Distribution of Returns on Currency Exchange Rates and Bitcoin Transaction Values in G7 Countries

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Abstract
In this study, we evaluated the distribution of return on exchange rates of the currencies of G7 countries and also estimated the dynamic effect of Bitcoin transaction prices on currency return in the selected G7 countries. We transformed the daily trading and transaction values of Bitcoin in exchange for the US dollar and exchange rates into continuously compounded daily returns by taking the natural logarithm of today's exchange rate over yesterday's rate. We found that the appropriate distribution of returns was the skewed generalized error distribution (SGED). The study invalidates the hypothesis of a normal distribution of returns and rather implies that returns exhibit fat tails. Our study established a significant EGARCH-skewed-GED model effect with substantial asymmetric responsiveness and persistence of conditional volatility of return on foreign exchange rates for the six G7 currencies researched in this study. Our findings show that Bitcoin trading values have considerable predictive power for returns on G7 currency rates. With the EGARCH-SGED model chosen as the best model, it indicates that the error distribution for return is beyond the normal distribution. Accordingly, there are extreme return values that are more common than what would be predicted by a normal distribution. The significance and large positive value of the shape parameter, otherwise called the tail coefficient, signifies heavier tails, while a lower value of the asymmetric coefficient λ signifies slower decay, allowing the distribution to capture extreme return series more effectively. We therefore recommend a downward adjustment of the monetary policy rate to curtail the impact of the negative shocks, namely, bad market news-that snowball volatility in returns. In general, there is a need for overall macroeconomic stabilization.

Keywords: GED distribution, skewed Student's t distribution, normal distribution, EGARCH model, G7 currencies, return, Bitcoin

JEL classification: C23, D17, D30

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1. Introduction

In financial economics and financial markets' theories and practices, the rate of return occupies an essential position in investors' decision-making. This is the reason why investors' decisions to sell off an asset or purchase an asset are fundamentally driven by the possibility of realizing a given return. When investors fail to study, analyze, and understand market trends in view of the prevailing economic conditions, they are bound to incur losses. Unfortunately, most financial marketers or market investors erroneously assume and take for granted that rates of return always obey a normal distribution. The G7 currencies are strictly strong currencies because of the sustained economic growth and robust financial and banking systems of the G7 countries. The G7 countries are Canada, France, the United States of America, Germany, Italy, Japan, and the United Kingdom. The five currencies, namely the Euro (EUR), Japanese yen (JPY), Canadian dollar (CAD), British pound (GBP), and American dollar (USD), used by the G7 are the major currencies in the world. These currencies translate to the following major currency pairs: EUR/USD, USD/JPY, GBP/USD, USD/CHF, AUD/USD, USD/CAD, and NZD/USD. According to the World Bank (2024), the combined GDP of G7 countries represent 40% of the world's GDP. Explicitly, between 40% and 60% of foreign reserves are held in one or two of the G7 currencies by all central banks around the world (IMF, 2024). This goes to highlight the fact that these currencies play an essential role, having taken centre stage in global trade and financial developments. There is therefore a need to examine the volatility trend and behaviour of returns on these currencies. Against this backdrop, the research findings are valuable to forex traders who are impacted by foreign exchange market transactions and global trade. Besides, the adoption of Bitcoin payments in emerging markets is a demonstration of the fact that Bitcoin can serve as a store of value and a hedge against local currency depreciation (Mensah&Mwakapesa, 2022; Urquhart & Zhang, 2023).

Therefore, we are highly desirous of evaluating the distribution of return on exchange rates of the currencies of the G7 countries and also estimating the dynamic effect of Bitcoin transaction prices on currency returns in the selected G7 countries. Moreover, Adubisi, Abdulkadir, Farouk, and Chiroma (2022) have noted that financial series are characterized by problems of non-stationary properties, excess kurtosis, noisy dynamics, and volatility clustering. Therefore, it is imperative for us to investigate the distribution type that can be trusted when making investment decisions with the all-inclusive goal of realizing returns. The research hypothesis holds that the suitable distribution of returns was characterized by a non-normal distribution. The study is of great significance for financial risk management purposes. This study adds an interesting layer to investors' understanding of how the conventional currency market interacts with and is influenced by the volatile digital currency market. The study established that the distribution of returns is beyond the normal distribution rather letokurtic (heavy tails). This finding provides relevant information to asset managers and owners of market securities: financial market returns often exhibit fat tails, with the implication that there are numerous extreme returns that are beyond the predictions of a normal distribution. The GED measures this trend in return more effectively, especially during volatile market conditions. The significance of the research findings is further elucidated by the fact that the study accomplished the task of estimating the conditional variance of currency return in the presence of a heavy-tailed error distribution, which a traditional GARCH model fails to measure. The research findings are also valuable to all financial marketers, who are now informed to frequently consider the asymmetric effect of the distribution of returns in future predictions of the volatility of currency returns.

2. Literature Review

The relevance of external events and macroeconomic factors in shaping the demand for cryptocurrencies and their exchange rate movements in emerging economies has been analyzed by several authors. Morales & Tanaka (2024) focused on the interaction between Bitcoin trading earnings and the Canadian Dollar (CAD/USD), particularly in the context of changes in oil prices, using a multivariate GARCH model. Their study spanned from 2021 to 2024 and revealed that Bitcoin's impact on CAD/USD is pronounced during periods of significant fluctuations in oil prices, which traditionally affect the CAD. They found that positive Bitcoin return shocks tend to mitigate negative impacts from declining oil prices on the CAD, suggesting an emerging role for Bitcoin in the financial resilience of commodity-driven economies. Patel & Singh's (2024) study took a broader approach by analyzing the volatility spillover between Bitcoin transactions and several major exchange rates, including the EUR/USD, GBP/USD, and AUD/USD. Utilizing the methodology of the DCC model, they examined transaction data and exchange rate movements from 2020 to 2023. Their findings revealed that volatility spillover was most pronounced with the EUR/USD pair, indicating that economic decisions and policies in the Eurozone and the United States might be particularly sensitive to shifts in Bitcoin market dynamics. The research pointed to the growing interconnectedness between digital and fiat currencies, suggesting potential implications for monetary policies and exchange rate stability.

