The Consequence of COVID-19 on Cryptocurrency Returns

Umesh Kumar and Biqing Huang*

Abstract

This study scrutinizes the COVID-19 measures and their effect on leading cryptocurrency returns. Our direct measures of COVID-19 show that cryptocurrency returns are significantly influenced by COVID-19 and are most visible throughout pre-vaccination phase. The intraday price movement becomes wider during vaccination period compared to cryptocurrency returns. The findings demonstrate that even negative news of COVID-19 did not deter investors from being optimistic in the pre-vaccination period. Further, COVID-19 impacts on the cryptocurrency market diverge depending on the size of currency once vaccination begins. It reflects a different underlying dynamic process in cryptocurrency trading.

JEL Classification: C 30 G11, G14, G15
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I Introduction

Cryptocurrency has been a significant innovation among financial products in recent years. It forms a digital version of a traditional currency and is usually resilient to inflation. The cryptocurrency market has undergone rapid growth and transformed into a global phenomenon. The ongoing pandemic, COVID-19, has brought unprecedented challenges to financial markets and affected the fragility of cryptocurrency markets. Academicians and policymakers have focused on the COVID-19 proliferation and its potential shock on the financial markets and overall economy. The current pandemic has generated excessive volatility, economic anxiety, and weakened economic sentiment in financial markets. It is perceived to be in response to COVID-19 policy measures (Baker et al., 2020; Fetzer et al., 2020).

Several studies have focused on the pandemic and examined the impact of COVID-19 on various asset classes such as stocks, bonds, currencies, commodities, and cryptocurrencies. However, most studies evaluating the effect of COVID-19 have examined volatility or asset returns. James et al. (2021) studied the erratic behavior of cryptocurrency during COVID-19 and concluded that cryptocurrency returns and variance perform differently pre-and post-pandemic. The volatility of central fiat and cryptocurrency markets has been severely stressed during COVID-19 (Umar & Gubareva, 2020). The pandemic has adversely affected the potential role of cryptocurrencies as diversifying investments (Gil-Alana et al., (2020). Mnif et al. (2020) show that COVID-19 positively influences the cryptocurrency market efficiency. Similarly, Montasser et al. (2022) analyze the cryptocurrency price bubbles and price stability during the pre and post-COVID-19 announcement and contend that the pandemic has impacted cryptocurrency market efficiency. However, recent literature (Filippou et al., (2021)) points out that the studies on cryptocurrency return predictability could be more extensive.

The COVID-19 pandemic has prompted substantial attention and research in decentralized finance (DeFi), particularly in cryptocurrencies. There has been significant research and interest in cryptocurrencies such as Bitcoin and Ethereum. However, many leading cryptocurrencies and

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their dynamics still need to be understood. We note that there need to be more studies addressing the pandemic response to the cryptocurrency market, given government measures, particularly vaccination. This study fills this research gap by exploring the linkage between cryptocurrency returns and COVID-19 contagion. It explores the relationship between cryptocurrency price and COVID-19 intensity using the top 10 cryptocurrencies.

Additionally, many recent papers have discussed and analyzed the economic effect of COVID-19 at global, country, and sectoral levels. However, there is a shortage of studies investigating the changes in COVID-19 measures such as vaccination and intensity, i.e., infections, deaths, and hospitalizations. We hypothesize that COVID-19 measures to prevent illnesses and deaths may influence cryptocurrency returns. The hypothesis is centered on the study that documents, using 146 observations (January 01, 2020, to June 15, 2020), how the varying intensity of COVID-19, characterized by infections and deaths, influences the daily returns of the top ten cryptocurrencies (Iqbal et al., 2021). They show that changes in pandemic intensity have a differential impact on cryptocurrencies. Therefore, it is interesting to see how cryptocurrencies perform in an ongoing pandemic, mainly because of vaccine availability and other government initiatives.

This paper extends the emerging literature on the cryptocurrency market and COVID-19. Regan (2021), in his Bloomberg article, reports that "institutional investor portfolios worth $7 trillion are exposed to cryptocurrencies". The role of algorithmic trading, the speed of information, and ever-expanding technological development in the financial markets have essential considerations for cryptocurrencies. Therefore, it is important to revisit and examine the relationship between COVID-19 and cryptocurrency return and intraday price movement. We use direct measures of COVID-19 intensity such as new covid cases, total covid cases, new covid deaths, total covid deaths, icu covid patients, and hospitalized covid patients on a given day. Most importantly, we use a more comprehensive data set to understand whether the returns of cryptocurrencies are related to COVID-19 intensity, given the role of vaccination and its effectiveness combined with other government measures. To the best of our knowledge, we are the first to use several measures of COVID-19 for cryptocurrencies during pre-and vaccination periods of an ongoing pandemic.

The paper uses a sample of the top 10 cryptocurrencies traded globally and COVID-19 variables from the U.S. It is noted that many cryptocurrency exchanges operate independently and nonintegrated. They exist in parallel across geographic regions. However, we restrict the COVID-19 intensity variables to the U.S. since the cryptocurrencies are reported in U.S. dollars, and COVID intensity variables are reliable. Further, the U.S. is a unique laboratory for evaluating and assessing COVID-19 policies. We employ multivariate regressions and generalized autoregressive conditional heteroskedasticity in mean (GARCH-M) to test the hypotheses.

Our study finds that COVID-19 intensity continues to affect the cryptocurrency market. First, we specifically study the effect during the pre-vaccination period. All statistical models suggest that COVID-19 has a positive and significant association with cryptocurrency returns/price movement in particular cryptocurrency or aggregate level. The results are consistent with the findings of prior literature. However, when we conduct a similar analysis during vaccination (immunization availability), the cryptocurrencies behavior varies with the COVID-19 variables. Several measures of COVID-19 intensity, i.e., ICU and Hospitalized COVID Patients, are negatively and significantly related to cryptocurrencies. Some variables have no or lower level of association with cryptocurrencies.

Further, we find that big and small cryptocurrencies differ during vaccination. Our contribution to the literature is from a methodological perspective using several models to confirm our findings. Second, we extend the study period to cover the vaccination period and other government initiatives for COVID-19.

II Literature Review

The cryptocurrency market, a pivot of decentralized finance and embodiment of blockchain technology, has drawn significant interest from academicians, researchers, policymakers, investors, and government bodies. There has been a growing number of empirical studies on COVID-19 and the cryptocurrency market in a short time. Research shows that the current COVID-19 episode differs from comparable pandemics/epidemics such as SARS and EBOLA in recent history. Albulescu (2020) considers that COVID-19 has generated considerable volatility in financial markets and the real economy. Baldwin and Mauro (2020) note that being a health or non-economic crisis, the pandemic has produced considerable turmoil in largescale economic activity and the financial markets, further impacting other sectors. Baker et al. (2020) suggest that government restriction on business activity and lockdowns during the COVID-19 pandemic has substantially caused stock market volatility in the history of pandemics.

Global financial market stress can cause significant variations in the returns of cryptocurrencies (Bouri, Gupta, Lau, et al., 2018). A recent study suggests that in times of severe financial and economic disruption, crypto-assets do not act as hedges or safe havens but, perhaps, instead, as a broadening of contagion (Conlon & McGee, 2020). Diversification benefits among cryptocurrencies are short-term, while market connectedness and volatility linkages are sensitive to liquidity and volatility (Omane-Adjepong & Alagidede, 2019). Further, the ongoing COVID-19 crisis will have enormous economic costs (Goodell, 2020).

The cryptocurrency market has been studied from several perspectives. Prior literature documents that even popular cryptocurrencies such as Bitcoin and Ethereum are not a safe bet and may need a better diversification strategy. Their addition augments to portfolio's downside risk. Portfolio risk can be reduced by including Bitcoin in a portfolio of gold, oil, and others (Conlon et al., 2020; Guesmi et al., 2019; Smales, 2019). In contrast, earlier Bouri et al. (2017) and Tiwari et al. (2019) report that Bitcoin is a weak hedge and unsuitable for diversification purposes. Liu et al. (2022) document that momentum and size are essential in depicting cryptocurrency returns.

Thus, a growing strand of financial studies investigates the cryptocurrency market from several dimensions and its implications on asset pricing. The consequences of COVID-19 on financial and cryptocurrency markets are studied; however, no direct measure of COVID-19 intensity is identified, such as covid cases, deaths, and hospitalization. Hence, it needs further investigation. This paper aims to extend the study of cryptocurrencies and understand their behavior before and during COVID-19.

III Data and Variables:

Cryptocurrency data is obtained from https://www.investing.com/crypto/ currencies. It is one of the leading price and trading volume providers for cryptocurrencies. The data comprises an opening, closing, high and low prices, and trading volume in USD terms. We select the daily frequency data of the top 10 cryptocurrencies since other currencies are less liquid and need more daily data. The sample period starts from the first COVID-19 case reported, i.e., January 22, 2020, to August 31, 2022. The COVID-19 variables dataset is collected from GitHub (https://github.com/owid/covid-19-data/tree/master/public/data). It contains comprehensive information on worldwide COVID-19 related to confirmed cases, deaths, hospitalizations, testing, and other variables of potential interest. We gather control variables data, i.e., Crypto Volatility

Index from https://cvi.finance/, the MSCI All-Country World Equity Index from https://www.investing.com/indices/msci-world-stock-historical-data, and one-year U.S. treasury bill from the Federal Reserve Bank of St. Louis.

