Bitcoin vs. Gold in Crisis: Evaluating Volatility Dynamics During COVID-19

1. Project Overview & Objectives

This study investigates the volatility dynamics of Bitcoin and Gold returns before and during the COVID-19 pandemic. The study applies ARMA and EGARCH models to daily return data. The sample is divided into two periods, pre-COVID and COVID-19, excluding the transitional crash period in early March 2020.

Results indicate that Bitcoin is an unreliable hedge, due to its speculative volatility patterns, which remains high and persistent in both periods. Although Gold experiences a significant increase in volatility during the crisis, it is still recommended for a downturn protection. Notably, the leverage effect for Gold changes from negative to positive during COVID-19, suggesting increased uncertainty in safe-haven assets. Meanwhile, Bitcoin exhibits a consistent but weakening positive leverage effect.

Keywords: Bitcoin, Gold, COVID-19, Volatility, EGARCH, Financial crisis, Leverage effect

2. Data and Methodology

The analysis is based on daily closing prices for Bitcoin (BTC-USD) and Gold (GC=F) sourced from Yahoo Finance. The dataset is split into two distinct periods to evaluate pandemic's impact:

- Pre-COVID: January 1, 2018 – February 28, 2020
- COVID-19: March 13, 2020 – April 30, 2022

The start date was chosen to begin the analysis after the 2017 Bitcoin bubble, while the transitional market crash in early March 2020 was intentionally excluded to ensure a stable comparison between the two regimes.

The complete step-by-step methodology is documented in the accompanying **Time series modelliing file (.html).** This file provides the full R code and a detailed walkthrough of the analytical process, including:

- Data scraping and transformation into log returns.
- Pre-estimation diagnostics (stationarity and normality tests).
- ARMA model selection for the mean equation.

- Testing for ARCH effects to justify GARCH modeling.
- EGARCH model specification, estimation, and final diagnostic checks.

This structured approach ensures that the final models are robust, statistically sound, and accurately capture the underlying dynamics of the assets.

3. Empirical Results

3.1 Exploratory Data Analysis

In Figure 1 and 2, we present the closing prices of Bitcoin and Gold, which seem to be nonstationary. In Figure 3 and 4, we present the closing returns after transformation. The red line separates those charts into two periods, before and during COVID-19.