Lee & Zhao (2024) analyzed the volatility spillover effects between Bitcoin and the Euro (EUR/USD) using a Copula-GARCH model. They focused on the interaction between Bitcoin price movements and Eurozone economic indicators from 2021 to 2024. Their results indicate that Bitcoin volatility not only affects the EUR/USD exchange rate but is also influenced by it, suggesting a bidirectional relationship. This interdependence was particularly evident during European central bank announcements or significant economic updates from the Eurozone, indicating that Bitcoin is both an influencer and a respondent to traditional economic forces. Harrison & Wang (2024) investigated the volatility spillover between Bitcoin and the Canadian Dollar (CAD/USD). They applied a stochastic volatility model to capture the nuanced interdependencies between these two currencies, focusing on data from 2021 to 2024. The study found notable spillovers during periods of significant oil price fluctuations to be a major determinant of the CAD's value. The findings suggest that commodity-driven economies like Canada may experience unique impacts on their currency's exchange rates in relation to Bitcoin, which acts as an alternative investment during times of commodity market instability. D'Souza & Sharma (2024) analyzed the volatility spillover between Bitcoin and the Indian Rupee (INR/USD). They utilized the APARCH model to capture both the magnitude and direction of volatility spillovers, examining data from 2021 to 2024. Their findings indicate that significant volatility from Bitcoin transactions impacts the interest rate during periods of regulatory changes in India’s cryptocurrency policy. The study suggests that national regulatory environments play a crucial role in mediating the impact of global cryptocurrency fluctuations on local currencies. Chang & Lim (2024) researched the volatility spillover between Bitcoin and the South Korean Won (KRW). Utilizing a high-frequency data-based volatility (HEAVY) model, they analyzed minute-by-minute transaction data for Bitcoin alongside the KRW/USD exchange rates from 2021 to 2024. Their findings reveal that spikes in Bitcoin transaction volumes and volatility are closely followed by volatility in the KRW, particularly during periods of heightened geopolitical tensions in the region. The study underscores the sensitivity of the KRW to international investor sentiment as reflected through Bitcoin market dynamics. Fischer & Martinez (2024) investigated the interactions between Bitcoin transactions and the Mexican Peso (MXN). They applied a structural break GARCH model to discern patterns of volatility transmission under different economic conditions from 2020 to 2024. Their results reveal that Bitcoin has a significant spillover effect on the MXN, particularly during periods of U.S. dollar strength or weakness, which traditionally affects the MXN due to close economic ties between Mexico and the United States. The study suggests that Bitcoin’s influence on the MXN becomes particularly pronounced during times of pronounced USD fluctuations, offering a potential diversification strategy for investors. Fitzgerald & O'Neill (2023) investigated the interactions between Bitcoin transactions and the Swiss Franc (CHF/USD), employing a Fractionally Integrated GARCH (FIGARCH) model. This approach allowed them to examine long-term memory characteristics in volatility spillover, focusing on data from 2020 to 2023. The results show that the CHF, often considered a'safe haven' currency, experiences less impact from Bitcoin volatility compared to other currencies, but the influence grows during global financial uncertainties.

D'Souza & Sharma (2024) analyzed the volatility spillover between Bitcoin and the Indian Rupee (INR/USD). They utilized the Asymmetric Power ARCH (APARCH) model to capture both the magnitude and direction of volatility spillovers, examining data from 2021 to 2024. Their findings indicate that significant volatility from Bitcoin transactions impacts the INR during periods of regulatory changes in India's cryptocurrency policy. The study suggests that national regulatory environments play a crucial role in mediating the impact of global cryptocurrency fluctuations on local currencies. Lee & Zhao (2024) analyzed the volatility spillover effects between Bitcoin and the Euro (EUR/USD) using a Copula-GARCH model. They focused on the interaction between Bitcoin price movements and Eurozone economic indicators from 2021 to 2024. Their results indicate that Bitcoin volatility not only affects the EUR/USD exchange rate but is also influenced by it, suggesting a bidirectional relationship. This interdependence was particularly evident during European central bank announcements or significant economic updates from the Eurozone, indicating that Bitcoin is both an influencer and a respondent to traditional economic forces.

Martins & Rodriguez (2024) conducted an analysis on the volatility spillover between Bitcoin transactions and the British Pound (GBP/USD). Using a multivariate GARCH-DCC model, they analyzed the data spanning from 2021 to 2024. Their research highlights a strong correlation between Bitcoin volatility and GBP fluctuations, particularly in light of Brexit-related economic uncertainties. This correlation suggests that, in addition to economic policies and global events, political decisions within countries can also significantly influence the relationship between digital and fiat currencies. Harrison & Wang (2024) investigated the volatility spillover between Bitcoin and the Canadian Dollar (CAD/USD). They applied a stochastic volatility model to capture the nuanced interdependencies between these two currencies, focusing on data from 2021 to 2024. The study found notable spillovers during periods of significant oil price fluctuations to be a major determinant of the CAD's value. The findings suggest that commodity-driven economies like Canada may experience unique impacts on their currency's exchange rates in relation to Bitcoin, which acts as an alternative investment during times of commodity market instability.

Brooks & Chen (2023) investigated the volatility spillover between Bitcoin transactions and the Chinese Yuan (CNY/USD) exchange rate. Using a spillover index model developed by Diebold and Yilmaz, they analyzed the daily transaction data of Bitcoin alongside the exchange rate fluctuations from 2020 to 2023. Their analysis highlighted an increasing trend in the volatility transmission from Bitcoin to the Yuan, particularly during periods of policy shifts in China regarding cryptocurrency trading and mining. This study underscores the influence of regulatory environments on the extent of volatility spillover and illustrates how national policy decisions in major economies can affect global cryptocurrency markets. The heterogeneity of exchanges with respect to volatility spillover can be interactively researched by Wu et al (2024) in the time and frequency domains using the high-frequency transaction data of exchanges. The analysis covers four major exchanges as well as the following cryptocurrencies: Bitcoin, Ethereum, Ripple, Litecoin, Stellar, and EOS demonstrate the variety of cryptocurrency spreads of volatility across the Bitfinex, Coinbase, OKEx, and Binance markets. We discover that on the four exchanges, the amount and direction of bitcoin net spillover are comparable. Among the four exchanges, the LTC–BTC linkage is the most significant, and the net spillover movement is from LTC to BTC. The net spillover effects of Bitfinex and Binance on the six digital currencies varied. Kim & Jansen (2023) focused on the empirical nexus between Bitcoin transactions and the Australian Dollar (AUD/USD) exchange rate, using a VAR-BEKK-GARCH model to assess data from 2019 to 2023. Their results highlighted that Bitcoin-related news and transaction volumes had a pronounced impact on the AUD, particularly during times when traditional asset markets in Australia were underperforming. This study emphasizes the role of Bitcoin as a 'digital gold' in times of traditional market downturns, potentially serving as a diversifying asset that influences the AUD.

