports the descriptive statistics of daily Cryptocurrencies returns (R), the global fear index (GFI) as well as other used control variables for the studied period.

4. Method

In order to examine the predictive power of the global fear index on cryptocurrencies returns, we use the following predictive model:

$$R_{i,t} = \alpha_{0,i} + \sum_{l=1}^{n} \beta_{i,l} R_{i,t-l} + \sum_{l=1}^{n} \gamma_{i,l} logGFI_{i,t-l} + \varepsilon_{i,t} \quad (1)$$

Where $R_{i,t}$ is a vector of returns for each cryptocurrency i and $logGFI$ refers to the log of the global fear index. $\alpha_{0,i}$ is a vector of constants and $\varepsilon_{i,t}$ is a vector of error terms. The lag-length (n) is determined using the Akaike Information Criterion (AIC).

We test for the overall sign and joint significance of lagged γ_i using the Wald test. The null hypothesis of no predictability is $H_0: \sum_{l=1}^{n} \hat{\gamma}_l = 0$. Then, we continue with the corresponding Granger causality tests in order to investigate the causal relationship between the variables.

For completeness, we include in our single-predictor model in equation (1) some other important factors that can influence cryptocurrencies' returns. Specifically, the Arbitrage Pricing Theory stipulates that incorporating systemic risks could enhance the predictability of stock returns. Hence, our model can be presented as follows:

$$R_{i,t} = \alpha_{0,i} + \sum_{l=1}^{n} \beta_{i,l} R_{i,t-l} + \sum_{l=1}^{n} \gamma_{i,l} logGFI_{i,t-l} + \varphi Z'_{i,t} + \varepsilon_{i,t} \quad (2)$$

Where $Z'_{i,t}$ is a $(1 \times K)$ vector of additional control variables and φ is a $(K \times 1)$ vector of parameters for the K regressors.

We also assume that positive and negative changes in the index have distinct effects of cryptocurrencies' returns and we try to examine the asymmetric impact of GFI on the studied variables. Specifically, we hypothesize that negative changes of GFI positively impact cryptocurrencies, while positive changes are expected to have a negative impact on them. Hence, we use the following predictive model:

$$R_{i,t} = \alpha_{i,0} + \delta_{i,1} R_{i,t-1} + \delta_{i,2} \Delta logGFI_{i,t-1} + \delta_{i,3} D_{i,t-1} + \delta_{i,4} D_{i,t} * \Delta logGFI_{i,t-1} + \epsilon_{i,t} \quad (3)$$

Where $D_{i,t-1}$ is a dummy variable that takes the value of 1 when $\Delta logGFI$>0 and 0 otherwise. We also control for past returns by including lagged R_i in the model. The impact of positive changes is evaluated at $D_{i,t}$=1 using ($\delta_{i,2}$+$\delta_{i,4}$) while negative changes are evaluated at $D_{i,t}$=0 using $\delta_{i,2}$. We test for asymmetry using the differential slope coefficient $\delta_{i,4}$ and its statistical significance implies the presence of asymmetry.

Finally, we investigate the out-of-sample forecast performance of global fear by comparing it to a forecasting model that suggests that investors predict no change in cryptocurrencies' returns from one period to another because past data do not provide information about the direction of future movements and, hence, returns are following a random walk. The model is presented as follows:

$$\hat{R}_{i,t+1} = R_{i,t} \quad (4)$$

We evaluate the out-of-sample predictive ability of global fear using the Campbell and Thompson (2008)—CT statistic: $CT = 1 - \frac{\widehat{MSE}_{i,1}}{\widehat{MSE}_{i,2}}$ where $\widehat{MSE}_{i,1}$ ($\widehat{MSE}_{i,2}$) is the mean squared error obtained from the unrestricted (restricted) model in eq.1, eq.2 or eq.3 (eq.4). If CT>0, then the predictive models in equations (1) or (2) or (3) outperform equation (4) in terms of forecast accuracy. The Campbell and Thompson out-of-sample statistic is a scale-free measure that has been widely used to compare forecasting models on return series.
We also use the Clark and West (2007) test specified as follows: CW = $(r_{t+s} - \hat{r}_{1t,t+s})^2 - [(r_{t+s} - \hat{r}_{2t,t+s})^2 - (\hat{r}_{1t,t+s} - \hat{r}_{2t,t+s})^2]$ where s is the forecast period, $(r_{t+s} - \hat{r}_{1t,t+s})^2$ is the squared error of the restricted model, $(r_{t+s} - \hat{r}_{2t,t+s})^2$ is the squared error of the unrestricted model, and $(\hat{r}_{1t,t+s} - \hat{r}_{2t,t+s})^2$ is the adjusted squared error used to correct for any noise associated with the unrestricted model's forecast. The test is used to test for equal MSE, CW is regressed on a constant and the resulting t-statistic for a zero coefficient. We reject the null hypothesis of equal MSEs if the regression of CW on a constant is statistically significant.

Following previous literature (Campbell and Thompson, 2008; Welch and Goyal, 2008), we use a recursive-window approach to generate our forecasts. The full sample period *T* is divided into an in-sample period consisting of the initial *m* observations and an out-of-sample period consisting of the last *s* observations (*s=T-m*). We use the first portion for the initial testing and the second portion for forecast evaluation purposes. We build from previous studies that have considered several forecast periods (Rapach et al., 2010; Welch and Goyal, 2008). Specifically, we consider two forecast periods of 50% and 75% of the total number of observations in this study.

5. Empirical results

Table II summarizes the estimation results of the predictability test of cryptocurrencies using the global fear index. Results of the impact of the fear index are estimated using equation (1) (model 1), equation (2) (model 2) [2] and equation (3) (model 3).
We begin with model 1, findings show that the global fear index contains relevant information that help predict cryptocurrencies' returns. More particularly, we find a significantly positive relationship between major cryptocurrencies returns and the global fear (except for Tether, which exhibits a significantly negative relationship with global fear). This result indicates that, in periods of high Covid-19 fear, returns of major cryptocurrencies tend to increase. The *p-values* from the Granger causality test indicate that we can reject the null hypothesis that the fear index does not Granger cause *R* for Bitcoin SV at the 10% level.
When estimating our model using equation (2), results show a divergence (in terms of sign) between the sampled cryptocurrencies. Specifically, the sign of the relationship between the fear index and Cryptocurrencies' returns seem to revert for ten cryptocurrencies (Bitcoin, Cardano, Litecoin, Bitcoin SV, NEM, Chainlink, Tron, Huobi Token, Dash and Zcash).

[2] Results of the optimal lag-length are available upon request.

Specifically, the impact of the fear index becomes significantly negative for these cryptocurrencies. Hence, we can say that, after controlling for contemporaneous asset-based sentiment (TV), uncertainty about policy measures (EPU), and fear in the equity and oil markets (VIX and OVX), the returns of the majority (eleven out of nineteen) cryptocurrencies seem to decrease when the fear of Covid-19 increases, suggesting that major cryptocurrencies are not very different from the other assets during the period of the pandemic. For the rest of the cryptocurrencies (Ethereum, Binance Coin, XRP, Bitcoin cash, Stellar, EOS, Tezos and Monero), there exists a persistent positive impact in the following days. In terms of magnitude, a similar reaction is found for cryptocurrencies which exhibit a moderate reaction to the Covid-19 GFI (the joint coefficient of the GFI lags $|\hat{\gamma}_{i,l}|$<1). When comparing this finding to those of Salisu and Akanni (2020) that studied the impact of Covid-19 GFI on stock markets and Salisu et al., (2020) on commodity markets, the reaction of cryptocurrencies to the fear of Covid-19 seems to be less aggressive as compared to other assets (the coefficients are higher than 1 in absolute value for both the stock and commodity markets).
We further extend our analysis by accounting for any possible asymmetries in cryptocurrencies' returns predictability using the global fear index. We hypothesize a negative impact of positive changes on cryptocurrencies' returns, while the inverse would be true for negative changes. The results of model 3 in table II show that positive asymmetry is negatively (positively) significant for Bitcoin and Monero (Chainlink and Huobi Token), which suggests that any increase in Covid-19 global fear index has a negative (positive) impact on the returns of these cryptocurrencies. The negative changes are found to be significantly positive (negative) for Bitcoin (NEM, Chainlink and Huobi Token). The statistical significance (*p-values*) of the differential slope coefficient between the two asymmetries is reported in the last column of the table. The coefficients are significant at the 10% level or less for these cryptocurrencies which further confirms the presence of asymmetry. For the rest of cryptocurrencies, positive and negative changes in the global fear index seem to have an identical impact on their returns.