Cryptocurrency data meets the requirements of the International Organization of Securities Commission (IOSCO) Principles for Financial Benchmarks and the criticism of Alexander and Dakos (2020). We use COVID-19 variables from the U.S. as it provides a representation of the pandemic impact on the cryptocurrency market. The MSCI All-Country World Equity Index is used as a representative of world equity markets, a one-year U.S. treasury bill as a risk-free measure. At the same time, the Crypto Volatility Index is selected to illustrate the volatility in cryptocurrency returns. All indices are priced in U.S. Dollars, and daily logarithmic returns are calculated. P_t, H_t, and L_t are a cryptocurrency's closing price, daily high and daily low, respectively, at time $_t$. R_t and HL_t are currency log returns and intraday movement, respectively.

$$R_t = \log\left(\frac{Pt}{Pt-1}\right)$$

$$HL_t = \log\left(\frac{logHt-logLt}{logPt}\right)$$

We explore the US COVID-19 data response on cryptocurrency prices. Therefore, the study period starts from the first COVID case reported in the U.S., i.e., January 22, 2020. Cryptocurrency Index is a value-weighted index of the leading ten cryptocurrencies. The biggest cryptocurrency, Bitcoin, has a 48.07% weightage in the index. Since cryptocurrencies are traded daily without holidays, these currencies' prices vary substantially during the day. Therefore, we use the log returns and intraday movement for each cryptocurrency and cryptocurrency index.

Based on prior literature on asset pricing, we use the control variables such as the MSCI All-Country World Equity Index, Crypto Volatility Index, one-year U.S. treasury bill rate, cryptocurrency trading volume based on each cryptocurrency trading volume and corresponding weight, and daily number of COVID-19 cases of the U.S. between January 22, 2020, to August 31, 2022. The COVID-19 cases are confirmed new and total cases, confirmed new and total deaths, and total ICU and hospitalized COVID-19 patients. Appendix 1 lists the top 10 cryptocurrencies globally based on market capitalization.

The COVID-19 data have followed varying protocols to count cases, deaths, and hospitalizations. New cases, total cases, new deaths, and total deaths of COVID-19 are clear cases whenever reported. Therefore, it is possible that these data variables of COVID-19 may not correctly represent the actual cases and deaths triggered by COVID-19. ICU and hospitalized COVID-19 patients are the number of COVID-19 patients in the hospital on a given day. In order to capture the effect of daily changes and the effect of COVID-19, we use COVID-19 proxies standardized per million people.

Figure 1 below displays daily new COVID-19 cases reported from 1st case on January 22, 2020, to August 31, 2022. The graph indicates three strong waves of COVID-19 spreading in the country. However, Figure 2 on total cases suggests steady upward daily total cases of COVID-19. Now, Figure 3 shows the base price series cryptocurrency and equity prices. It is apparent that the crypto and equity markets fell once COVID-19 was considered a pandemic on March 11, 2020. Both markets recovered and started doing well. The equity market is growing steadily with lower volatility, while the crypto market later in 2020 picked up with much volatility. Figure 4 illustrates the volatility in the cryptocurrencies returns and has been volatile during the sample period. Overall, the graphs signal a volatile cryptocurrency market.

IV Methodology and Results

Multivariate regressions such as Ordinary Least Squares (OLS), Seemingly Unrelated Regression (SUR), Cointegration, and Granger Causality, among others, have been applied in analyzing asset prices. Financial market data often present volatility clustering, where time series data display high and low volatility cycles. Time-varying volatility is more common, particularly with economic and financial data, and therefore, a good model of time-varying volatility is crucial in analyzing data.

Recent studies show that the association of cryptocurrency, such as Bitcoin, with equity markets is not symmetric (Gajardo et al., 2018). Further, Iqbal et al. (2021) find that COVID-19 has asymmetric dynamics with cryptocurrencies. This paper uses the autoregressive error model since COVID data and cryptocurrency variables are asymmetrical. We use the following model that estimates regression models for time series data. The effects of the regressor variables are distributed across time. It can include any number of regressors with distribution lags and any number of covariates.

$$Y_t = \alpha + \sum_{i=0}^{p} \beta_i X_{t=i} + \gamma z_t + \ \dots\dots \ + \varepsilon_t \qquad (1)$$

Here, x_t is the regressor with a distributed lag effect. z_t is a simple covariate, and $\boldsymbol{\varepsilon}_t$ is an error term. Almon lag polynomials model the distribution of the lagged effects. The coefficients b_i of the lagged values of the regressor are assumed to lie on a polynomial curve.

$$b_i = \alpha_0^* + \sum_{j=1}^{d} \alpha_j^* i^j$$

Where d ($\leq p$) is the degree of the polynomial. For efficient estimation, orthogonal polynomials as follow is used.

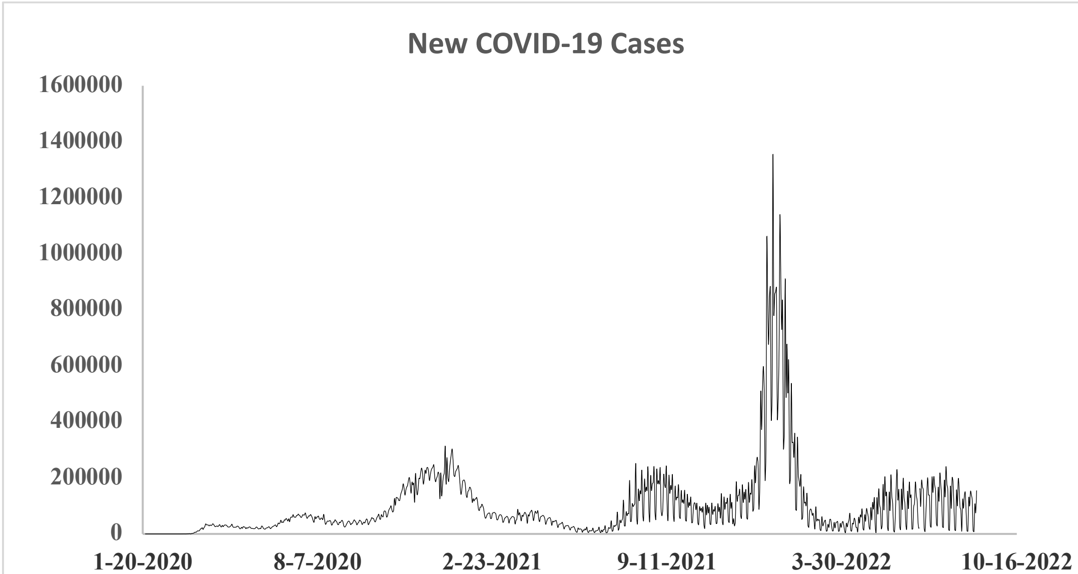
$$b_i = \alpha_0 + \sum_{j=1}^{d} \alpha_j f_j(\dot{i})$$

Where $f_j(\dot{i})$ is a polynomial of degree j in the lag length i, and α_j is a coefficient estimated from the data. The model can specify a minimum degree and a maximum degree for the lag distribution polynomial, and the procedure fits polynomials for all degrees in the specified range. Therefore, the equation can be written as follows:

$$CryIndRet_t = \alpha + \sum_{i=0}^{p} \beta_i COVID - 19\ Cases_{t=i} + \sum_{i=0}^{j} \gamma\ Control\ Variables_{t=i} + \ \dots\dots\dots\dots\dots \ + \varepsilon_t$$

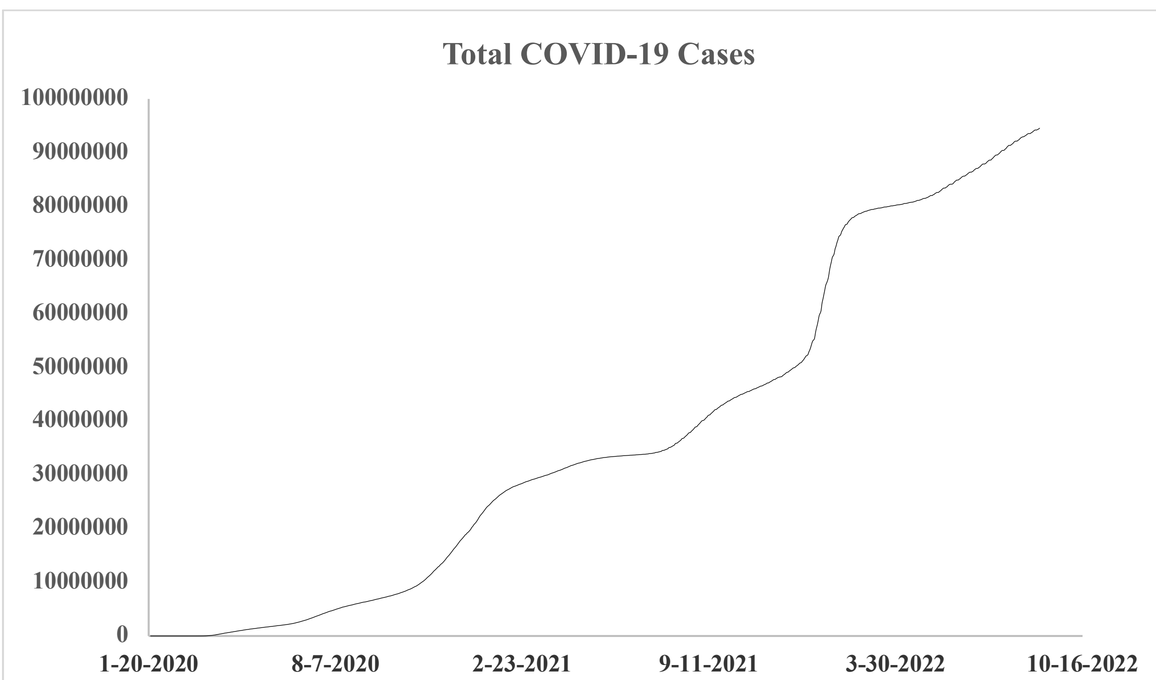
$CryIndRet_t$ is the Cryptocurrencies Index Return, a log value proxy using leading ten cryptocurrencies by market capitalization. COVID-19 cases are the log-transformed cases per million population. Control Variables are the change in Crypto Volatility Index, MSCI World Index Return, One-Year Risk-Free Rate, and Crypto Trading Volume, and $\boldsymbol{\varepsilon}$t is an error term.