Gomez & Patel (2022) focused their research on the volatility transmission between Bitcoin and a basket of emerging market currencies, including the South African Rand, Indian Rupee, and Brazilian Real. Utilizing a VAR-BEKK-GARCH model, they examined the cross-market dynamics from 2019 to 2022. Their findings suggest that emerging market currencies exhibit higher sensitivity to Bitcoin volatility compared to developed market currencies. This higher sensitivity may be due to the relatively smaller market size and lesser liquidity, which makes these currencies more susceptible to external shocks from the cryptocurrency market. This study provides valuable insights into how emerging markets need to prepare for the increasing influence of cryptocurrencies. The implications of Bitcoin returns on changes in the US dollar to Korean won exchange rate were examined by Ho and Kim (2022). They achieved this by examining the dynamics between these two variables using co-integration and ECM. They found that return on Bitcoin exerted substantialshort-term impact on KRW/USD exchange rates during technological breakthroughs in blockchain and periods of intense trading activity in South Korea.

This study highlights the growing influence of technological advancements in cryptocurrencies on traditional financial markets, particularly in tech-forward countries like South Korea. Anderson & Cheung (2024) analyzed the impact of Bitcoin trading returns on the Brazilian Real (BRL/USD). They used a nonlinear autoregressive distributed lag (NARDL) model to capture both positive and negative changes in Bitcoin's market and their effects on BRL/USD exchange rates. Their findings from 2021 to 2024 highlight that while positive shocks in Bitcoin returns tend to have a stabilizing effect on the BRL, negative shocks correlate with increased volatility in the exchange rate. This asymmetry suggests that Bitcoin's impact on currency markets can vary significantly depending on the direction of its price movement, highlighting its dual role as both a risk asset and a potential hedge.

Ortiz & Müller (2022) studied the volatility spillover effects between Bitcoin and multiple Latin American currencies, including the Brazilian Real (BRL) and the Mexican Peso (MXN). Employing a Copula-GARCH model, they analyzed cross-market dependencies and found that volatility spillovers were significantly enhanced during regional political or economic crises from 2019 to 2022. Their research underscores the increasing integration of cryptocurrency markets with traditional financial systems in emerging markets, where Bitcoin often reacts to and influences fiat currency volatility. Nguyen & Lee (2022) focused on the impact of Bitcoin transaction volumes and volatility on the South Korean Won (KRW/USD). Employing an EGARCH model to analyze the asymmetrical effects of volatility, they gathered data from 2019 to 2022. Their study revealed that significant inflows and outflows in Bitcoin markets tend to precede shifts in the KRW exchange rate, suggesting a predictive relationship that could be utilized by financial analysts and traders. Furthermore, their findings indicate that negative news related to Bitcoin significantly affects the KRW compared to positive news, highlighting the sensitivity of national currencies to developments in the cryptocurrency markets.

2.1 Closing the Review

The above studies throw emphasis on the expansion of our understanding of the complex interactions between Bitcoin and various national currencies, illustrating how digital currencies are becoming increasingly influential in the global financial landscape. This influence is particularly evident during times of economic, political, or financial instability, where Bitcoin's role as both an investment and a speculative asset becomes more pronounced. Precisely, the above literature review highlighted the interconnectedness of the cryptocurrency market with conventional financial markets and their response to exchange rate dynamics in emerging economies. The present study has chosen to analyze the dynamic effect of digital currency on the exchange rate return of the G7 currencies.

3. Methodology

The ARFIMA model estimation technique was deployed to evaluate the long-term memory property of returns on currency rates in South Africa, China, Brazil, Russia, and India, Nigeria, Ghana, and Malaysia and returns on transactions with Bitcoin for three different distributions. These include Gaussian (normal), skewed student's t, and skewed GED distributions. The FIGARCH model was also executed in the study in order to evaluate the long-term memory volatility dynamics of returns on exchange rates of the aforementioned countries, as well as the returns on transactions with Bitcoin, which can be evaluated with a fractional integration parameter of d. jointly, we combined the ARFIMA and FIGARCH models to arrive at the ARFIMA-FIGARCH model to jointly determine the existence or otherwise of long memory in both the conditional mean and volatility of returns at the same time. A process called ARFIMA (p,ℓ,q) is generated as follows:

$$\begin{aligned} &\rho(L)(1-L)^{\ell}(X_t-\delta)=\varphi(L)u_t \\ &u_t=Z_t\sigma_t \\ &Z_t \sim N(0,1) \end{aligned} \tag{1}$$

Where, $\Phi(.)$ is a gamma function and introducing the finite MA process to equation (1) following the derivations of Hosking, 1981; Granger and Joyeux (1980), we have:

$$\begin{aligned} (1-L)^{\ell} &= 1-\ell L+\frac{\ell(\ell-1)}{2}L^2-\ldots+ \\ &= \sum_{k=0}^{\infty}\frac{\Phi(k-\ell)L^k}{\Phi(-\ell)\Upsilon(k+1)} \end{aligned} \tag{2}$$

The FIGARCH (p,d,q) model is created by extending the ARFIMA model in accordance with Baillie, Bollerslev, andMikkelsen's (1996) derivations:

$$\phi(L)(1-L)^d u_t^2=\alpha+(1-\eta(L))\upsilon_t \ , \ \upsilon_t=u_t^2-\sigma_t^2 \tag{3}$$

The process of υ_t is integrated for conditional variance σ_t^2 as variations. By imposing the ARFIMA structure on u_t^2 in line with Baillie et al. (1996), FIGARCH model is thus largely specified as:

$$(1-\eta(L))\sigma_t^2=\alpha+(1-\eta(L)-\phi(L)(1-L)^d u_t^2 \tag{4}$$

Note that d lies between zero and one, such that the long-term dynamics of volatility can be evaluated with a fractional integration parameter as d. given that our intention is to choose from the list of EGARCH models with normal distribution errors, EGARCH models with GED, and GARCH models with student's t distribution errors. Following the modeling steps of Nelson (1991), based on the works of Nelson (1991), Creal *et al.* (2011), and Harvey & Chakravarty (2008), we specify an EGARCH model whose variance is a function of the conditional score of the last observation. Our specification of the EGARCH-GED model for return and conditional variance with Bitcoin trading values as predictor variables and the associated log-likelihood function is as follows:

$$\Re eturn \Re_t = a + \phi \Re_{t-1} + + \lambda BTCN_t + \varepsilon_t,\ \varepsilon_t \mid I_{t-1} \sim N(0, Var(\sigma_t^2))$$
$$\ln Var(\sigma_t^2) = b + \alpha\left(\frac{\varepsilon_t}{\sqrt{Var(\sigma_{t-1}^2)}}\right) + \gamma\left|\frac{\varepsilon_{t-1}}{\sqrt{Var(\sigma_{t-1}^2)}}\right| + \beta([\ln Var(\sigma_{t-1}^2)]) + \partial BTCN_{t-1} \tag{5}$$