Table II. Predictability of cryptocurrencies' returns results

	Model 1		**Model 2**		**Model 3**		
	$\hat{\gamma}_{i,l}$	H_0: $logGFI$ does not Granger cause R	$\hat{\gamma}_{i,l}$	H_0: $logGFI$ does not Granger cause R	$logGFI^{+}$	$logGFI^{-}$	Asymmetry test
Bitcoin	0.007 (755.600) [0.000]	1.939 [0.747]	-0.069 (5245.860) [0.000]	9.253* [0.055]	-0.006* (0.470) [0.492]	0.012* (3.180) [0.078]	0.099*
Altcoin							
Ethereum	0.030 (889.910) [0.000]	2.767 [0.598]	0.029 (3740.530) [0.000]	16.118*** [0.003]	0.005 (0.160) [0.689]	0.003 (0.020) [0.892]	0.941
Tether	-0.0005 (778.320) [0.000]	5.097 [0.531]	-0.023 (1486.170) [0.000]	2.979 [0.561]	-0.001 (1.480) [0.226]	-0.001 (0.200) [0.659]	0.952
Cardano	0.017 (764.280) [0.000]	1.741 [0.628]	-0.044 (99.160) [0.000]	1.833 [0.608]	-0.011 (0.660) [0.417]	0.017 (1.250) [0.264]	0.190
Binance coin	0.004 (750.140) [0.000]	2.364 [0.669]	0.140 (3994.260) [0.000]	9.554** [0.049]	-0.015 (0.910) [0.403]	-0.013 (0.840) [0.361]	0.949
XRP	0.017 (761.070) [0.000]	2.931 [0.570]	0.095 (2999.12) [0.000]	4.158 [0.385]	0.004 (0.100) [0.751]	-0.002 (0.030) [0.868]	0.741
Litecoin	0.013 (773.570) [0.000]	3.019 [0.555]	-0.002 (4181.38) [0.000]	6.073 [0.194]	-0.013 (1.380) [0.241]	0.016 (0.820) [0.365]	0.178
Bitcoin cash	0.010 (756.210) [0.000]	4.892 [0.299]	0.044 (4815.280 [0.000]	21.248*** [0.000]	-0.019 (1.350) [0.247]	0.003 (0.040) [0.836]	0.338
Bitcoin SV	0.021	9.181*	-0.059	3.869	-0.038	0.006	0.195