Figure 1. Daily Bitcoin closing prices

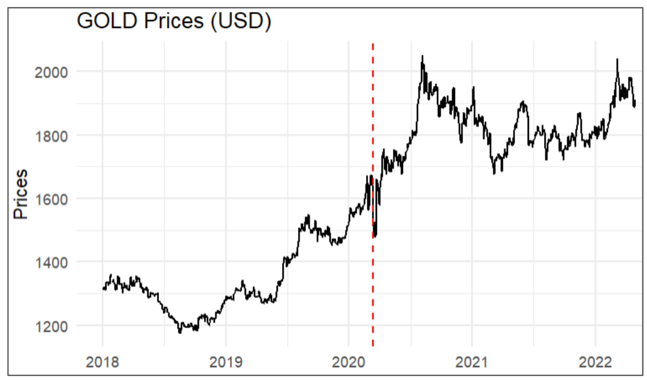

Figure 2. Daily Gold closing prices

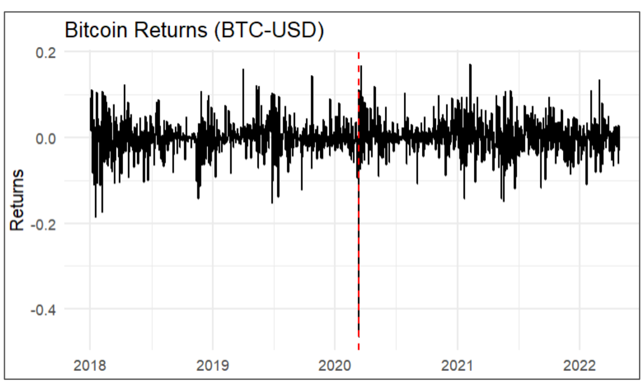

Figure 3. Daily Bitcoin returns

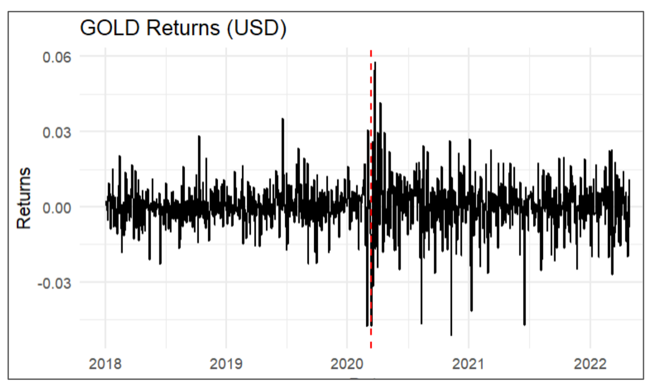

Figure 4. Daily Gold returns

Table 1 presents key descriptive statistics for daily log returns of Bitcoin and Gold, comparing pre-COVID-19 with COVID-19 period. The difference in observations between Bitcoin and Gold is expected. Bitcoin trades continuously, 24 hours a day, 7 days a week, on global cryptocurrency exchanges, whereas Gold follows traditional commodity exchange schedules, which are closed on weekends and relevant market holidays.

During COVID-19, average daily return of Bitcoin turned positive (0.00246). This shift likely reflects the significant bull market experienced from late 2020, fueled by unprecedented monetary and fiscal stimulus globally, and a growing narrative of Bitcoin as an inflation hedge. Intriguingly, despite widespread perception of heightened volatility during crisis, Bitcoin's standard deviation and kurtosis decreased slightly, though both remained high. This reduction may partly result from the exclusion of the extremely volatile early March 2020 period, which may have excluded some extreme negative returns, slightly understating overall volatility. Furthermore, the skewness of Bitcoin returns changed to slightly positive during this time, potentially suggesting large upward price movements, driven by speculative buying and FOMO during perceived dips.

Table 1. Descriptive Statistics of Daily Bitcoin and Gold Returns

	Pre-COVID-19		COVID-19	
	BITCOIN	GOLD	BITCOIN	GOLD
Mean	-0.00058	0.00043	0.00246	0.00043
Std. dev.	0.03860	0.00699	0.03720	0.01124
Min	-0.18458	-0.02280	-0.14811	-0.05107
Max	0.16004	0.03529	0.17182	0.05778
Skewness	-0.24862	0.16353	0.06883	-0.134098
Kurtosis	6.12640	5.30914	5.42285	7.03847
JB test	329.04***	122.15***	190.91***	366.53***
Observations	788	539	778	537

While Gold average daily return remained near zero, its volatility increased, and skewness also shifted to slightly negative. These changes show that traditional safe-haven assets were still impacted by volatile environment. Comparing the two assets, Bitcoin was approximately 5.5 times more volatile than Gold pre-COVID. This ratio decreased to about 3.3 times during COVID-19, indicating that Gold became relatively risker and more sensitive under crisis. However, Bitcoin remained consistently more volatile in both periods.

Finally, both return series clearly deviate from normality. This is evidenced by the observed skewness, high kurtosis (greater than 3 for all), and formally confirmed by the highly significant Jarque-Bera (JB) test statistics.

3.2 Mean Equation

Before modeling the conditional mean, we assess the stationarity using ADF test. Table 2 shows highly significant test statistics for Bitcoin and Gold returns. This confirms that all return series are stationary and suitable for ARMA modeling. We then inspected the ACF and PACF correlogram (Appendix A and B) to suggest candidate ARMA (p,q) specifications. The appropriate lags for the mean equation are evaluated based on AIC and BIC in Appendix C and D. Finally, ARMA (0,0) is chosen as the optimal model for both Bitcoin and Gold before and during COVID-19.

Table 2. ADF test of Bitcoin and Gold returns

Assets	Pre-COVID-19	COVID-19
BITCOIN	-19.268***	-19.913***
GOLD	-16.104***	-16.625***

3.3 Justifications for E-GARCH and Model Selection

The high kurtosis indicating fat tails, along with visual inspection of return plots (Figure 2) showing volatility clustering, suggest the presence of conditional heteroskedasticity for Bitcoin and Gold. Then, ARCH-LM tests on ARMA(0,0) residuals also confirmed significant ARCH effects at relevant lags for both assets across (Table 3). It is noteworthy that ARCH test results are sensitive to extreme events. This is because, for Bitcoin, during COVID-19, ARCH tests with data of the sudden crash on March 1, showed insignificant results, while tests starting from March 13 (post-crash) showed clear significance at relevant lags. This confirms the decision to exclude the beginning of March 2020 to avoid transitional distortions.