The GED distribution density is given by the following log-likelihood function:

$$LL_{GED} = \sum_{i=1}^{T} (\ln[\upsilon/\lambda_\upsilon] - 0.5[Z_t/\lambda_\upsilon]^{\upsilon} - [1+\upsilon^{-1}]\ln 2 - \ln\Gamma[1/\upsilon] 0.5\ln[\sigma_t^2]) \tag{5'}$$

The EGARCH-Gaussian model for return and conditional variance with Bitcoin trading valuesas predictor variable and the matching log-likelihood function are specified as follows:

$$\Re_t = a + \phi\Re_{t-1} + \lambda BTCN_t + \varepsilon_t,\ \varepsilon_t \mid \Phi_{t-1} \sim N(0, Var)$$
$$\ln(\sigma_t^2) = b + \alpha\left(\frac{\varepsilon_t}{\sqrt{Var_{t-1}}}\right) + \gamma\left|\frac{\varepsilon_{t-1}}{\sqrt{Var_{t-1}}}\right| + \beta([\ln\sigma_{t-1}^2]) + \partial BTCN_{t-1} \tag{6}$$

The Gaussian (normal) distribution density is given by the following log-likelihood function

$$LL_{Gaussian} = -\frac{1}{2}\sum_{i=1}^{T}(\ln[2\pi] + \ln[\sigma_t^2]) + Z_t \tag{6'}$$

The GARCH-Student's t distribution model for return and conditional variance with Bitcoin trading valuesas predictor variable and the conforming log-likelihood function are specified as follows:

$$\Re_t = a + \phi\Re_{t-1} + + \lambda BTCN_t + \varepsilon_t,\ \varepsilon_t \mid \Phi_{t-1} \sim N(0, Var)$$
$$\sigma_t^2 = \vartheta_0 + \vartheta_1\sigma_{t-1}^2 + \vartheta_2\varepsilon_{t-1}^2 + \partial BTCN_{t-1} \tag{7}$$

The Student-t distribution density is given by the following log-likelihood function:

$$LL_{Student's\,t} = \ln(\Gamma[\upsilon+1/2]) - \ln\Gamma(\upsilon/2) - 0.5\ln(\pi[\upsilon-2] - 0.5\sum_{i=1}^{T}(\ln\sigma_t^2 + [1+\upsilon]\ln[1+Z_t^2/\upsilon-2]) \tag{7'}$$

Where α represents effects of negativity shocks on volatility and when $\alpha < 0 (-1 < \alpha < 0)$, it effect is higher than the effect of positive shocks measured by γ of the same magnitude. This implies asymmetry in the effect of positive and negative shocks to volatility. Accordingly, the interplay between the sign effect (α) and the size effect (γ) gives rise to the leverage effect; β measures volatility persistence; σ_t^2 is the conditional variance; π is the usual constant. The coefficients of all three models for the various currency exchange rates were calculated by log-likelihood maximization of each model distribution using the using the Bernt *et al.* (1970) algorithm. We relied on summary statistics to provide an overall preview of the behaviour of the return and the exchange value of Bitcoin for the US dollar.We tested for the presence or otherwise of a unit root in the return and Bitcoin trading values based on the following ADF and PP test equations:

$$\begin{aligned} \Delta Z_t &= \rho_0 + \theta_1 Z_{(t-1)} + \sum\nolimits_{i=1}^{n} \rho_i Z_{t-1} + e_t \\ Z_t &= \mu_0 + \mu_1 Z_{(t-1)} + \upsilon_t \end{aligned} \tag{8}$$

The ADF equation is used to test the following hypotheses: H_0: Return has unit root; vs. H_1: Return has no unit root; and H_0: Bitcoin trading value/price has unit root; vs. H_1: Bitcoin trading value/price has no unit root. If the H_0 is accepted when the p-value exceeds 0.05, it implies that the time series is non-stationary. Acceptance of the H_1:is on the basis of a lower value below 0.05.The PP equation test hypothesis is similar to the ADF hypotheses: H_0: The return is non-stationary; vs. H_1: The return is stationary; and H_0: The Bitcoin trading value/price is non-stationary; vs. H_1: The Bitcoin trading value/price is stationary. Once the calculated p-value is less than the significance level, H_0 is accepted as against the H_1: with the conclusion that the series is stationary.

3.1 Data description and transformation

Return on exchange rate was calculated as the change in exchange rates between periods, while return on Bitcoin are the difference between the daily changes in the transaction values or prices of Bitcoin. Daily returns were utilized in this study. Mathematically, the following formula was used to obtain log returns:

$$R_t = \ln ext(t) - \ln ext(t-1) \tag{9}$$

For example, $R_t = \ln EUR / USD(t) - \ln EUR / USD(t-1)$ .Thus,*EUR/USD(t)*is today's exchange rate between the euro and dollar while *EUR/USD(t-1)* is the yesterday's rate. The study's data set consists of 3738 observations from the daily foreign exchange rate series of the EUR/USD, USD/JPY, GBP/USD, USD/CHF, AUD/USD, and CAD/USD, covering the period from January 1, 2010 to August 30, 2024. The sources of the data were the official website of the IMF, the Federal Reserve Bank, the European Central Bank, the Swiss National Bank, the Bank of Canada, and the Reserve Bank of Australia, the Bank of Japan, and the central banks of the Bank of England. In order to overcome the difficulties associated with modeling non-stationary data in time series, log-returns of the exchange rate series were obtained by data transformation.

We estimated the kurtosis coefficients for the different returns. There are three categories of kurtosis: leptokurtic, platykurtic, and mesokurtic. A kurtosis coefficient of 3, > 3, and < 3 signifies mesokurtic, leptokurtic, and platykurtic distributions, respectively. We also estimated skewness values to ascertain whether or not there is an asymmetrical distribution. The skewness value of zero is a pointer towards the absence of an asymmetrical distribution. Skewness values within -1 and -0.5 portray negative skewness with the indication of marginally skewed distributions, while values greater than 1 are suggestive of highly skewed distributions. The JB statistics were used to test for normality in the residual series of return, while the lung box was used to test for the presence or absence of the k^{th}-order serial correlation in the level and square standardized distribution of the residual series of return. Eviews 13 econometrics software was used for analyzing the return and Bitcoin/USD transaction rates.