	(734.590) [0.000]	[0.057]	(4071.580) [0.000]	[0.424]	(2.880) [0.091]	(0.250) [0.616]	
Stellar	0.021 (758.010) [0.000]	4.772 [0.311]	0.038 (3604.400) [0.000]	11.197** [0.024]	-0.011 (0.950) [0.331]	0.001 (0.000) [0.959]	0.551
EOS	0.019 (759.610) [0.000]	2.682 [0.443]	0.008 (94.910) [0.000]	2.542 [0.468]	-0.015 (0.840) [0.359]	0.009 (0.680) [0.412]	0.220
Tezos	0.053 (901.710) [0.000]	2.995 [0.559]	0.015 (3644.320) [0.000]	4.496 [0.343]	0.005 (0.110) [0.737]	-0.037 (1.230) [0.269]	0.252
NEM	0.006 (780.180) [0.000]	0.287 [0.963]	-0.100 (93.230) [0.000]	2.382 [0.497]	0.002 (0.030) [0.864]	-0.037* (3.230) [0.074]	0.100*
Exchange Token							
Chainlink	0.015 (776.260) [0.000]	2.206 [0.531]	-0.089 (98.060) [0.000]	0.908 [0.823]	0.039*** (10.300) [0.001]	-0.073*** (7.910) [0.005]	0.000***
Tron	0.022 (762.600) [0.000]	1.535 [0.674]	-0.035 (91.040) [0.000]	1.828 [0.609]	0.003 (0.050) [0.824]	-0.017 (0.330) [0.563]	0.539
Huobi Token	0.012 (765.220) [0.000]	5.714 [0.126]	-0.054 (76.840) [0.000]	3.761 [0.288]	0.062*** (35.040) [0.000]	-0.029* (2.740) [0.099]	0.000***
Privacy coin							
Monero	0.045 (874.030) [0.000]	4.196 [0.380]	0.129 (3652.64) [0.000]	5.269 [0.261]	-0.017*** (2.290) [0.132]	0.027 (3.180) [0.076]	0.023**
Dash	0.020 (756.540) [0.000]	2.304 [0.512]	-0.090 (93.220) [0.000]	1.777 [0.620]	-0.006 (0.210) [0.651]	-0.011 (0.520) [0.472]	0.800
Zcash	0.022 (757.330) [0.000]	2.775 [0.428]	-0.035 (93.390) [0.000]	0.899 [0.825]	-0.028 (2.630) [0.106]	0.001 (0.000) [0.963]	0.194

Note: this table reports the results of models 1, 2 and 3, respectively. For models 1 and 2, we report the sum of the coefficients of the lagged log of global fear index up to n lags ($\sum_{l=1}^{n} logGFI_{i,t-l}$), where the number of lags n is selected based on Akaike Information Criterion (AIC). We use the Wald test to test for the joint significance of the coefficients. The F-statistics are in parentheses and the corresponding p-values are in brackets. The null hypothesis of no predictability is: $H_0: \sum_{l=1}^{10} \hat{\gamma} = 0$. The p-values for Granger causality test results from fear index to cryptocurrencies' returns are reported. The null hypothesis is that $logGFI$ does not Granger cause R.
For model 3, the table reports the positive ($logGFI^{+}$) and negative ($logGFI^{-}$) asymmetries of the fear index. The asymmetry test reported is the p-value of the differential slope coefficient and its statistical significance implies the presence of asymmetry. .***,** and * indicate significance at the 10%, 5% and 1% level, respectively.

Table III reports the evaluation results of the respective predictive models in equations (1), (2) and (3) using the root mean square error (RMSE). By nature, RMSE explains the deviation of the forecast series from the actual series. A value of zero of RMSE indicates perfect forecasts and the closer the value to zero, the better the forecasts. Hence, when comparing the three predictive models, we assume that the lower the in-sample RMSE of a model, the better is the model in predicting cryptocurrencies' returns. The table also reports the out-of-sample RMSEs of the models. Specifically, we divide our initial sample into two subsamples: The in-sample period (i.e., the training set) and the out-of-sample period (i.e., the test set). When the out-of-sample RMSE is lower than the in-sample RMSE, then the respective model delivers sizeable reductions in terms of RMSE implying its efficiency in the predictability of returns.
For the in-sample forecast performance evaluation of our empirical models, results show that the RMSEs for cryptocurrencies' returns in the predictive model 1 are lower than those of the multiple-factor model in equation (2) and the asymmetric model in equation (3) under the 50% and 75% sample size for the majority of the sampled cryptocurrencies (Bitcoin, Ethereum, Tether, Binance coin, XRP, Litecoin, Bitcoin SV, Stellar, EOS, Tezos, Tron, Huobi Token and

Monero). This indicates that the single-factor predictive model in equation (1) is better than the two other models and that the extension of the single-factor model to account for other control variables and asymmetry does not seem to improve its forecast performance for these thirteen cryptocurrencies. The RMSE for the asymmetric model in equation (3) is lower for five cryptocurrencies (Cardano, Bitcoin cash, NEM, Chainlink and Dash) under the 50% and 75% sample sizes as compared to the single-factor and the multiple-factor models. A similar inference can be drawn for the multi-factor model in equation (2) as compared to the single-factor and asymmetric models with respect to Zcash. These findings are confirmed by the Out-of-sample RMSEs. The latters are lower for the test set as compared to the training set regarding the selected models for the respective cryptocurrencies.