Figure 1: New COVID-19 Confirmed Cases



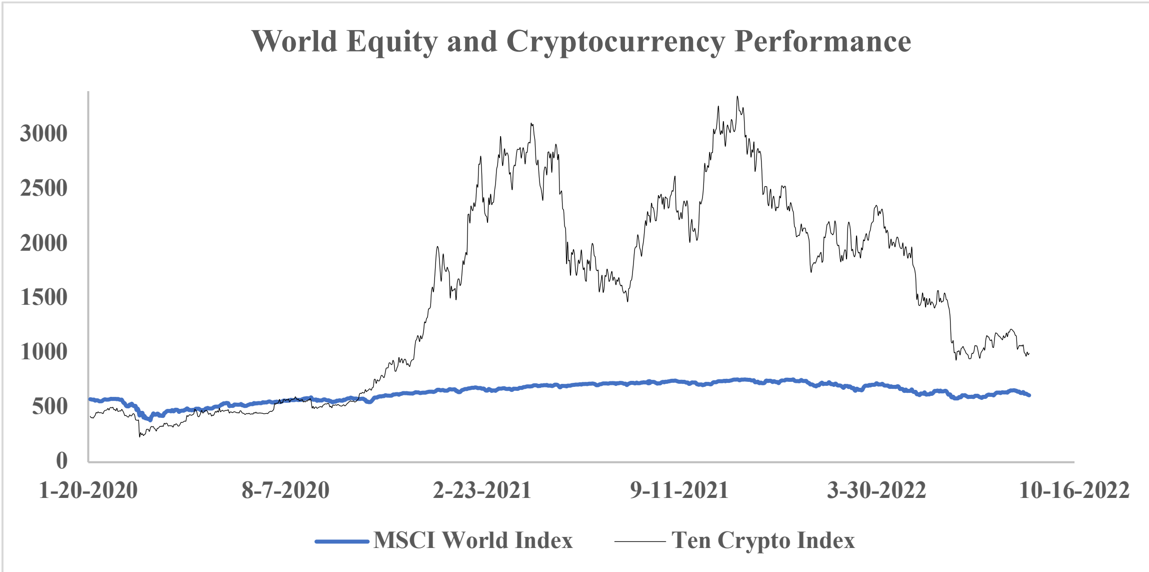
This figure presents new COVID-19 cases reported daily. There are waves of higher new cases during November -December 2020, August-September 2021, and increasing in March 2021.

Figure 2: Total COVID-19 Confirmed Cases



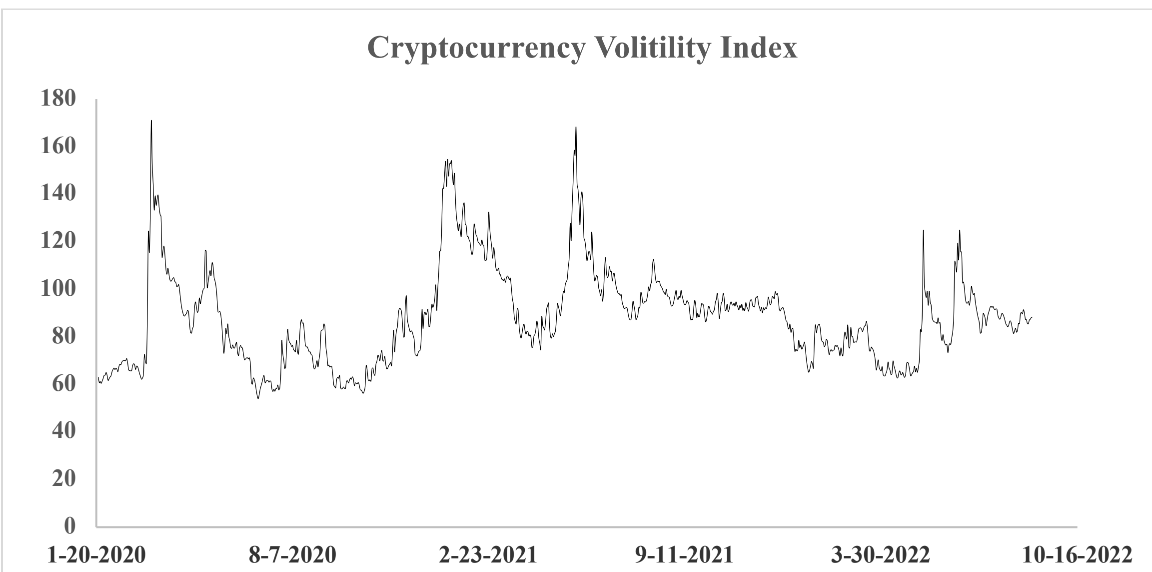
This figure plots total COVID-19 cases reported.

Figure 3: World Equity and Top 10 Cryptocurrency Index



This figure illustrates the daily index value of World Equity and the Top 10 Cryptocurrency movement. The Cryptocurrency Index is based on market capitalization as on August 2022. The y-axis is the index value of both indices. The graph indicates that cryptocurrencies are more volatile.

Figure 4: Cryptocurrency Volatility Index Movement



This figure illustrates daily volatility of Cryptocurrencies.

Daily asset prices, such as stock returns, can have heavy-tailed probability distributions or outliers. The conditional variance changes and the outliers occur when the variance is significant, as exhibited in cryptocurrency prices. Therefore, we use alternative models to augment the analysis of the results using two generalized autoregressive conditional heteroscedasticities (GARCH) Models. GARCH is used considerably within the economic or return data as asset prices are conditional heteroskedastic. First, we use the GARCH model of Bollerslev (1986), an essential time series model for heteroscedastic data. It unequivocally models a time-varying conditional variance as a linear function of past squared residuals and their past values.

$$Y_t = x_t\beta + \gamma\sqrt{h_t} + \varepsilon_t$$

The residual ε_t is modeled as

$$\varepsilon_t = \sqrt{h_t} * v_t$$

Where v_t is *i.i.d.* with zero mean and unit variance, and where h_t is expressed as

$$h_t = \kappa + \delta_1 h_{t-1} + \delta_2 h_{t-2} + \ldots + \delta_{p1} h_{t-p} + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \ldots + \alpha_{q1} u_{t-q}^2$$

Alternative GARCH model is the Exponential GARCH (EGARCH) model used in this study has the conditional variance of u_t as follows:

$$\log h_t = \omega + \sum_{i=1}^{q} \alpha_i \, g(z_{t-i}) + \sum_{j=1}^{p} \gamma_j \, ln\big(h_{t-j}\big)$$

Where

$$g(z_t) = \theta z_t + \gamma[|z_t| - E|z_t|]$$
$$z_t = u_t/\sqrt{h_t}$$

The EGARCH (1, 1) model has additional leverage terms to denote asymmetry in volatility clustering. Further, the GARCH (1,1) model has a minor information criterion according to Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Hannan-Quinn Criterion (HQC) values.

Descriptive Statistics

Summary statistics are presented in Table 1. It defines the primary variables of interest. Panel A of Table 1 presents the summary of variables prior to vaccination, while Panel B of Table shows the statistics of the vaccination period. The average cryptocurrency index return is 0.305% daily during the pre-vaccination period. The daily difference between the high and low prices of cryptocurrencies is 4.474%. The volatility Index is 77.98 with a standard deviation of 19.32. Further, the mean value of the World Equity Index Return and One-year Risk-Free Rate is 0.026% and 0.313% per day. The average logarithmic trading volume of cryptocurrencies is 6.127 per day.

Learning about vaccines' availability during the pandemic was essential as they changed investor sentiment from being optimistic, pessimistic, or neutral. There may need to be more than the development and availability of vaccines to be optimistic towards the economy; instead, it needs more assurance in the efficacy of the vaccination. Government initiates policy measures to

Table 1: Summary Statistics

Panel A: Descriptive Statistics for Pre-Vaccination Period

Variables	No. of Obs.	Mean	Median	Standard Deviation	Minimum	Maximum
Cryptocurrencies Index Return (%)	324	0.305%	0.333%	3.373%	-32.515%	14.537%
Cryptocurrencies Intraday Movement (%)	324	4.474%	3.697%	4.225%	1.037%	60.492%
Crypto Volatility Index	324	77.98	72.23	19.32	54.00	170.55
MSCI World Index Return (%)	324	0.026%	0.080%	1.684%	-9.510%	8.390%
One-Year Risk-Free Rate	324	0.313%	0.150%	0.416%	0.100%	1.510%
Crypto Trading Volume (log)	324	6.127	6.143	0.293	5.428	7.086
New COVID Cases Per Million	323	145.09	102.69	150.76	0	699.45
Total COVID Cases Per Million	324	12348.78	8088.51	12139.03	0.003	46863.63
New COVID Deaths Per Million	286	3.06	2.84	1.95	0	8.757
Total COVID Deaths Per Million	286	414.96	422.13	244.28	0.003	876.24
ICU COVID Patients Per Million	149	37.61	33.92	13.64	0.003	73.104
Hospitalized COVID Patients Per Million	149	139.08	118.64	65.12	75.61	311.72