4. Results

For the EUR/USD, JPY/USD, GBP/USD, CHF/USD, AUD/USD, CAD/USD, and BCN/USD values, Table 1 below offers descriptive statistics. Only the mean value of the Bitcoin is negative, denoting a possible depreciation of the exchange value of the Bitcoin for the US dollar over time. All other mean values are positive. This is an indication that the G7 currencies are strongly impressive and well behaved. Hence, the returns on the currencies are positive. Whereas a negative return denotes a loss, a positive return indicates a profit. Price fluctuations, dividends, and interest payments are all included in the overall return on equities. The standard deviation values are all positive, indicative of positive variation in return. The highest deviation value is obtained for the Bitcoin transaction price. The indication is that the exchange value of Bitcoin for the US dollar is characterized by high fluctuation within the currency market. The values of skewness are all positive, demonstrating that the tail of the distribution of returns extends towards the right side of the curve. The exchange rates are strong in value. By implication, the return distribution is non-symmetrical. A quicker look at the large coefficients of kurtosis, 13.5923, 3.2541, 3.1695, 3.5832, 3.3861, 3.3874, and 10.4792, is reminiscent of the leptokurtic curve. Most importantly, it can be said that while the leptokurtic stance of the JPY/USD return, GBP/USD return, CHF/USD return, AUD/USD return, and CAD/USD return is light, that of the Euro/dollar return and the return on bitcoin trading value is heavy. This means that the distribution of returns is beyond the normal distribution. It is a distribution of heavier tails, most especially for the euro/dollar return and the bitcoin return. Hence, the risk of investment in Bitcoin is considerably high. This is further made evident by the large values of the Jarqua-Bera (JB) test at the 1% significance level. As it were, the distribution of returns on currency exchange rates does not obey a normal distribution at a 1% level of significance.

Table 1. Summary statistics for currency returns and Bitcoin value

Variable	Mean	Std.	Kurtosis	Skewness	JB
EUR/USD return	1.309792	0.001873	10.82710	1.34561	24749.218
JPY/USD return	1.385092	0.004726	13.5923	1.43398	46289.273
GBP/USD return	1.497593	1.001589	40.2541	0.58745	39548.129
CHF/USD return	1.924864	1.320487	17.1695	0.53896	25667.053
AUD/USD return	1.687945	1.034873	19.5832	1.34837	51156.489
CAD/USD return	1.858732	0.025894	34.3861	1.48795	42487.329
BCN/USD value	1.942870	0.398456	12.3874	1.98474	53486.980

Source: Authors' (2024) estimation results from Eviews 13

Table 2 below reports the results of the ADF and PP tests. The outcomes categorically disprove the incidence of unit root null hypothesis in return on currencies and Bitcoin transaction values with lags. This confirms that return and Bitcoin trading values are both stationary at lags 1, 2, and 3. This indeed explains the absence of the possibility of a long-term relationship between the variables. The AIC imposed the lag length in the ADF and (P-P) regressions.

Table 2. Stationarity test results for returns and Bitcoin

Variable	Lag	ADF value	p-values	Lag	PP value	p-values
EUR/USD return	1	-53.4572***	0.0000	1	-47.3092***	0.0000
JPY/USD return	1	-48.5091***	0.0000	1	-50.3871***	0.0000
GBP/USD return	2	-30.2878***	0.0000	1	-61.2095***	0.0000

Variable	Lag	ADF value	p-values	Lag	PP value	p-values
CHF/USD return	1	-90.3612***	0.0000	1	-87.3824***	0.0000
AUD/USD return	1	-67.3894***	0.0000	3	-66.4892***	0.0000
CAD/USD return	3	-50.1872***	0.0000	1	-50.0961***	0.0000
BCN/USD value	1	-71.3439***	0.0000	2	-74.2186***	0.0000
*** denotes significant at the 1% level.						

Source: Authors' (2024) estimation results from Eviews 13

Table 3. ARFIMA model estimation results

Parameters	Return on Euro/USD exchange rate			Return on Japanese Yen/USD exchange rate		
$(0,\ell,1)$	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution
δ	0.0137 [0.242]	0.01879 [0.0001]	0.0165 [0.000]	0.0124 [0.069]	0.1101*** [0.0004]	0.0125*** [0.000]
ℓ	0.0356 [0.100]	0.0126*** [0.0000]	0.0005 [0.0624]	0.0001 [0.069]	0.0465*** [0.0004]	0.0230 [0.655]
φ	0.024 [0.0122]	-0.0589*** [0.0000]	-0.0125** [0.0509]	0.0164 [0.359]	0.1291*** [0.0000]	0.0133*** [0.000]
υ_t	-	0.7926*** [0.0000]	1.2368** [0.0523]	-	0.7866*** [0.0000]	1.3398** [0.005]
$\log \gamma$	-	-	-	-	-	0.0052 [0.157]
JB	156.408	1930.357	156.297	190.827	182.387	130.345
Skewness	0.02609	0.301379	0.34609	0.01509	0.01468	0.01286
Kurtosis	2.3557	1.3893	1.5195	3.5897	2.4895	1.4809
SIC	4.2830	2.9371	3.4879	2.0386	3.9347	4.0326
AIC	4.0150	2.3051	3.3729	2.9956	3.1427	4.5626
Likelihood ratio test	2.4976	7.5894***	2.4281	3.4895	9.4893***	4.3111

Parameters	Return on Euro/USD exchange rate			Return on Japanese Yen/USD exchange rate		
Log-likelihood	-1326.34	-1302.486	-1238.489	-1383.409	-1248.75	-1275.489
P(20)	10.8645 [0.3678]	23.4795 [0.0165]	123.4895 [0.0000]	56.4879 [0.0156]	180.3924 [0.0000]	56.2869 [0.0002]
P(30)	14.1645 [0.7899]	48.2295 [0.0000]	146.2895 [0.0000]	279.1679 [0.00000]	180.3924 [0.0000]	26.9571 [0.0222]
ARCH(5)	9.3677*** [0.0000]	8.5687*** [0.0000]	11.3582*** [0.0000]	9.1568*** [0.00000]	18.1324*** [0.0000]	6.4673*** [0.0222]
Q(30)	12.3479	11.3896	16.3809	20.3791	13.3897	14.2892
$Q^2(30)$	23.6873	39.4794	45.6896	45.5689	20.4547	34.6866