Table III. In-sample and out-of-sample RMSEs for predictive models

	50% of full sample						75% of full sample					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
Bitcoin	0.0211	0.0153	0.0232	0.0159	0.0213	0.0153	0.0182	0.0178	0.0199	0.0193	0.0184	0.0183
Altcoin												
Ethereum	0.0259	0.0220	0.0275	0.0222	0.0264	0.0228	0.0239	0.0223	0.0244	0.0235	0.0241	0.0262
Tether	0.0027	0.0008	0.0033	0.0009	0.0029	0.0010	0.0023	0.0001	0.0027	0.0001	0.0025	0.0001
Cardano	0.0285	0.0279	0.0291	0.0281	0.0281	0.0278	0.0261	0.0335	0.0269	0.0322	0.0258	0.0236
Binance coin	0.0242	0.0199	0.0268	0.0198	0.0251	0.0205	0.0230	0.0198	0.0245	0.0201	0.0237	0.0202
XRP	0.0212	0.0208	0.0219	0.0379	0.0208	0.0378	0.0181	0.0141	0.0190	0.0129	0.0184	0.0024
Litecoin	0.0229	0.0244	0.0240	0.0235	0.0231	0.0244	0.0216	0.0209	0.0221	0.0286	0.0217	0.0213
Bitcoin cash	0.0259	0.0242	0.0285	0.0236	0.0245	0.0105	0.0232	0.0308	0.0253	0.0235	0.0229	0.0135
Bitcoin SV	0.0281	0.0245	0.0300	0.0204	0.0292	0.0257	0.0249	0.0209	0.0263	0.0243	0.0256	0.0328
Stellar	0.0232	0.0156	0.0237	0.0221	0.0237	0.0228	0.0214	0.0188	0.0217	0.0156	0.0216	0.0183
EOS	0.0247	0.0214	0.0252	0.0221	0.0246	0.0226	0.0213	0.0206	0.0229	0.0260	0.0215	0.0209
Tezos	0.0308	0.0245	0.0331	0.0254	0.0309	0.0275	0.0283	0.0264	0.0299	0.0246	0.0287	0.0264
NEM	0.0214	0.0306	0.0211	0.0281	0.0211	0.0207	0.0249	0.0319	0.0246	0.0298	0.0236	0.0105
Exchange Token												
Chainlink	0.0314	0.0324	0.0342	0.0306	0.0308	0.0301	0.0324	0.0307	0.0338	0.0266	0.0320	0.0288
Tron	0.0243	0.0232	0.0264	0.0232	0.0248	0.0234	0.0247	0.0221	0.0254	0.0228	0.0249	0.0226
Huobi Token	0.0212	0.0152	0.0236	0.0162	0.0219	0.0156	0.0185	0.0176	0.0205	0.0183	0.0191	0.0184
Privacy coin												
Monero	0.0232	0.0100	0.0253	0.0200	0.0239	0.0199	0.0215	0.0212	0.0234	0.0219	0.0220	0.0217
Dash	0.0258	0.0247	0.0261	0.0226	0.0255	0.0224	0.0233	0.0304	0.0245	0.0225	0.0232	0.0197
Zcash	0.0239	0.0229	0.0244	0.0230	0.0255	0.0247	0.0245	0.0238	0.0257	0.0231	0.0254	0.0249

Note: this table reports the Root Mean Square Error (RMSE) values for the three used predictive models. A value of zero of RMSE indicates perfect predictability. Hence, the lower the value of RMSE, the higher the predictive power of the used model.