Table 3. Residuals test for ARCH effect

ARCH LM (lags = 5 or 10)	Pre-COVID-19		COVID-19	
Assets	Test stat	p-value	Test stat	p-value
BITCOIN	56.577	0.00000***	23.332	0.00958***
GOLD	17.818	0.05812*	21.668	0.00061***

Appendices E and F present the criterion values to compare GARCH-family models. For the pre-COVID, EGARCH (1,1) was the optimal model. During COVID-19, conflicts among criterion values arise. Although GARCH(1,1) was favored by some criteria, it consistently failed stability

Nyblom tests (Appendix G). As EGARCH (1,1) models passed stability tests, it was ultimately selected for both assets during COVID-19. EGARCH model is helpful to capture leverage effects allowing for asymmetric volatility responses to positive and negative shocks (crucial for crisis like COVID-19).

3.4 Estimation of EGARCH (1,1) and Post-Estimation Checks

Table 4. EGARCH (1,1) Model Results

BITCOIN	Pre-COVID-19		COVID-19	
	Coefficient	p-value	Coefficient	p-value
Constant (μ)	0.000970	0.000000***	0.002475	0.000000***
Omega (ω)	-0.167344	0.000000***	-0.111973	0.000789***
ARCH (α)	-0.010198	0.721489	0.006969	0.708780
GARCH (β)	0.975158	0.000000***	0.983345	0.000000***
α + β	0.96496		0.990314	
Leverage (γ)	0.208286	0.000000***	0.109084	0.050163**
Shape	0.858596	0.000000***	1.061493	0.000000***
GOLD	Pre-COVID-19		COVID-19	
	Coefficient	p-value	Coefficient	p-value
Constant (μ)	0.000378	0.0000***	0.000951	0.241309
Omega (ω)	-0.237415	0.0000***	-0.281777	0.000000
ARCH (α)	0.055510	0.0000***	0.066143	0.009745
GARCH (β)	0.976126	0.0000***	0.968854	0.000000
α + β	1.03164		1.034997	
Leverage (γ)	-0.085489	0.0000***	0.066184	0.062053*
Shape	1.179810	0.0000***	1.097821	0.000000

Table 4 presents the estimation results for the selected EGARCH(1,1) models. Diagnostic tests performed on the standardised residuals and squared residuals (Appendix H) generally show high p-values, suggesting the chosen EGARCH models adequately capture the serial correlation in returns and volatility clustering. It is noteworthy that EGARCH models do not require parameter constraints $\alpha+\beta$ to be less than 1, as noted by Levi (2023).

High volatility persistence (β near 1) was evident for both assets across periods, indicating long-lasting shock impacts, a stylized fact common in financial markets (Bollerslev et al., 1994). Bitcoin's persistence slightly increased during COVID while Gold's remained extremely high in both periods. Regarding shock impact (α), volatility of Gold showed significant sensitivity to shock magnitude pre-COVID and during COVID. This implies Gold's volatility consistently reacted to the size of daily news or events in both periods. By contrast, Bitcoin's volatility showed insensitivity to the magnitude of shocks, suggesting its volatility dynamics are driven more by persistence (β) and asymmetry (γ) rather than the size of immediate market surprises.

The primary focus is the asymmetric volatility response (γ). Here, the two assets displayed distinct behaviors under crisis. Bitcoin presented an inverse leverage effect. Pre-COVID, it exhibited a strong positive leverage effect ($\gamma = 0.208$), which is often attributed to speculative nature and FOMO amplifying volatility during rallies. During COVID-19, while the leverage parameter remained positive, its statistical significance weakened. The weakened effect during the crisis might reflect the dilution of retail-driven FOMO by broader macro factors or increasing institutional flows, or the overwhelming influence of market-wide volatility during the pandemic.

Interestingly, Gold displayed shifts in leverage parameter. Pre-COVID, it showed a standard negative leverage effect ($\gamma = -0.085$), where negative shocks increased volatility more. However, during COVID-19, this shifted to a positive effect ($\gamma = 0.066$, $p=0.062$). This aligns with findings of Yousef and Shehadeh (2020) and resonates with explanations of Baur (2012). Baur (2012) explains that during market downturns, investors tend to flock to gold, leading to price increases that reflect heightened uncertainty. Traditionally, it was observed that gold's volatility would increase more in response to negative news than to positive news. However, during the pandemic, the increased demand for gold as a safe-haven asset in response to positive developments (such as stimulus measures or vaccine news) led to greater volatility following positive shocks.