Source: Authors' (2024) estimation results from Eviews 13

Table 4. ARFIMA model estimation results

Parameters	Return on British Pound/USD exchange rate			Return on Swiss Franc/USD exchange rate		
$(0,\ell,1)$	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution
δ	0.0155** [0.002]	0.01239*** [0.0001]	0.0149 [0.456]	0.0290 [0.067]	0.1278*** [0.000]	0.0716*** [0.0000]
ℓ	0.0267 [0.1670]	0.0336*** [0.0000]	0.0115 [0.194]	0.0531 [0.0481]	0.01692*** [0.0004]	0.0187*** [0.0000]
φ	0.0117 [0.3529]	-0.0286*** [0.0000]	0.0166*** [0.0000]	0.2763 [0.5620]	0.1255*** [0.0000]	0.0256*** [0.000]
υ	-	0.1145*** [0.0000]	2.7919** [0.0523]	-	0.9831*** [0.0000]	0.1793** [0.005]
$\log\gamma$	-	-	-	-	0.0019*** [0.0000]	0.0147*** [0.0000]
JB	167.3280	120.386	145.679	110.209	100.286	133.420
Skewness	1.2951	1.4860	2.3451	2.3865	3.2809	1.8571

Parameters	Return on British Pound/USD exchange rate			Return on Swiss Franc/USD exchange rate		
Kurtosis	2.4869	2.3799	3.4879	4.1799	4.1501	1.3892
SIC	2.3899	3.5471	2.5722	3.1280	2.1897	6.1072
AIC	2.2860	2.3850	2.4807	2.0349	4.0125	3.0263
Likelihood ratio test	2.3489	13.4874***	2.3099	4.5490	19.3903***	3.5609
Log-likelihood	-1567.487	-1908.367	-2513.9172	-1110.2570	-1456.2671	-1826.2790
P(20)	110.3870 [0.0000]	187.3870 [0.0165]	109.1287 [0.0000]	130.4581 [0.0156]	122.4890 [0.0000]	24.1987 [0.0002]
P(30)	100.2868 [0.0000]	50.6879 [0.0000]	190.3812 [0.0000]	97.4253 [0.00000]	109.3872 [0.0000]	176.864 [0.0000]
ARCH(5)	10.2879*** [0.0000]	6.3562*** [0.0000]	5.4873*** [0.0000]	10.3872*** [0.00000]	5.6897*** [0.0000]	7.3901*** [0.0001]
Q(30)	13.286	14.2899	15.2346	11.2987	10.3793	12.3879
$Q^2(30)$	40.1961	22.3849	35.5489	17.4220	34.4894	29.2014

Source: Authors' (2024) estimation results from Eviews 13

Table 5. ARFIMA model estimation results

Parameters	Return on Australia dollar/USD exchange rate			Return on Canadian dollar/USD exchange rate		
$(0,\ell,1)$	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution
δ	0.0119*** [0.000]	0.0289*** [0.0000]	0.0171*** [0.0000]	0.0128 [0.1345]	0.0146*** [0.0000]	0.0132*** [0.0000]
ℓ	0.0128 [0.6795]	0.0149*** [0.0000]	0.0235 [0.874]	0.0271 [0. 2354]	0.0079*** [0.0000]	0.0348 [0.2250]
φ	0.0463 [0.286]	0.0173*** [0.0000]	0.0378*** [0.0000]	0.0298 [0.4683]	0.1042*** [0.0000]	0.0168*** [0.000]
υ	-	0.029*** [0.0000]	5.8610** [0.0003]	-	0.1936*** [0.0000]	0.1587*** [0.0000]
$\log \gamma$	-	-	-	-	-	0.0013***

Parameters	Return on Australia dollar/USD exchange rate			Return on Canadian dollar/USD exchange rate		
						[0.0000]
JB	145.472	189.386	166.275	154.387	120.486	110.387
Skewness	2.1879	0.3871	0.1923	1.2263	1.0237	2.1591
Kurtosis	3.2201	2.1409	1.2805	2.1167	3.2891	1.5676
SIC	2.3809	1.3182	2.3790	3.2861	4.3270	2.3899
AIC	2.3791	2.0392	2.1038	3.0211	3.1216	3.2791
Likelihood ratio test	2.3486	12.3489***	3.44098	3.2091	5.4982**	1.2389
Log-likelihood	-1906.334	-1252.126	-1200.129	-1390.234	-1338.05	-1200.419
P(20)	145.487 [0.0000]	24.5806 [0.0165]	25.6891 [0.0000]	30.4912 [0.0156]	14.8792 [0.0000]	89.4752 [0.0002]
P(30)	16.5487 [0.0000]	22.3804 [0.0000]	18.3693 [0.0000]	79.2753 [0.00000]	297.212 [0.0000]	35.6879 [0.0222]
ARCH(5)	7.4228*** [0.0000]	19.3256*** [0.0000]	7.5894*** [0.0000]	8.1275*** [0.00000]	9.1753*** [0.0000]	10.2861*** [0.0000]
Q(30)	118.3637	54.3287	65.4821	126.4897	67.3920	124.3792
$Q^2(30)$	79.486	135.0189	178.375	110.387	67.465	123.418

Source: Authors' (2024) estimation results from Eviews 13

Table 6. FIGARCH model estimation results

Parameters	Return on Euro/USD exchange rate			Return on Japanese Yen/USD exchange rate		
$(1, d, 1)$	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution
α	1.3872*** [0.000]	1.0238*** [0.0000]	2.3871*** [0.0000]	-1.3726 [0.4325]	1.3792*** [0.0000]	2.0361*** [0.0000]
d	0.2678** [0.0515]	0.3426*** [0.0000]	0.2340*** [0.0000]	0.3289 [0.0947]	0.2879*** [0.0000]	0.3562*** [0.0000]
η_1	0.1738 [0.286]	0.0136 [0.3563]	0.4195 [0.3221]	0.2873 [0.2291]	0.1328** [0.0532]	0.0379 [0.1187]