Panel B: Descriptive Statistics for Vaccination Period

Variables	No. of Obs.	Mean	Median	Standard Deviation	Minimum	Maximum
Cryptocurrencies Index Return (%)	629	0.165%	0.239%	3.457%	-16.675%	14.698%
Cryptocurrencies Intraday Movement (%)	629	5.697%	4.941%	3.324%	1.644%	38.764%
Crypto Volatility Index	629	93.40	91.55	18.18	62.79	168.18
MSCI World Index Return (%)	629	-0.001%	0.500%	0.952%	-3.650%	2.760%
One-Year Risk-Free Rate	629	0.796%	0.115%	1.041%	0.040%	3.370%
Crypto Trading Volume (log)	629	6.09	5.92	0.63	4.12	8.96
New COVID Cases Per Million	629	371.57	239.45	466.70	12.66	4021.90
Total COVID Cases Per Million	629	158476.72	134681.74	72172.58	47566.88	280582.94
New COVID Deaths Per Million	629	3.56	2.39	3.14	0.02	13.04
Total COVID Deaths Per Million	629	2207.36	2174.64	634.26	886.13	3105.65
ICU COVID Patients Per Million	629	35.03	28.29	25.13	4.25	85.73
Hospitalized COVID Patients Per Million	629	155.92	116.69	108.15	29.28	458.50

This table presents summary statistics of variables scrutinized for the top 10 cryptocurrencies and COVID-19. Cryptocurrencies Index Return is the daily percentage return in the top 10 cryptocurrencies prices. Cryptocurrencies Intraday Movement is the percentage difference between daily high and low prices. Crypto Volatility Index is a decentralized VIX for crypto that allows users to hedge against market volatility and impermanent loss. MSCI World Index Return is the percentage change in the MSCI World index value. One-Year Risk Free-Rate is the one-year U.S. treasury bill daily yield. Crypto Trading Volume is the average trading volume of the top 10 cryptocurrencies. New COVID Cases Per Million is new confirmed cases of COVID-19 per million population. Total COVID Cases Per Million is the total number of confirmed cases of COVID-19 per million population. New COVID Deaths Per Million is new deaths attributed to COVID-19 per million population. Total COVID Deaths Per Million is the total number of deaths attributed to COVID-19 per million population. ICU COVID Patients Per Million is the total number of COVID-19 patients in hospitals on a given day per million population. Hospitalized COVID Patients Per Million is the total number of COVID-19 patients in hospitals on a given day per million population.

leverage its effect and positively induce investor sentiment, thus lowering pessimism. Rouatbi et al. (2021) conclude that COVID-19 vaccination stabilizes the financial markets, particularly equity markets, and its impact is much more substantial within advanced economies.

After the vaccine's introduction on December 11, 2020, the government's measures to restrict the pandemic contagion can have very different pricing behavior in cryptocurrencies. The vaccination began with medical professionals and increasingly expanded to a broader population. We anticipate that the expansion and availability of vaccination will subdue the number of covid cases. Panel B of Table shows that the cryptocurrency index return is lower (0.165%) than in the pre-vaccination period. The volatility in their price and the daily high-low price have increased on an aggregate basis. An important question arises whether vaccination availability has affected cryptocurrency prices. The daily return has moderated during the vaccination period, but the volatility has increased, as observed in standard deviations. Analysis of COVID-19 variables reveals that vaccination availability has not improved the situation of COVID-19-related cases.

We check the correlations of variables used in the analysis and find that the correlations are within the range below 0.50. However, the correlations of returns of individual cryptocurrencies are all highly correlated and consistent with prior studies (Hu et al. (2018)). As expected, cryptocurrencies are negatively and highly correlated with the crypto volatility index suggesting the fears associated with the market risk premium. COVID-19 variables have solid associations and correlations, but we use them in the regression analysis individually. Therefore, they do not warrant the problem of multicollinearity. However, we test the multicollinearity issue in our regressions using the variance inflation factor. For brevity, we do not report the correlation statistics in a table.

Regression Results

To assess the importance of COVID-19 variables to the cryptocurrencies, we use the baseline model, i.e., ordinary least squares, to examine the structural relationship between cryptocurrencies and COVID-19 variables. The t-statistics in parentheses below the estimates follow heteroskedasticity and autocorrelation-robust standard errors. Tables 2 and 3 contain standard multivariate cross-sectional regressions for cryptocurrencies index returns and covid cases. The relationship between cryptocurrencies and COVID-19 has been assessed during pre-and post-vaccination periods. Based on existing literature in asset pricing, we initially use the control variables such as cryptocurrency volatility, world equity measure, and risk-free rate in the regressions as reported in Table 2. Panel A of Table 2 reports the regressions results. Covid Cases, an independent variable, represents the covid intensity, such as new covid cases, total covid cases, new covid deaths, total covid deaths, icu covid patients, and hospitalized covid patients. They show that all COVID-19 variables positively and statistically significant with cryptocurrencies index return. Panel B of Table 2 shows that icu and hospitalized covid patients are negatively and significantly related to cryptocurrencies. However, total covid cases, new covid deaths, and total covid deaths positively relate to cryptocurrencies index return.

Table 2: Multivariate Cross-Sectional Regression for Cryptocurrencies Market

Panel A: Pre-Vaccination Period Analysis

Variables	Cryptocurrencies Index Return as Dependent Variable					
	New COVID Cases	**Total COVID Cases**	**New COVID Deaths**	**Total COVID Deaths**	**ICU COVID Patients**	**Hospitalized COVID Patients**
Δ Crypto Volatility Index	**-0.003**	**-0.005**	**-0.006**	**-0.005**	**-0.003**	-0.003
	(-2.51)	**(-2.23)**	**(-2.62)**	**(-2.27)**	**(-1.75)**	(-1.56)
MSCI World Index Return	**2.173**	**2.230**	**3.439**	**2.799**	**2.472**	**2.146**
	(9.97)	**(6.68)**	**(13.02)**	**(8.58)**	**(10.95)**	**(9.63)**
One-Year Risk-Free Rate	**-2.939**	**-2.051**	**-3.526**	**-2.581**	**-3.202**	**-3.102**
	(-5.31)	**(-2.71)**	**(-4.59)**	**(-3.25)**	**(-5.39)**	**(-5.55)**
COVID Cases	**0.180**	**0.251**	**0.076**	**0.333**	**0.276**	**0.255**
	(12.94)	**(6.62)**	**(4.10)**	**(4.79)**	**(11.15)**	**(12.65)**
Intercept	**-5.698**	**-7.724**	**-12.795**	**-10.894**	**-7.590**	**-5.780**
	(-4.14)	**(-4.10)**	**(-7.41)**	**(-5.94)**	**(-5.32)**	**(-4.15)**
Adj.R Square	0.90	0.84	0.81	0.82	0.89	0.90

Panel B: Vaccination Period Analysis

Variables	Cryptocurrencies Index Return as Dependent Variable					
	New COVID Cases	**Total COVID Cases**	**New COVID Deaths**	**Total COVID Deaths**	**ICU COVID Patients**	**Hospitalized COVID Patients**
Δ Crypto Volatility Index	0.007	0.001	0.005	0.090	0.055	0.054
	(0.38)	(0.61)	(0.31)	(0.54)	(0.31)	(0.30)
MSCI World Index Return	**2.682**	**1.126**	**2.726**	**0.491**	**2.645**	**2.613**
	(16.31)	**(4.69)**	**(16.52)**	**(1.98)**	**(16.33)**	**(16.02)**
One-Year Risk-Free Rate	**-0.100**	**-0.304**	**-0.091**	**-0.336**	**-0.134**	**-0.116**
	(-9.78)	**(-11.80)**	**(-8.11)**	**(-14.44)**	**(-10.88)**	**(-10.77)**
COVID Cases	-0.002	**0.364**	**0.015**	**0.632**	**-0.057**	**-0.051**
	(-1.57)	**(8.57)**	**(2.04)**	**(11.10)**	**(-4.86)**	**(-4.44)**
Intercept	**-7.518**	**-1.571**	**-7.884**	2.090	**-7.122**	**-6.868**
	(-6.95)	**(-1.26)**	**(-7.27)**	(1.58)	**(-6.67)**	**(-6.36)**
Adj.R Square	0.63	0.67	0.63	0.69	0.64	0.64

This table presents the regressions results of the top cryptocurrencies index return and COVID-19 variables. The regression models present the response of COVID-19 variables on cryptocurrencies after controlling for financial market variables. The variables are defined in Table 1 legend. The regression estimates are reported in the upper part, and t-statistics are in parenthesis.