In summary, the EGARCH (1,1) models reveal crucial insights into the evolving asymmetric volatility of Bitcoin and Gold. Bitcoin maintained its positive asymmetrical nature (linked to speculation) but saw the effect weaken during the pandemic. Gold demonstrated a notable shift from a standard negative leverage effect to a positive one during COVID-19, potentially linked to its safe-haven characteristics under stress. These findings underscore the importance of modeling asymmetric effects and recognising their potential instability across market situations.

4. Discussion and Conclusion

Our analysis reveals that although volatility of Gold increased much higher under crisis, Bitcoin consistently exhibited higher volatility than Gold (SD pre-COVID: 3.86% vs. 0.69%; COVID: 3.72% vs 1.12%). This theme persisted in the EGARCH analysis finding Bitcoin to have strong volatility persistence (β= 0.983) and was insensitive to shock magnitude (α=0.007,p=0.709) and a weakened leverage effect during COVID. Suggesting Bitcoin's volatility was driven by speculative momentum rather than the shock itself. EGARCH parameters are empirically supported by Conlon & McGee (2020) and Goodell & Goutte (2021) who found it behaved as a risk-on asset during COVID-19.

Gold had significant shock sensitivity (α=0.066) with a leverage effect that switched from negative to positive during COVID, indicating safe-haven demand during the turmoil. This adaptive volatility, reacting strongly to shocks and changing to a positive leverage, makes it an ideal hedge as its risk sensitivity escalates precisely when needed. Our findings are aligned with prior research with Gold maintaining its safe-haven status during COVID-19.

For investors, during similar shocks as COVID, Bitcoin is an unreliable hedge based on our findings during COVID-19 due to its speculative volatility patterns (high β, and shock-insensitive α). Gold maintains its superior safe-haven traits as a volatility dampener during market turmoil. Investors should treat Bitcoin as a high-risk diversifier with potential to make large gains out of turmoil, however, maintaining Gold is recommended for downside protection. For policy makers, regulatory measures should be enhanced to warn investors about crypto speculative nature and monitor the leverage effect in the crypto market to prevent spillovers. Therefore, during COVID Bitcoin's behavior aligned with that of a speculative asset (high persistence, momentum-driven volatility) rather than a safe-haven asset. In comparison, Gold's volatility and leverage shift confirm its traditional safe-haven status under stress.

This study conducts an in-depth analysis into Bitcoin and Gold, there are limitations. First, uniqueness of the pandemic limit's generalisability to other cases (parallels potentially drawn to Spanish flue 1918-1920); however, it gives insights if another pandemic occurs. Second, while the study focuses on volatility dynamics using EGARCH models, it does not examine the time-varying correlation between Bitcoin and Gold, or broader market indices. This limits the ability to fully assess their hedging effectiveness, as correlation is a critical factor in determining whether an asset provides diversification or moves inversely to market risk. Additionally, while Gold and Bitcoin are comparable, we exclude other markets (stocks, bonds, currencies) and macroeconomic variables (interest rates). Therefore, future research may extend the analysis to include other assets for cross-market comparison in addition to including macroeconomic drivers to isolate more of the pandemic effects.