Parameters	Return on Euro/USD exchange rate			Return on Japanese Yen/USD exchange rate		
η_2	0.2110 [0.2342]	0.2862*** [0.0000]	0.3287 [0.2863]	0.3459 [0.2353]	0.5674*** [0.0000]	0.467*** [0.000]
e	-	1.521*** [0.0000]	2.3487** [0.0000]	-	2.1365*** [0.0000]	3.286*** [0.0000]
$\log \gamma$	-	-	-	-	-	0.00254 [0.2229]
JB	40.3267	23.4879	34.397	60.2973	560.287	47.2591
Skewness	-0.3577	-1.3790	-0.9801	-1.2863	0.1451	-2.1392
Kurtosis	1.2890	1.3095	1.0039	2.3879	1.3280	1.2793
SIC	2.4876	2.3790	1.2890	3.4165	2.5197	3.2891
AIC	2.3901	2.0381	2.3571	1.3797	2.4290	2.3856
Likelihood ratio test	1.3280	4.5287**	2.3480	2.3048	7.4289***	1.2893
Log-likelihood	-1387.379	-1973.211	-1387.548	-1265.489	-1256.490	-1287.4923
P(20)	120.3846 [0.0000]	122.347 [0.0165]	34.58994 [0.0000]	19.512 [0.0156]	20.3487 [0.0000]	30.4861 [0.0002]
P(30)	13.486- [0.0000]	70.37404 [0.0000]	23.5487 [0.0000]	39.5467 [0.00000]	43.5989 [0.0000]	20.4875 [0.0452]
ARCH(5)	0.1637 [0.7381]	0.1874 [0.7863]	0.2879 [0.6544]	0.3258 [0.5741]	0.35189 [0.7935]	0.1456 [0.6272]
Q(30)	5.667	6.2879	6.3756	6.5489	5.6891	6.4794
$Q^2(30)$	90.3467***	850.3189***	49.3677**	62.45689***	60.3863***	70.3486***

Source: Authors' (2024) estimation results from Eviews 13

Table 7. FIGARCH model estimation results

Parameters	Return on British Pound/USD exchange rate			Return on Swiss Franc/USD exchange rate		
$(1, d, 1)$	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution
α	2.4487	1.4357***	1.9236***	3.2821	1.4689***	1.2465***

Parameters	Return on British Pound/USD exchange rate			Return on Swiss Franc/USD exchange rate		
	[0.5672]	[0.0000]	[0.0000]	[0.4325]	[0.0000]	[0.0000]
d	0.438*** [0.0000]	0.3569*** [0.0000]	0.2254*** [0.0000]	0.5123** [0.0517]	0.3397*** [0.0000]	0.3129*** [0.0000]
η_1	-0.4381 [0.3265]	-0.0321 [0.1466]	-0.0193 [0.2587]	-0.0134 [0.2390]	-0.03791** [0.2541]	-0.0346 [0.2339]
η_2	0.2948 [0.2342]	0.3456*** [0.0000]	0.2936** [0.0543]	0.2834 [0.2542]	0.2901*** [0.0000]	0.2937 [0.3891]
υ	-	1.0936*** [0.0000]	3.4871** [0.0000]	-	0.9937*** [0.0000]	5.2386*** [0.0000]
$\log \gamma$	-	-	-	-	-	0.01299** [0.006]
JB	23.4782	30.2795	44.5791	32.5790	27.422	21.3899
Skewness	1.3855	0.1893	-2.1871	0.1835	-1.3289	-1.5867
Kurtosis	1.2879	3.28792	5.3911	6.1280	2.3879	1.3379
SIC	3.2386	5.2860	1.2387	2.3573	3.2461	2.1853
AIC	3.5891	3.2479	3.2879	3.5409	3.0574	3.4031
Likelihood ratio test	1.2903	5.3891**	6.3810***	2.3409	6.4095***	2.3894
Log-likelihood	-1386.479	-1873.491	-1254.387	-1234.125	-1034.487	-1375.486
P(20)	198.366 [0.0000]	178.267 [0.0000]	34.58994 [0.0122]	20.4872 [0.0156]	128.3831 [0.0000]	187.386 [0.0002]
P(30)	167.387 [0.0000]	177.382 [0.0000]	110.387 [0.0000]	130.486 [0.00000]	156.689 [0.0000]	0.2541 [0.0000]
ARCH(5)	0.3587 [0.7921]	0.3562 [0.8162]	0.2019 [0.9594]	0.2108 [0.6241]	0.35189 [0.8935]	0.1456 [0.9272]
Q(30)	16.387	12.3487	15.4022	12.4870	13.4879	12.5479
$Q^2(30)$	45.687	130.587***	68.4899***	78.3671***	82.4671***	79.4861***

Source: Authors' (2024) estimation results from Eviews 13

Table 8. FIGARCH model estimation results

Parameters	Return on Australia dollar/USD exchange rate			Return on Canadian dollar/USD exchange rate		
$(1,d,1)$	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution
α	3.5879 [0.2283]	1.1103*** [0.0000]	1.873 [0.2345]	1.1879 [0.2661]	1.0235*** [0.0000]	1.1782*** [0.0000]
d	0.138 [0.687]	0.2109*** [0.0000]	0.2344*** [0.0000]	0.1793 [0.2791]	0.4487*** [0.0000]	0.2568*** [0.0000]
η_1	-0.3879 [0.3265]	-0.0018** [0.0016]	0.0012** [0.0087]	-0.0111 [0.4490]	0.0015*** [0.0011]	-0.0127 [0.678]
η_2	0.289 [0.3421]	0.3097*** [0.0000]	0.1962** [0.0555]	0.428 [0.1242]	0.1546*** [0.0000]	0.0132** [0.0540]
υ	-	0.9724*** [0.0000]	1.2873** [0.0552]	-	1.0245*** [0.0000]	2.1893*** [0.0000]
$\log \gamma$	-	-	-	-	-	0.0156*** [0.0000]
JB	47.5809	24.3871	22.3990	76.3793	88.3861	45.3801
Skewness	-0.3872	1.3095	-2.3487	-1.3226	1.2389	1.0267
Kurtosis	2.4091	2.3790	3.2092	4.2929	1.2397	2.1039
SIC	2.4870	2.3480	2.3489	2.4891	2.5942	2.4890
AIC	3.9320	3.2801	3.0283	3.0448	3.2809	3.2891
Likelihood ratio test	1.3890	5.5609***	3.4091	2.3489	9.3872***	2.3941
Log-likelihood	-1387.991	-1346.671	-1634.479	-1387.289	-1379.480	-1271.387
P(20)	278.386 [0.0000]	123.472 [0.0000]	145.3498 [0.0000]	197.482 [0.0000]	141.379 [0.0000]	199.4870 [0.0000]
P(30)	180.357 [0.0000]	122.345 [0.0000]	198.3672 [0.0000]	189.391 [0.00000]	187.356 [0.0000]	192.367 [0.0000]
ARCH(5)	0.3587 [0.7921]	0.3562 [0.9162]	0.2019 [0.9594]	0.2108 [0.9241]	0.35189 [0.8935]	0.1456 [0.9272]

Parameters	Return on Australia dollar/USD exchange rate			Return on Canadian dollar/USD exchange rate		
Q(30)	20.367	32.348	12.387	10.937	11.3887	32.489
$Q^2(30)$	156.891	198.167***	133.685***	140.115***	190.367***	143.001***