To better enhance our analysis, we use the Clark and West (2007) in order to complement the preliminary evaluation using RMSEs in Table III. Particularly, unlike RMSE that does not account for the noise associated with larger models, the Clark and West (2007) test adjusts for the noise associated with larger models' forecasts and assesses the significance of the difference in the predictive accuracy of two competing models. Results of this evaluation are reported in Table IV. Specifically, three cases of model comparison are presented. The first is the case of model 1 vs. model 2. The second is the case of model 1 vs. model 3 and, finally, the third case is model 2 vs. model 3. For the first case, if the CW statistic and positive and significant than the extended model in equation (2) outperforms the parsimonious model in equation (1). For the second case, when the CW test is significantly positive, then accounting for asymmetries improves the predictability of returns, and finally, for the third case, if the CW test is positive and significant, then model 3 is preferred to model 2.

CW test results show that the extended model in equation (2) is preferred to the single-factor model in equation (1) and the asymmetric model in equation (3) in terms of forecast accuracy both in- and out-of-sample. We begin by the first case. CW statistics are positive and significant for all cryptocurrencies (except for Tether) which suggests that the extended model in equation (2) is preferred to the single-factor model in equation (1) both in- and out-of-sample under the 50% and 75% sample sizes. For the second and third cases, in-sample results show that the asymmetric model in equation (3) is preferred to both the single-factor and multiple-factor models in equations (1) and (2), respectively. However, out-of-sample CW statistics show mixed results; Specifically, accounting for asymmetry seems to worsen the forecast performance as compared to the single-factor model in equation (1) for Bitcoin, Cardano, Litecoin, Bitcoin cash, Bitcoin SV, EOS, Tezos, NEM, Chainlink, Huobi Token, Dash and Zcash; and as compared to the multiple-factor model for all cryptocurrencies except for Tether, implying that the single-factor and multiple-factor predictive models are sufficient in predicting returns for these cryptocurrencies. The only exception is Tether, in- and out-of-sample evaluation tests show that accounting for asymmetries seems to enhance the fitness of the forecasts.

Taking together, these findings stipulate that cryptocurrencies' returns are better predicted using the multiple-factor model in equation (2), whereas returns of Tether are better predicted using the asymmetric model in equation (3).