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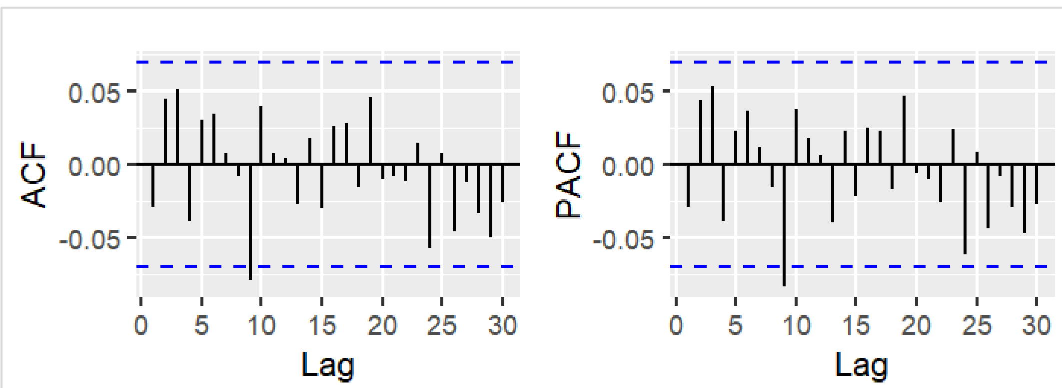
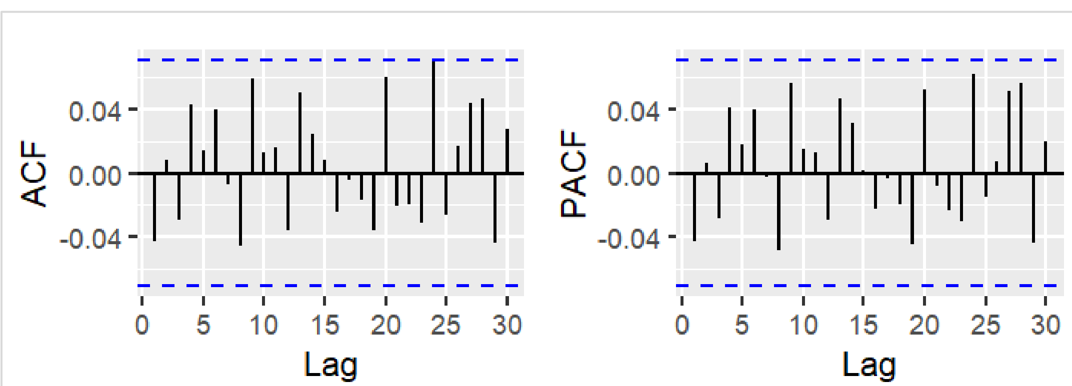
APPENDIX

Appendix A. ACF and PACF of Bitcoin returns

Pre-COVID

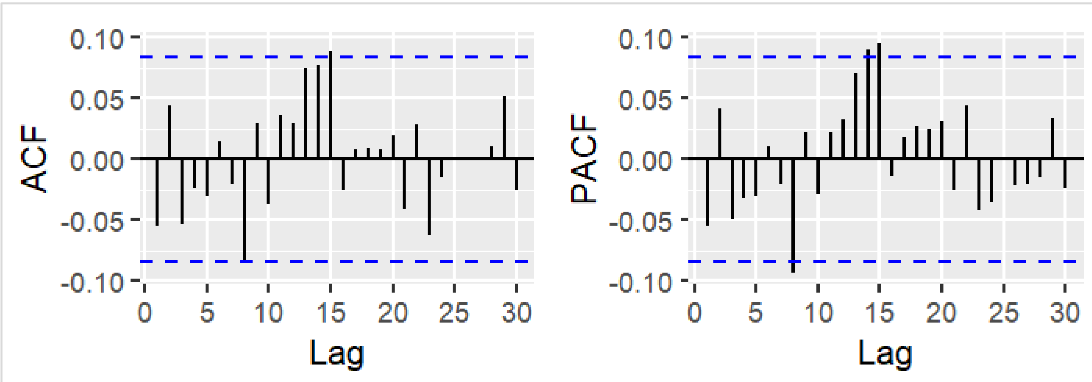


During COVID

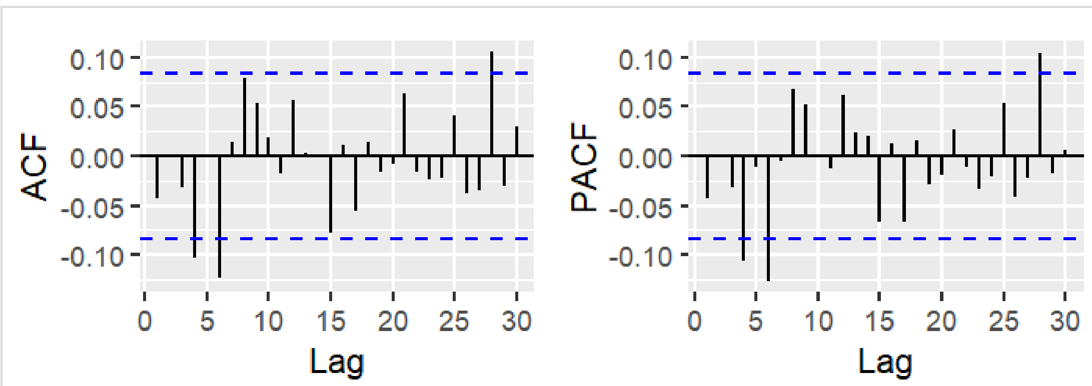


Appendix B. ACF and PACF of Gold returns

Pre-COVID



During COVID



Appendix C. ARMA model Identification for Bitcoin returns.