Table 3: Multivariate Cross-Sectional Regression for Cryptocurrencies Market

Panel A: Pre-Vaccination Period Analysis

Variables	Cryptocurrencies Index Return as Dependent Variable					
	New COVID Cases	Total COVID Cases	New COVID Deaths	Total COVID Deaths	ICU COVID Patients	Hospitalized COVID Patients
Δ Crypto Volatility Index	**-0.003**	-0.003	**-0.006**	-0.003	**-0.005**	**-0.004**
	(-2.06)	(-1.29)	**(-2.60)**	(-1.43)	**(-2.65)**	**(-2.17)**
MSCI World Index Return	**2.120**	**1.851**	**3.450**	**2.440**	**2.459**	**2.156**
	(9.57)	**(5.27)**	**(12.94)**	**(6.96)**	**(11.31)**	**(9.85)**
One-Year Risk-Free Rate	**-2.895**	**-1.666**	**-3.537**	**-2.199**	**-3.257**	**-3.150**
	(-5.23)	**(-2.22)**	**(-4.59)**	**(-2.77)**	**(-5.68)**	**(-5.73)**
Crypto Trading Volume	0.020	**0.059**	-0.008	**0.056**	**-0.059**	**-0.039**
	(1.27)	**(2.89)**	(-0.35)	**(2.52)**	**(-3.49)**	**(-2.49)**
COVID Cases	**0.181**	**0.288**	**0.077**	**0.403**	**0.305**	**0.267**
	(13.02)	**(7.36)**	**(4.08)**	**(5.47)**	**(12.07)**	**(13.10)**
Intercept	**-5.717**	**-6.785**	**-12.724**	**-10.119**	**-6.545**	**-5.192**
	(-4.17)	**(-3.64)**	**(-7.30)**	**(-5.54)**	**(-4.66)**	**(-3.74)**
Adj.R Square	0.90	0.84	0.81	0.82	0.89	0.90

Panel B: Vaccination Period Analysis

Variables	Cryptocurrencies Index Return as Dependent Variable					
	New COVID Cases	Total COVID Cases	New COVID Deaths	Total COVID Deaths	ICU COVID Patients	Hospitalized COVID Patients
Δ Crypto Volatility Index	0.026	0.025	0.026	0.024	0.024	0.024
	(1.49)	(1.49)	(1.49)	(1.44)	(1.37)	(1.38)
MSCI World Index Return	**2.864**	**1.619**	**2.874**	**0.939**	**2.833**	**2.823**
	(18.31)	**(6.71)**	**(18.31)**	**(3.80)**	**(18.08)**	**(17.89)**
One-Year Risk-Free Rate	**-0.094**	**-0.254**	**-0.093**	**-0.298**	**-0.111**	**-0.102**
	(-9.73)	**(-9.85)**	**(-8.80)**	**(-13.00)**	**(-9.14)**	**(-9.77)**
Crypto Trading Volume	**0.093**	**0.075**	**0.093**	**0.072**	**0.085**	**0.087**
	(8.83)	**(7.10)**	**(8.66)**	**(7.23)**	**(7.72)**	**(7.91)**
COVID Cases	-0.007	**0.183**	0.018	**0.244**	**-0.027**	**-0.023**
	(-1.03)	**(2.67)**	(0.26)	**(3.70)**	**(-2.29)**	**(-2.02)**
Intercept	**-10.435**	**-5.234**	**-10.545**	-1.512	**-7.122**	**-9.972**
	(-9.72)	**(-4.01)**	**(-9.85)**	(-1.11)	**(-6.67)**	**(-9.05)**
Adj.R Square	0.67	0.69	0.67	0.71	0.67	0.67

This table presents the regression results of the top cryptocurrencies index return and COVID-19 variables. The regression models present the response of COVID-19 variables on cryptocurrencies after controlling for financial market variables. The variables are defined in Table 1 legend. The regression estimates are reported in the upper part, and t-statistics are in parenthesis.

Table 3 multivariate regressions include cryptocurrencies trading volume, a measure of liquidity. Panel A of Table 3 results show that the cryptocurrency index return is positively and significantly associated with COVID-19 variables, as reported in Table A of Table 2. The estimates and t-statistics are of similar magnitude. It indicates that during the pre-vaccination period, COVID-19 proxies are significantly associated with cryptocurrencies' return. The results in Panel B of Table 3 show that the inclusion of liquidity factor, i.e., trading volume, has decreased the magnitude of estimates and t-statistics for COVID-19 variables during the vaccination period. As reported in Panel B of Table, total covid cases and deaths are positively related to cryptocurrency return, while icu and hospitalized patients are negatively related to cryptocurrency return. The results show varying responses of COVID-19 variables on returns for cryptocurrencies. Notably, the risk-free rate is significantly and negatively associated with cryptocurrencies. Treasury bill is a predictor of cryptocurrency returns. It only suggests that lower returns on treasury bills induce the investor to bet on cryptocurrencies. It may arise because cryptocurrencies are unregulated and considered fiat currency alternatives.

We consider the vaccination period, i.e., starting on December 11, 2020, and onwards, a significant policy measure to combat the COVID-19 crisis. Muller (2020) contends that governments should minimize uncertainty through precise communication and fast implementation of policy measures. The regression analysis during the vaccination period and other policy measures for COVID-19 may be somewhat not so sensitive to factors influencing cryptocurrency returns. Therefore, using multivariate models to understand better the daily variation in cryptocurrency intraday price (high and low) and whether they are affected similarly to COVID-19 proxies. Panel A of Table 4 provides the results for the pre-vaccination period. The analysis shows that COVID-19 variables are positively and significantly related to the intraday price movement of cryptocurrencies. However, the responses to COVID-19 have become negative to the cryptocurrency intraday movement during the vaccination period. The fact that cryptocurrencies are decentralized financial assets that do not respond to the traditional market fundamentals could be a factor for showing asymmetric response to COVID-19 proxies during the pre-and vaccination period. It suggests that traditional financial asset price factors differ from cryptocurrency price movement.

It is vital to test whether similar results come out for individual cryptocurrency return analysis. Table 5 provides the results where each model represents the regression for individual cryptocurrencies. For brevity, we report each row's estimates of covid proxy variables. The results are obtained similarly to the regression model of Table 3 using control variables and a single covid proxy in the model. Panel A of Table 5 reveals that overall, individual cryptocurrency returns have a significant relationship to contemporaneous new covid cases, new covid deaths, total covid deaths, icu covid patients, and hospitalized covid patients. In a few cases, estimates are negative and significant. It is noted that those cryptocurrencies are smaller in size as model 1 represents the most prominent cryptocurrency and model 10 the smallest cryptocurrency. The top 3 cryptocurrencies behave in tandem and drive the cryptocurrency market. A notable point in Model 1 is that it shows the similar and significant relationship of Bitcoin to COVID-19 variables, as reported in Panel A of Tables 2-4.

Panel B of Table 5 examines the relationship of individual cryptocurrency returns to COVID-19 proxies during the vaccination period. Model 1, representing Bitcoin, shows a negative and significant relationship with COVID-19 variables. Most cryptocurrencies have a negative association with COVID-19 variables. Overall, our results show that significant cryptocurrencies generate lower returns during vaccination and become moderate in price movement. The smaller cryptocurrencies have higher price fluctuation making cryptocurrencies riskier. Consistent with the asset pricing literature, it contends that risk-averse investors demand higher returns to hold riskier assets.

Consistent with evidence on the time-series behavior of daily observations of covid variables and cryptocurrencies, we find that covid variables are autocorrelated. Further, Liu and Serletis (2019) employ the GARCH-M and find significant shock and volatility transmission

Table 4: Multivariate Cross-Sectional Regression for Cryptocurrencies Market

Panel A: Pre-Vaccination Period Analysis

Variables	Cryptocurrencies Intraday Movement as Dependent Variable					
	New COVID Cases	Total COVID Cases	New COVID Deaths	Total COVID Deaths	ICU COVID Patients	Hospitalized COVID Patients
Δ Crypto Volatility Index	**-0.044**	**-0.039**	**-0.050**	**-0.040**	**-0.046**	**-0.044**
	(-3.76)	**(-3.42)**	**(-4.12)**	**(-3.45)**	**(-3.90)**	**(-3.77)**
MSCI World Index Return	**0.366**	-0.033	**0.608**	0.111	**0.493**	**0.441**
	(2.31)	(-0.17)	**(4.32)**	(0.60)	**(3.23)**	**(2.75)**
One-Year Risk-Free Rate	-0.455	0.165	-0.563	0.054	-0.547	-0.528
	(-1.11)	(0.40)	(-1.38)	(0.13)	(-1.36)	(-1.32)
Crypto Trading Volume	**0.643**	**0.808**	**0.578**	**0.822**	**0.515**	**0.545**
	(5.85)	**(7.20)**	**(5.00)**	**(7.07)**	**(4.33)**	**(4.74)**
COVID Cases	**0.362**	**1.074**	**0.201**	**1.723**	**0.482**	**0.428**
	(3.64)	**(5.00)**	**(2.02)**	**(4.48)**	**(2.71)**	**(2.88)**
Intercept	**-3.085**	**-1.800**	**-4.321**	**-2.754**	**-3.629**	**-3.389**
	(-3.14)	**(-1.76)**	**(-4.70)**	**(-2.89)**	**(-3.68)**	**(-3.34)**
Adj.R Square	0.54	0.58	0.52	0.56	0.53	0.53

Panel B: Vaccination Period Analysis

Variables	Cryptocurrencies Intraday Movement as Dependent Variable					
	New COVID Cases	Total COVID Cases	New COVID Deaths	Total COVID Deaths	ICU COVID Patients	Hospitalized COVID Patients
Δ Crypto Volatility Index	**-0.022**	**-0.021**	**-0.023**	**-0.022**	**-0.022**	**-0.022**
	(-5.06)	**(-5.12)**	**(-5.33)**	**(-5.22)**	**(-5.06)**	**(-5.08)**
MSCI World Index Return	-0.312	**-1.167**	-0.257	**-2.304**	-0.332	-0.347
	(-0.82)	**(-1.92)**	(-0.67)	**(-3.60)**	(-0.86)	(-0.90)
One-Year Risk-Free Rate	**-0.325**	**-0.432**	**-0.297**	**-0.535**	**-0.321**	**-0.328**
	(-13.73)	**(-6.65)**	**(-11.61)**	**(-8.99)**	**(-10.81)**	**(-12.83)**
Crypto Trading Volume	**0.263**	**0.246**	**0.242**	**0.237**	**0.262**	**0.259**
	(10.27)	**(9.29)**	**(9.29)**	**(9.15)**	**(9.67)**	**(9.62)**
COVID Cases	**-0.038**	**-0.185**	**-0.052**	**-0.550**	0.011	0.005
	(-2.19)	**(-3.73)**	**(-3.04)**	**(-3.79)**	(0.37)	(0.04)
Intercept	0.421	**0.818**	**0.437**	**1.385**	**0.452**	**0.471**
	(1.61)	**(2.49)**	**(1.68)**	**(3.92)**	**(1.69)**	**(1.75)**
Adj.R Square	0.43	0.43	0.42	0.44	0.42	0.41

This table presents regression results of top cryptocurrencies' intraday movement and COVID-19 variables. The regression models present the response of COVID-19 variables on cryptocurrency intraday movement after controlling for financial markets variables. The variables are defined in Table 1 legend. The regression estimates are reported in the upper part, and t-statistics are in parenthesis.