Table IV. In-sample and out-of-sample results of the Clark and West test

	50% of full sample						75% of full sample					
	Model 1 vs. Model 2		Model 1 vs. Model 3		Model 2 vs. Model 3		Model 1 vs. Model 2		Model 1 vs. Model 3		Model 2 vs. Model 3	
	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
Bitcoin	0.005***	0.032**	0.003***	0.057	0.099***	3.328	0.004***	0.121**	0.002***	0.327	0.001***	6.794
Altcoin												
Ethereum	0.074***	0.047**	0.076***	0.825*	0.074***	6.886	0.006***	0.269***	0.038***	1.969*	0.068***	9.727
Tether	-0.059***	0.036**	0.009***	0.003**	1.740***	0.005*	-0.002**	0.001***	0.009***	1.814**	0.001***	0.0006**
Cardano	0.063***	0.149*	0.045***	0.118	0.0001***	4.020	0.049***	0.661*	0.028***	0.576	0.0001***	4.950
Binance coin	0.036***	0.147*	0.058***	0.804**	2.615***	3.492	0.031***	0.347*	0.039***	0.906*	0.732***	1.640***
XRP	0.013***	0.067*	0.086***	3.058*	0.843***	8.369	0.022***	0.341***	0.051***	9.337**	0.651***	20.538*
Litecoin	0.004***	0.105**	0.047***	0.400	0.085***	7.599	0.003***	0.282***	0.021***	0.656	0.065***	13.107
Bitcoin cash	0.027***	0.068**	0.058***	0.855	0.098***	10.395	0.027***	0.146**	0.038***	1.883	0.073***	11.905
Bitcoin SV	0.098***	0.052**	0.088***	0.424	0.002***	15.432	0.051***	0.114**	0.059***	1.170	0.0001***	22.484
Stellar	0.127***	0.674**	0.069***	1.415*	0.0002***	1.797*	0.062***	1.167**	0.039***	4.534**	0.0001***	2.622
EOS	0.044***	0.029*	0.290***	-0.079	0.0001***	2.626	0.037***	0.091**	0.183***	0.418	0.075***	3.739
Tezos	0.037***	0.067**	0.060***	1.535	0.0001***	6.195	0.036***	0.267**	0.039***	1.487	0.0001***	4.395
NEM	0.018***	0.035	0.025***	2.154	0.053***	2.653	0.020***	0.311*	0.011***	5.459	0.054***	3.048
Exchange Token												
Chainlink	0.048***	0.039**	0.060***	0.430	0.0001***	6.024	0.041***	0.249**	0.031***	0.564	0.0001***	1.903
Tron	0.023***	0.029*	0.033***	0.379*	0.0001***	4.512	0.037***	0.064**	1.590***	0.919	0.082***	4.764
Huobi Token	0.021***	0.022*	0.025***	0.123	0.063***	6.203	0.019***	0.089*	0.210***	0.337	0.051***	6.224
Privacy coin												
Monero	0.013***	0.027**	0.051***	0.836*	0.0001***	6.958	0.028***	0.069**	0.036***	3.831*	0.069***	7.617
Dash	0.378*	0.065**	0.011***	0.329	0.0005**	9.080	0.013***	0.419*	0.008***	0.505	0.054***	12.400
Zcash	0.079***	0.026*	0.025***	0.319	0.0001***	6.943	0.024***	0.073**	0.015***	0.967	0.071***	12.690

Note: this table reports the Clark and West test for the three used predictive models. A positive and significant CW indicates that the second model outperforms the first model in terms of forecast accuracy for the three cases. The reverse holds if the C-W statistic is negative and significant.

Based on the initial proposal to determine the better predictive model, it is pertinent, for robustness purposes, to examine whether our proposed predictive models also outperform the historical average model. The latter is usually considered as a benchmark for predictive models. We use the Campbell and Thompson (2008) statistic to compare the forecast performance of our three predictive models to the historical average model. Our proposed models outperform the historical average model if the CT statistic is positive. The inverse holds if the CT statistic is negative.
Table V reports the results of the predictive evaluation in- and out-of-sample. The focus remains on the augmented model in equation (2) since it is shown to be better predictive model in forecasting cryptocurrencies' returns. Results show that CT statistics for the comparison of the performance of the multiple-factor model to the historical average are positive both in- and out-of-sample for all cryptocurrencies. Results are mixed for models 1 and 3. Specifically, model 1 (model 3) generates positive CT statistics both in-sample and out-of-sample with respect to the 50% and 75% sample sizes for Tether, Binance coin, Bitcoin cash, Bitcoin SV and Huobi Token (NEM only). These findings confirm the superiority of model 2 in predicting cryptocurrencies' returns.

Table V. In- and Out-of-sample forecast evaluation of used predictive models (comparison to the historical average).