Order	Pre-COVID-19	
	AIC	BIC
(0, 0)	*-2889.939*	*-2880.600*
(1,0)	-2888.622	-2874.613
(1, 1)	-2886.924	-2868.246
(1, 2)	-2887.354	-2864.006
(2, 1)	-2887.256	-2863.909
(4, 0)	-2887.644	-2859.627
(4, 4)	-2885.182	-2838.487

Order	COVID-19	
	AIC	BIC
(0,0)	*-2910.761*	*-2901.447*
(1,1)	-2910.165	-2896.194
(1,2)	-2908.826	-2890.199
(1,4)	-2906.839	-2883.556
(2,1)	-2906.792	-2883.509
(4,1)	-2905.017	-2872.420
(4,4)	-2905.989	-2859.421

(*) minimum value to criterion

Appendix D. ARMA model Identification for Gold returns.

Order	Pre-COVID-19	
	AIC	BIC
(0,0)	*-3817.747*	*-3809.167*
(1,0)	-3817.359	-3804.490
(1,1)	-3816.731	-3799.572
(1,2)	-3814.884	-3793.436
(6,6)	-3825.169	-3765.113

Order	COVID-19	
	AIC	BIC
(0,0)	-3293.716	*-3285.144*
(0,1)	-3292.744	-3279.886
(3,2)	-3297.058	-3267.056
(4,4)	-3301.005	-3258.145
(6,6)	*-3301.136*	-3241.132

(*) minimum value to criterion

Appendix E. GARCH model Identification for Bitcoin returns.

Order	Pre-COVID-19			COVID-19		
	AIC	BIC	LogLik	AIC	BIC	LogLik
GARCH(1,1)	-4.032964	-4.003335	1593.988	*-3.916569*	*-3.886641*	1528.545
GARCH(1,2)	-4.029726	-3.994172	1593.712	-3.913354	-3.877441	1528.295
GARCH(2,2)	-4.027261	-3.985781	1593.741	-3.914360	-3.872461	*1529.686*
EGARCH(1,1)	*-4.034329*	*-3.998775*	1595.526	-3.916466	-3.880553	1529.505
EGARCH(1,2)	-4.032041	-3.990561	*1595.624*	-3.913260	-3.871361	1529.258

(*) minimum value to criterion

Appendix F. GARCH model Identification for Gold returns.

Order	Pre-COVID-19			COVID-19		
	AIC	BIC	LogLik	AIC	BIC	LogLik
GARCH(1,1)	-7.164908	-7.125115	1935.943	-6.305315	*-6.265408*	1697.977
GARCH(1,2)	-7.161605	-7.113853	1936.053	-6.300042	-6.252153	1697.561
GARCH(2,1)	-7.161273	-7.113521	1935.963	-6.307168	-6.259280	1699.475
GARCH(2,2)	-7.157860	-7.102150	1936.043	-6.304529	-6.248660	1699.766
EGARCH(1,1)	*-7.193067*	*-7.145315*	1944.532	*-6.309523*	-6.261635	1700.107
EGARCH(1,2)	-7.190216	-7.134506	*1944.763*	-6.307090	-6.251221	*1700.454*

(*) minimum value to criterion

Appendix G. Nyblom Parameter Stability Test Results for GARCH(1,1) Models (COVID Period)

Asset	Joint Test Statistic	5% Critical Value	Stability Conclusion
Bitcoin	2.4105	1.47	Unstable
Gold	38.7553	1.47	Unstable

Appendix H. Post-Estimation Checks

BITCOIN	Pre-COVID-19		COVID-19	
Diagnostic Test	Test stat	p-value	Test stat	p-value
Ljung-box (R)	24.501	0.2212	10.664	0.9545
Ljung-box (R^2)	10.632	0.9552	9.8137	0.9714
ARCH-LM test (lags = 10)	7.684	0.6597	5.9477	0.8196
GOLD	Pre-COVID-19		COVID-19	
Diagnostic Test	Test stat	p-value	Test stat	p-value
Ljung-box (R)	22.101	0.3351	20.747	0.4122
Ljung-box (R^2)	29.747	0.07406	8.5706	0.9874
ARCH-LM test (lags = 10)	13.243	0.2104	8.124	0.6167