Table 5: Multivariate Cross-Sectional Regression for Cryptocurrencies Market

Panel A: Pre-Vaccination Period Analysis

Variables	Top 10 Cryptocurrencies Price Return as Dependent Variable									
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**
Δ Crypto Volatility Index										
MSCI World Index Return										
One-Year Risk-Free Rate										
Crypto Trading Volume										
New COVID Cases	**0.243**	**0.199**	**0.100**	-0.008	**0.088**	**0.277**	**-0.203**	**-0.066**	**-0.047**	0.045
	(17.31)	**(2.08)**	**(3.92)**	(-0.25)	**(5.40)**	**(1.67)**	**(-2.77)**	**(-5.03)**	**(-4.50)**	(1.17)
Total COVID Cases	**0.410**	0.051	**0.409**	**-0.189**	**0.083**	0.100	**0.426**	**-0.090**	-0.035	**0.167**
	(9.58)	(1.03)	**(9.23)**	**(-2.96)**	**(2.14)**	(1.17)	**(2.68)**	**(-2.96)**	(-1.45)	**(2.05)**
New COVID Deaths	**0.086**	**0.470**	-0.025	0.021	**0.038**	**0.828**	**-0.133**	**-0.033**	-0.015	0.049
	(3.68)	**(2.46)**	(-1.00)	(0.73)	**(2.32)**	**(2.76)**	**(-1.92)**	**(-2.51)**	(-1.50)	(1.38)
Total COVID Deaths	**0.660**	**0.288**	**0.812**	**-0.432**	0.0.82	**0.555**	**1.087**	**-0.014**	-0.057	0.213
	(7.64)	**(2.27)**	**(10.51)**	**(-3.73)**	(1.13)	**(2.92)**	**(3.81)**	**(-2.46)**	(-1.29)	(1.41)
ICU COVID Patients	**0.515**	0.803	-0.011	**0.293**	**0.283**	**2.282**	**-1.028**	**-0.122**	**-0.074**	**0.374**
	(19.41)	(1.02)	(-0.20)	**(5.11)**	**(10.56)**	**(2.29)**	**(-8.29)**	**(-4.40)**	**(-3.32)**	**(5.25)**
Hospitalized COVID Patients	**0.449**	0.803	0.070	**0.165**	0.212	**2.282**	**-0.696**	**-0.106**	**-0.069**	**0.249**
	(27.61)	(1.02)	(1.56)	**(3.32)**	(9.00)	**(2.29)**	**(-6.31)**	**(-4.73)**	**(-3.88)**	**(4.12)**

Panel B: Vaccination Period Analysis

Variables	Top 10 Cryptocurrencies Price Return as Dependent Variable									
	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**	**Model 10**
Δ Crypto Volatility Index										
MSCI World Index Return										
One-Year Risk-Free Rate										
Crypto Trading Volume										
New COVID Cases	**-0.047**	**0.051**	**-0.018**	**-0.042**	**-0.039**	**-0.057**	**-0.034**	**-0.062**	**0.054**	**-0.062**
	(-9.52)	**(2.16)**	**(-3.28)**	**(-4.52)**	**(-6.52)**	**(-7.16)**	**(-3.84)**	**(-3.10)**	**(2.20)**	**(-11.09)**

Total COVID Cases	**-0.205**	**-0.005**	**-0.172**	**-1.019**	**-0.241**	**-0.832**	**-0.651**	**0.034**	0.009	**-0.366**
	(-4.52)	**(-0.27)**	**(-3.83)**	**(-17.10)**	**(-4.67)**	**(-14.80)**	**(-9.61)**	**(1.98)**	(0.45)	**(-7.18)**
New COVID Deaths	**-0.030**	-0.035	**-0.021**	-0.005	**-0.031**	**-0.033**	**-0.037**	0.011	-0.035	**-0.022**
	(-6.06)	(-1.58)	**(-4.25)**	(-0.60)	**(-5.56)**	**(-4.28)**	**(-4.50)**	(-0.60)	(-1.50)	**(-3.61)**
Total COVID Deaths	-0.140	**0.080**	0.120	**-0.257**	-0.101	**-0.161**	**-0.863**	-0.006	**0.112**	**-0.809**
	(-1.39)	**(1.84)**	(1.21)	**(-2.37)**	(-0.87)	**(-2.47)**	**(-5.40)**	(-0.16)	**(2.46)**	**(-7.30)**
ICU COVID Patients	**-0.144**	-0.034	**0.078**	-0.028	**-0.136**	**-0.112**	**-0.124**	0.025	-0.033	-0.091
	(-6.56)	(-0.78)	**(7.26)**	(-1.38)	**(-12.21)**	**(-6.59)**	**(-6.93)**	(0.67)	(-1.59)	(-0.77)
Hospitalized COVID Patients	**-0.165**	-0.002	**-0.081**	-0.100	**-0.149**	**-0.170**	**0.154**	**0.019**	0.023	-0.142
	(-20.36)	(-0.47)	**(-7.34)**	(-0.49)	**(-3.29)**	**(-4.10)**	**(8.56)**	**(4.42)**	(0.43)	(-1.18)

This table presents the regression results of the top 10 cryptocurrencies' prices and COVID-19 variables. The regression models present the effect of COVID-19 variables on cryptocurrency price return after controlling for financial market variables. Each model represents an induvial cryptocurrency result. The variables are defined in Table 1 legend. The regression estimates are reported in the upper part, and t-statistics are in parenthesis.

among cryptocurrencies. Katsiampa (2017) shows, using GARCH models, that volatility in Bitcoin arises from the short- and long-run component of the conditional variance. Therefore, we account for this behavior and examine the impact covid variables have on the returns of cryptocurrencies. The distribution of variables is non-normal, heteroskedasticity is present, and return variables are stationary. These statistics motivate the choice of an autoregressive error model, i.e., GARCH (1, 1). A VAR model is unsuitable in our analysis since it ignores heteroskedasticity.

A GARCH (1,1) model with a t-distribution is used to estimate the marginal distribution for the return series. Similar to prior multivariate regressions, we include control variables in our autoregressive error model that also controls for endogeneity. Table 6 presents the results of this model. Panel A of Table 6 shows that all covid variables except total covid cases and deaths positively and significantly influence cryptocurrency index returns. Even the sign of total covid cases estimate is positive; however, when the same regression analysis is performed during the vaccination period, we find that total covid cases and deaths are positive and significant. Hospitalized and icu covid estimates are negative and significant. Overall, the results suggest that the role of covid cases has become imprecise after vaccination started. GARCH parameters (including the asymmetry term) are generally significant, and the equations are well specified regarding residual ARCH and other specification errors.

For the robustness of our analysis, we perform several robustness tests. We use four GARCH models to verify the sensitivity of our findings. Prior studies note that GARCH orders are crucial in models. The role of higher orders is checked based on Akaike Information Criterion. Finally, we use several higher-order GARCH-M models, such as GARCH-M (2,1), GARCH-M (1,2), and GARCH-M (2,2). Table 7 shows the results of these models.

We analyze the GARCH model results in Panel A of Table 7. GARCH-M (2, 1) shows that all covid variables except total covid cases are positive and significant. Similar results show for GARCH (2, 2) except in total covid deaths. In the case of GARCH (1, 2), new covid deaths, icu covid patients, and hospitalized covid patients are positive and significant. Lastly, the EGARCH model is employed to verify the sensitivity of GARCH results. The outcomes of the EGARCH model are similar to various GARCH model conclusions.

Table 6: Time-Series Regression Model

Panel A: Pre-Vaccination Period Analysis

Variables	Cryptocurrencies Index Return as Dependent Variable					
	New COVID Cases	**Total COVID Cases**	**New COVID Deaths**	**Total COVID Deaths**	**ICU COVID Patients**	**Hospitalized COVID Patients**
Δ Crypto Volatility Index	0.015	0.029	0.013	0.019	**-0.045**	**-0.035**
	(1.10)	(1.56)	(0.93)	(1.37)	**(-2.65)**	**(-2.17)**
MSCI World Index Return	**2.366**	**2.421**	**2.482**	**2.507**	**2.458**	**2.156**
	(28.49)	**(25.30)**	**(32.43)**	**(27.63)**	**(11.31)**	**(9.85)**
One-Year Risk-Free Rate	0.113	**-0.113**	-0.137	**-0.347**	**-0.326**	**-0.315**
	(1.44)	**(-1.75)**	(-1.18)	**(-2.60)**	**(-5.68)**	**(-5.73)**
Crypto Trading Volume	**0.073**	**0.075**	**0.068**	**0.065**	**-0.059**	**-0.039**
	(4.34)	**(4.50)**	**(3.88)**	**(3.29)**	**(-3.49)**	**(-2.49)**
COVID Cases	**0.038**	0.009	**0.021**	-0.020	**0.305**	**0.267**
	(4.54)	(1.58)	**(2.75)**	(-0.28)	**(12.07)**	**(13.10)**
Intercept	**-7.672**	**-8.096**	**-8.301**	**-8.329**	**-6.545**	**-5.192**
	(-11.43)	**(-11.84)**	**(-12.06)**	**(-11.82)**	**(-4.66)**	**(-3.74)**
R Square	84.45%	83.35%	84.04%	83.48%	89.73%	90.58%