	50% of full sample						75% of full sample					
	Model 1		Model 2		Model 3		Model 1		Model 2		Model 3	
	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample	In-sample	Out-of-sample
Bitcoin	0.001	-0.010	0.029	0.031	-0.0004	-0.007	0.005	-0.020	0.035	0.032	-0.003	-0.011
Altcoin												
Ethereum	0.022	-0.003	0.051	0.025	0.005	-0.003	0.009	-0.004	0.062	0.003	-0.002	-0.003
Tether	0.067	0.112	0.015	0.154	-0.006	-0.0001	0.078	0.086	0.033	0.192	-0.004	0.071
Cardano	-0.006	0.004	0.045	0.044	0.008	-0.007	0.001	-0.007	0.042	0.076	-0.0003	-0.011
Binance coin	0.034	0.022	0.013	0.060	0.001	-0.004	0.025	0.018	0.021	0.061	-0.003	-0.0009
XRP	0.021	-0.015	0.024	0.002	-0.002	0.001	0.013	-0.034	0.037	-0.008	-0.003	-0.002
Litecoin	0.013	-0.010	0.029	0.054	0.001	-0.007	0.0009	-0.025	0.031	0.038	-0.003	-0.016
Bitcoin cash	0.015	0.018	0.002	0.024	-0.004	-0.005	0.011	0.010	0.011	0.022	-0.003	-0.010
Bitcoin SV	0.036	0.042	0.048	0.049	-0.002	-0.003	0.027	0.047	0.044	0.043	-0.002	-0.011
Stellar	0.008	-0.005	0.069	0.122	0.006	-0.007	0.006	-0.025	0.062	0.157	-0.001	-0.014
EOS	-0.002	-0.0008	0.039	0.016	0.002	-0.005	0.0008	-0.014	0.039	0.006	-0.001	-0.012
Tezos	0.010	-0.001	0.029	0.027	0.006	-0.005	0.014	-0.016	0.041	0.021	-0.0007	-0.014
NEM	-0.008	0.0002	0.032	0.021	0.008	0.004	-0.007	-0.022	0.029	0.111	-0.002	0.022
Exchange Token												
Chainlink	-0.004	-0.005	0.023	0.039	0.013	0.001	-0.005	-0.007	0.021	0.129	0.0009	-0.014
Tron	-0.004	-0.006	0.022	0.013	0.001	-0.001	0.0002	0.009	0.027	0.001	-0.003	-0.013
Huobi Token	0.038	0.018	0.008	0.059	0.015	-0.007	0.041	0.032	0.018	0.036	0.011	-0.015
Privacy coin												
Monero	0.027	-0.006	0.031	0.002	-0.0008	0.001	0.020	-0.006	0.031	0.030	-0.0009	0.019
Dash	-0.014	-0.006	0.035	0.037	-0.004	0.006	-0.008	-0.014	0.009	0.172	-0.003	0.013
Zcash	-0.012	-0.003	0.039	0.026	0.004	0.010	-0.006	-0.011	0.018	0.012	-0.001	0.026

Note: this table reports the Campbell and Thompson (2008)—CT statistic. Forecast performance of the models in equations 1, 2 and 3 is evaluated and compared to the performance of the forecasting model in eq.(4).

6. Conclusion

This paper investigates whether global fear of health risks matters for major cryptocurrencies. Specifically, we propose a predictive model that uses the Covid-19 global fear index and test for its significant impact on subsequent cryptocurrencies' returns. We contribute to the literature on the predictability of the cryptocurrency markets in four main ways. First, we introduce global fear as a predictor of future cryptocurrencies' returns by formulating a fear-based predictive model. Second, we combine the fear of Covid-19 pandemic's health risks with other selected fear and uncertainty proxies that gauge for the asset-based fear, the economic uncertainty about policy measures and the fear in the stock and oil markets and we present a multiple-factor fear-based predictive model. Third, we examine whether accounting for asymmetries would improve the predictability of returns. Finally, we test for the robustness of our results in multiple sample periods. The empirical findings show that global fear of the Covid-19 pandemic is a relevant predictor of major cryptocurrencies' returns and that extending the single-factor fear-based predictive model to capture the effect of other economic and financial fear variables improves the forecasts of cryptocurrencies' returns. Specifically, results of the multiple-factor model show a negative relationship between global fear of Covid-19 pandemic and returns of the majority of the sampled cryptocurrencies. Our findings provide statistically significant out-of-sample forecast performance.

While the reaction of cryptocurrencies to the fear environment is found to be smaller, in terms of magnitude, as compared to the stock and commodity markets (Salisu and Akanni, 2020; Salisu et al., 2020), our results suggest that cryptocurrencies are not very different from other assets during the pandemic and do not support the findings of some empirical studies that have presented cryptocurrencies as safe-havens during the recent Covid-19 pandemic (e.g., Caferra, 2020; Corbet et al., 2020).

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