Panel B: Vaccination Period Analysis

Variables	Cryptocurrencies Index Return as Dependent Variable					
	New COVID Cases	**Total COVID Cases**	**New COVID Deaths**	**Total COVID Deaths**	**ICU COVID Patients**	**Hospitalized COVID Patients**
Δ Crypto Volatility Index	0.026	0.025	0.026	0.024	0.024	0.025
	(1.52)	(1.50)	(1.49)	(1.48)	(1.39)	(1.41)
MSCI World Index Return	**2.867**	**1.629**	**2.875**	**0.958**	**2.836**	**2.825**
	(18.37)	**(6.79)**	**(18.31)**	**(3.90)**	**(18.15)**	**(17.95)**
One-Year Risk-Free Rate	**-0.095**	**-0.253**	**-0.093**	**-0.297**	**-0.111**	**-0.102**
	(-9.82)	**(-9.89)**	**(-8.80)**	**(-13.03)**	**(-9.22)**	**(-9.85)**
Crypto Trading Volume	**0.093**	**0.075**	**0.093**	**0.073**	**0.085**	**0.087**
	(8.87)	**(7.13)**	**(8.66)**	**(7.26)**	**(7.75)**	**(7.94)**
COVID Cases	-0.074	**0.182**	0.002	**0.240**	**-0.028**	**-0.024**
	(-1.06)	**(1.67)**	(0.26)	**(2.68)**	**(-2.31)**	**(-2.03)**
Intercept	**-1.045**	**-0.529**	**-1.055**	**-0.161**	**-1.005**	**-0.998**
	(-9.76)	**(-4.08)**	**(-9.85)**	**(-1.19)**	**(-9.27)**	**(-9.09)**
R Square	67.84%	69.93%	67.40%	72.00%	68.06%	67.99%

The regression model estimates time series data in which the effects of the regressor variables are distributed across time.

$$CryIndRet_t = \alpha + \sum_{i=0}^{p} \beta_i COVID - 19\ Cases_{t=i} + \sum_{i=0}^{j} \gamma\ Control\ Variables_{t=i} + \ \dots\dots\ + \varepsilon_t$$

$CryIndRet_t$ is the Cryptocurrencies Index proxied using the top 10 cryptocurrencies by market capitalization. COVID-19 cases are the log-transformed cases per million population. Control Variables are the change in the Crypto Volatility Index, World Equity represented by the MSCI World Index, the One-year U.S. treasury bill, the trading volume of cryptocurrencies, and an error term. The variables are defined in Table 1 legend. The regression estimates are reported in the upper part, and t-statistics are in parenthesis.

Table 7: GARCH Model

Panel A: Pre-Vaccination Period Analysis

Variables	Cryptocurrencies Index Return as Dependent Variable			
	GARCH (2, 1)	**GARCH (1, 2)**	**GARCH (2, 2)**	**EGARCH (1, 1)**
New COVID Cases	**0.038**	0.063	**0.029**	0.021
	(5.34)	(1.55)	**(4.13)**	(0.21)
	R^2 = 84.42%	R^2 = 84.33%	R^2 = 82.94%	R^2 = 78.22%
Total COVID Cases	0.091	0.027	0.084	**0.049**
	(0.50)	(0.92)	(1.37)	**(2.30)**
	R^2 = 82.01%	R^2 = 79.18%	R^2 = 83.26%	R^2 = 73.01%
New COVID Deaths	**0.073**	**0.153**	**0.201**	**0.100**
	(1.79)	**(3.52)**	**(3.21)**	**(4.59)**
	R^2 = 82.09%	R^2 = 85.61%	R^2 = 84.01%	R^2 = 73.17%
Total COVID Deaths	**0.148**	0.104	-0.026	0.013
	(4.17)	(1.49)	(-0.37)	(0.19)
	R^2 = 81.48%	R^2 = 87.29%	R^2 = 83.45%	R^2 = 76.43%
ICU COVID Patients	**0.305**	**0.288**	**0.305**	0.288
	(11.91)	**(17.95)**	**(12.52)**	(1.12)
	R^2 = 89.70%	R^2 = 88.14%	R^2 = 89.73%	R^2 = 87.65%
Hospitalized COVID Patients	**0.265**	**0.279**	**0.266**	**0.292**
	(15.79)	**(15.13)**	**(15.64)**	**(2.92)**
	R^2 = 90.29%	R^2 = 89.82%	R^2 = 90.45%	R^2 = 87.81%

Panel B: Vaccination Period Analysis

Variables	Cryptocurrencies Index Return as Dependent Variable			
	GARCH (2, 1)	**GARCH (1, 2)**	**GARCH (2, 2)**	**EGARCH (1, 1)**
New COVID Cases	-0.007	**-0.037**	-0.007	**-0.040**
	(-0.83)	**(-13.49)**	(-0.80)	**(-11.23)**
	R^2 = 67.84%	R^2 = 65.93%	R^2 = 67.80%	R^2 = 66.28%
Total COVID Cases	**0.282**	**0.271**	**0.281**	**0.187**
	(5.01)	**(17.00)**	**(4.99)**	**(1.01)**
	R^2 = 69.93%	R^2 = 68.78%	R^2 = 69.99%	R^2 = 67.29%
New COVID Deaths	0.002	**-0.010**	0.001	**-0.010**
	(0.19)	**(-3.73)**	(0.17)	**(-4.11)**
	R^2 = 67.40%	R^2 = 66.35%	R^2 = 67.38%	R^2 = 66.09%
Total COVID Deaths	**0.540**	**0.395**	**0.538**	**0.398**
	(7.63)	**(20.52)**	**(7.58)**	**(16.96)**
	R^2 = 72.00%	R^2 = 69.96%	R^2 = 69.99%	R^2 = 68.15%
ICU COVID Patients	**-0.028**	**-0.129**	**-0.027**	**-0.135**
	(-1.80)	**(-22.46)**	**(-1.77)**	**(-52.63)**
	R^2 = 68.06%	R^2 = 62.46%	R^2 = 68.04%	R^2 = 60.58%
Hospitalized COVID Patients	-0.024	**-0.207**	-0.023	-0.161
	(-1.59)	**(-37.67)**	(-1.56)	(-0.90)
	R^2 = 67.99%	R^2 = 62.17%	R^2 = 67.96%	R^2 = 53.78%

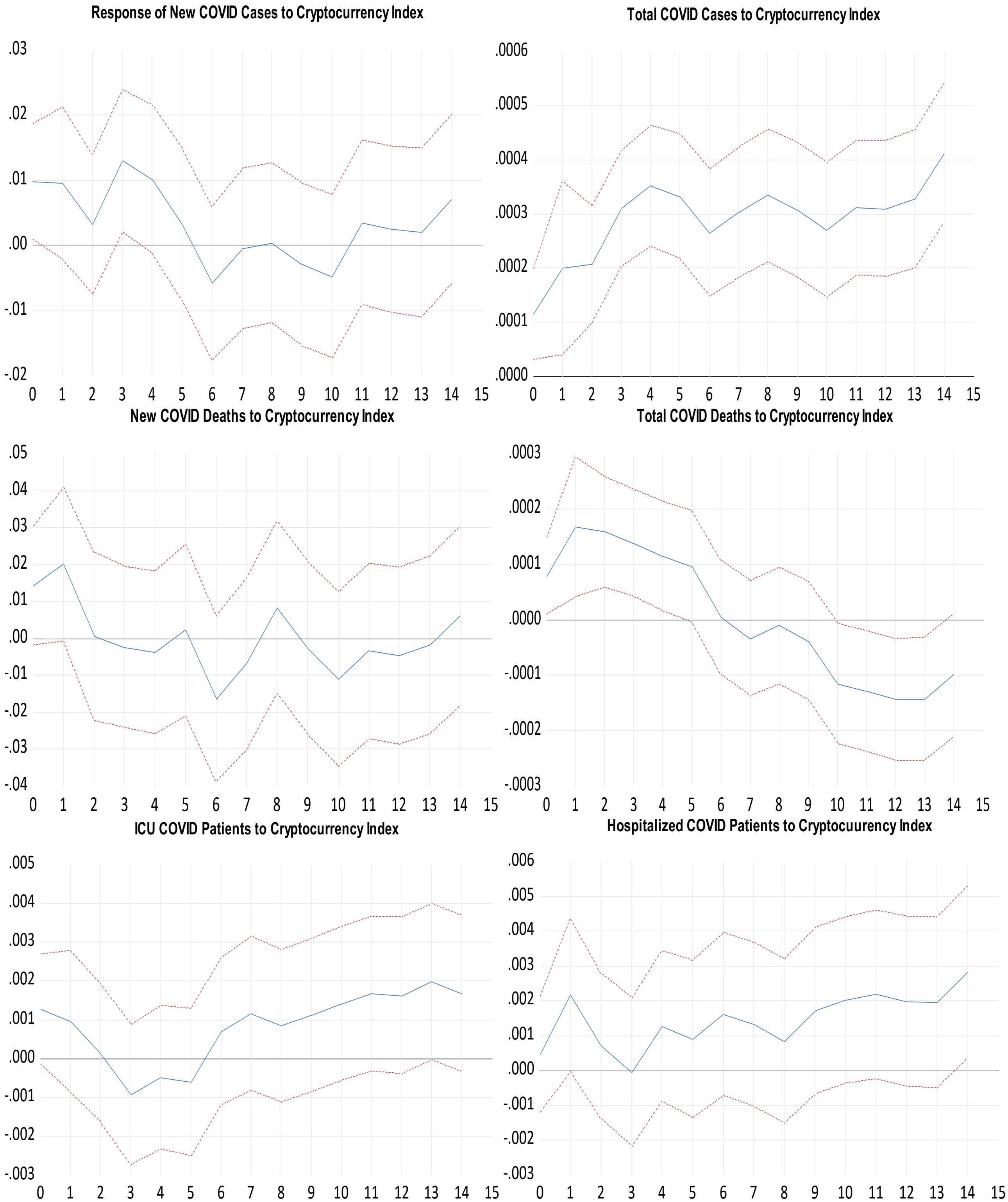
This table reports the effect of COVID-19 variables on cryptocurrencies from alternative GARCH models.

$$CryIndRet_t = \alpha + \sum_{i=0}^{p} \beta_i COVID - 19\ Cases_{t=i} + \sum_{i=0}^{j} \gamma\ Control\ Variables_{t=i} + \ \dots\dots\ + \varepsilon_t$$

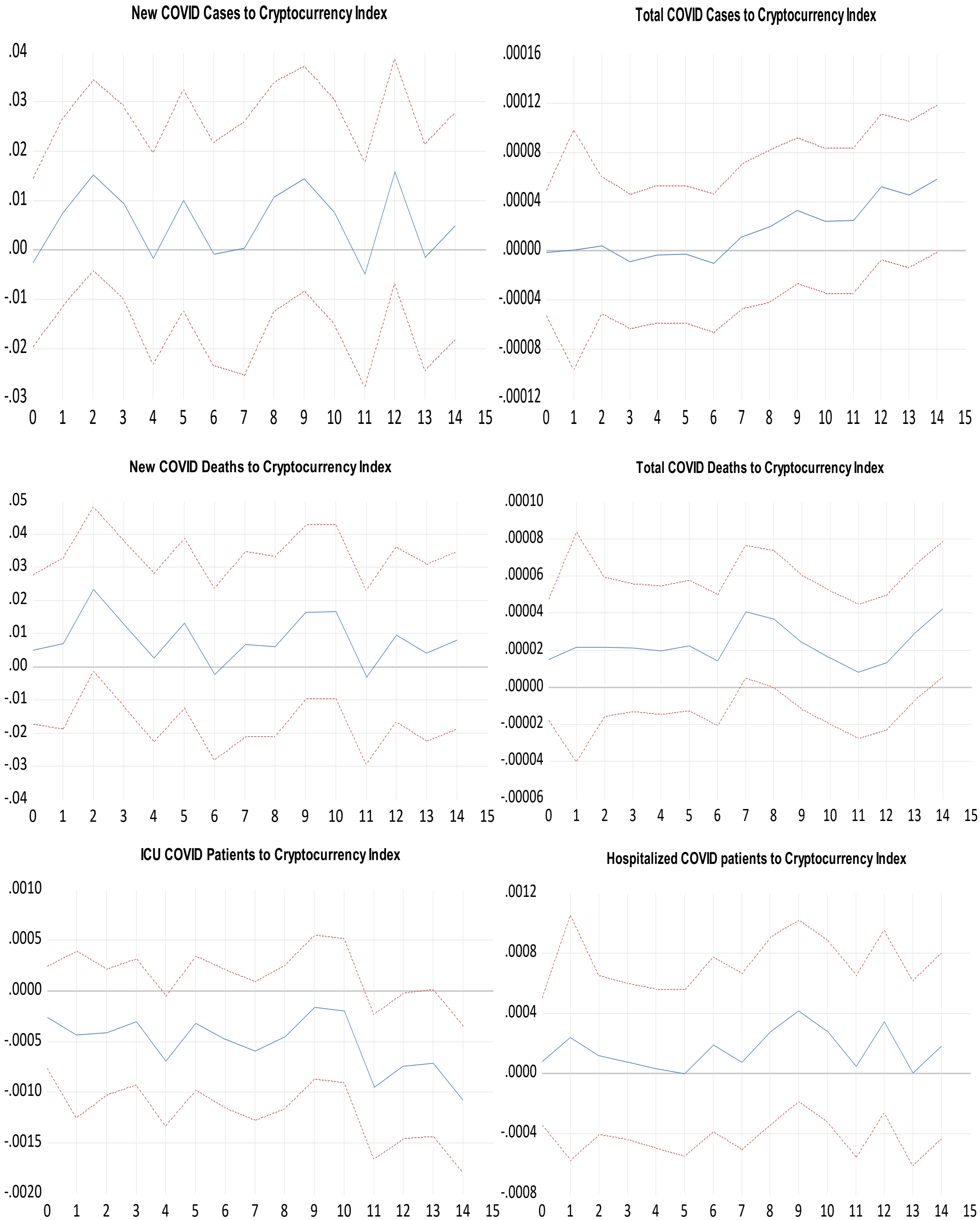
GARCH-M orders, p, and q are set to (2,1), (1,2), and (2,2). These models report the results in columns 2 to 4. Column 5 reports the exponential GARCH (EGRACH) with the mean version of the model. We estimate the model using the quasi-maximum likelihood function (QMLF) of Bollerslev and Wooldridge (1992) to obtain robust estimates of the standard errors. We only report the coefficients relating to COVID-19 variables. Moreover, these models contain all controls. Numbers in parentheses are t-statistics.

Figure 5: Impulse Response Function

Panel A: Impulse Response Function during Pre-Vaccination Period



Panel B: Impulse Response Function during Vaccination Period



This figure measures the response of COVID-19 variables on cryptocurrency index returns.

When we look at the as reported in Panel B of Table 7 shows the GARCH model results during the vaccination period. We find that the new covid deaths variable is significant and positive in all GARCH models, while icu covid patients are positive and significant in three models except in GARCH (1, 2). Thus, similar to prior results, we find that covid proxies are not so specifically related to cryptocurrency returns during vaccination. This application conveys that our primary conclusions are unaltered, and the findings persist on different modeling tests.

Lastly, we use the impulse response function (IRF) to measure the response of COVID-19 variables on the cryptocurrency index returns and their reactions. The impulse response functions are based on local projections based on Jorda (2009). They do not require an estimation or specific specification of the unknown multivariate dynamic system. Since the coefficients of the impulse response function can have a serial correlation, leading to a broader marginal error band, the function applies a conditional error band to mitigate the variability arising out of serial correlation. Figure 5 exhibits the impulse response functions measuring the response of COVID-19 variables to a shock in cryptocurrency index returns. Panel A of Figure 5 indicates that COVID-19 generates positive shocks in cryptocurrency returns. It shows that the shocks dissipate slowly and disappear in a week during the pre-vaccination period. Panel B of Figure 5 indicates that the effect of COVID-19 variables on the cryptocurrency returns becomes slightly lower. Once the vaccination has started and restrictions on commercial activities loosened up, the investors are less concerned about the COVID-19 economic woes and looking for alternative investment opportunities.

V Concluding Remarks

Cryptocurrency markets are of great importance to both investors and financial markets. The pandemic crisis presents a new perspective for investors and portfolio managers for asset pricing and risk management. In this paper, we evaluate the COVID-19 impact in explaining cryptocurrency returns. The leading ten cryptocurrencies are analyzed based on trading volume and market capitalization, representing the cryptocurrency market. The sample period runs from January 22, 2020, to August 31, 2022. For a better understanding of the behavior of cryptocurrencies during the pandemic, the study is conducted on two sub-sample periods: the pre-vaccination sub-period (from January 22, 2020, to December 10, 2020) and the vaccination sub-period (from December 11, 2020, to August 31, 2022), thus analyzing the COVID-19 measures.

The findings show that cryptocurrency returns are significantly affected by the COVID-19 pandemic and are most visible during the pre-vaccination period. Even during vaccination, COVID-19 is a statistically significant determinant of cryptocurrency returns. The intraday price movement shows a negative relationship during the vaccination period in contrast to cryptocurrency returns. Our main contribution to the literature is the direct measures of COVID-19 measures used in the study and their influence on the behavior of cryptocurrencies.

Our findings suggest that COVID-19 has influenced the cryptocurrency market, but its influence varies depending on the size of the currency during vaccination. These results show apparent differences in the impact of changes in the smaller size of currencies. We argue that more major currencies have higher liquidity and more investor participation, bringing market efficiency and risk adjustment as an academic interpretation of the cryptocurrency market behavior. These findings can help policymakers and investors understand that financial markets value a sound health policy. The implications of our research could instigate further research into the role of health policies in the financial markets.

Limitation of the Paper

This paper uses only the top 10 cryptocurrencies. Some currencies are not directly traded against fiat money in small exchanges. It can bring inaccuracy in pricing and volume. Crypto exchanges are decentralized and traded 24 hours across globally. The data provided by Investing.com is aggregated from many exchanges and denominated in U.S. dollars. The data aggregation process may also lead to ballpark pricing. However, this is a crucial starting avenue for future research in decentralized financial markets. The findings of the paper devise trading strategies for long-term investment.

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Appendix 1

Top 10 cryptocurrencies used in this study are as follow:

Cryptocurrency	Market Capitalization as on September 01, 2022	Weight
Bitcoin	$368,616,658,388	48.07%
Ethereum	$159,717,882,226	20.83%
Tether	$67,952,277,033	8.86%
USD	$47,261,155,810	6.16%
BNB	$46,058,751,565	6.01%
XRP	$22,936,407,710	2.99%
Binance	$21,053,447,315	2.75%
Cardano	$14,624,881,010	1.91%
Solana	$11,582,275,936	1.51%
Polkadot	$7,054,526,600	0.92%