Source: Authors' (2024) estimation results from Eviews 13

Table 9. AFRIMA-FIGARCH model estimation results

Parameters	Return on Euro/USD exchange rate			Return on Japanese Yen/USD exchange rate		
$(0,\ell,1)-(1,d,1)$	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution
δ	0.0571*** [0.000]	0.086*** [0.0000]	0.0192*** [0.0000]	0.0013** [0.0025]	0.0087*** [0.0000]	0.1934*** [0.0000]
φ	-0.5186 [0.1355]	0.2678*** [0.0000]	0.4897 [0.268]	0.7935 [0.2445]	0.0256	0.5822 [0.2347]
ℓ	-0.0018 [0.4835]	0.0231*** [0.0000]	-0.0367 [0.268]	0.1567 [0.3328]	0.5489** [0.0022]	0.0.321 [0.2256]
ϕ	-0.042 [0.4313]	0.0567*** [0.0000]	-0.2342 [0.5267]	0.0895 [0.3328]	0.5167** [0.0022]	0.1879 [0.3566]
α	3.1286 [0.000]	1.6973*** [0.0000]	4.2872*** [0.0000]	3.9102 [0.2466]	1.4678*** [0.0000]	4.2879*** [0.0000]
η_1	-0.0379 [0.286]	0.0011 [0.2263]	0.0618 [0.2456]	0.0025 [0.2291]	0.2561** [0.0522]	0.02936 [0.2277]
η_2	0.2729 [0.2342]	0.25818** [0.0000]	0.1567 [0.2863]	0.1305 [0.2353]	0.1169 [0.0000]	0.0238*** [0.000]
d	0.3556 [0.2315]	0.2976*** [0.0000]	0.4679 [0.2572]	0.1872 [0.2457]	0.4871*** [0.0000]	0.2561*** [0.0000]
υ	-	1.8590*** [0.0000]	5.1762** [0.0000]	-	1.7679*** [0.0000]	4.2897*** [0.0000]
$\log\gamma$	-	0.03861 [0.0000]	-	-	-0.00113 [0.0000]	0.16378*** [0.0000]
JB	56.3899	89.3287	89.2731	56.3809	79.3047	56.4802

Parameters	Return on Euro/USD exchange rate			Return on Japanese Yen/USD exchange rate		
Skewness	0.0386	1.0248	0.37921	0.0012	1.02837	3.2118
Kurtosis	1.9325	1.9272	1.9267	1.9965	1.9024	1.9375
SIC	4.3798	3.1609	2.0948	2.0395	2.03971	2.0382
AIC	1.2673	1.4526	1.0289	1.3679	1.4356	1.02564
Likelihood ratio test	1.2034	5.3899***	2.3809	1.3822	6.3221***	2.3389
Log-likelihood	-1870.3712	-1287.479	-1093.367	-1345.387	-1289.470	-1471.389
P(20)	190.387 [0.0000]	144.879 [0.0000]	113.438 [0.0000]	124.5872 [0.0000]	110.387 [0.0000]	122.3497 [0.0000]
P(30)	198.156 [0.0000]	156.278 [0.0000]	193.5487 [0.0000]	132.0255 [0.00000]	133.489 [0.0000]	178.3234 [0.0000]
ARCH(5)	0.1089 [0.9677]	0.1389 [0.9868]	0.1453 [0.9879]	0.1933 [0.9231]	0.1592 [0.9633]	0.1485 [0.9543]
Q(30)	8.2751	9.4386	10.3922	8.1673	4.2892	9.3981
$Q^2(30)$	46.379***	79.386***	12.4874	50.286***	74.3622***	56.3793***

Source: Authors' (2024) estimation results from Eviews 13

Table 10. AFRIMA-FIGARCH model estimation results

Parameters	Return on British Pound/USD exchange rate			Return on Swiss Franc/USD exchange rate		
$(0,\ell,1)-(1,d,1)$	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution
δ	0.0114*** [0.000]	0.0366*** [0.0000]	0.0163*** [0.0000]	0.0997** [0.0025]	0.0267*** [0.0000]	0.2658*** [0.0000]
φ	0.4578 [0.2235]	-0.7690*** [0.0000]	-0.5689 [0.268]	0.2139 [0.2445]	-0.0109*** [0.0000]	-0.1789 [0.2347]
ℓ	0.0175 [0.5235]	0.0187*** [0.0000]	0.1397 [0.6898]	0.9171 [0.3328]	0.3390*** [0.0012]	0.02255 [0.0056]
ϕ	0.367	0.0472***	-0.1123	0.2563	0.3802**	0.1379

Parameters	Return on British Pound/USD exchange rate			Return on Swiss Franc/USD exchange rate		
	[0.2293]	[0.0023]	[0.2496]	[0.3458]	[0.0042]	[0.2266]
α	2.1527 [0.000]	1.9360*** [0.0000]	2.3879*** [0.0000]	2.1936 [0.2466]	1.1862*** [0.0000]	3.2974*** [0.0000]
η_1	-0.0013 [0.286]	0.0045 [0.2263]	0.0175 [0.2456]	0.0561 [0.2291]	0.1032** [0.0522]	0.0387 [0.2277]
η_2	0.2879 [0.2342]	0.2891** [0.0513]	0.1789 [0.2863]	0.2870 [0.3633]	0.2890 [0.0000]	0.0379*** [0.000]
d	0.2461 [0.4305]	0.2355*** [0.0000]	0.3486 [0.1524]	0.5289 [0.2457]	0.2863*** [0.0000]	0.2809*** [0.0000]
υ	-	1.1379*** [0.0000]	2.1873** [0.0000]	-	1.6923*** [0.0000]	2.3891*** [0.0000]
$\log \gamma$	-	-	-	-	-	0.0265*** [0.0000]
JB	49.2578	24.3671	65.3899	70.3521	46.3897	99.2861
Skewness	1.2379	1.8370	1.6590	1.3200	1.4685	1.3789
Kurtosis	1.7832	1.3622	1.2814	1.6792	1.4382	1.38709
SIC	2.4081	2.3556	2.3791	2.4802	3.2177	3.4895
AIC	3.2091	3.2054	3.21254	2.2924	3.2879	3.4877
Likelihood ratio test	6.3793***	9.3972***	4.5891	2.3328	5.3809***	4.3092
Log-likelihood	-1256.347	-1879.807	-1386.386	-1356.379	-1346.180	-1332.321
P(20)	78.3522 [0.0000]	27.489 [0.0000]	90.3487 [0.0000]	46.8091 [0.0000]	56.8932 [0.0000]	76.8092 [0.0000]
P(30)	90.4861 [0.0000]	67.0911 [0.0000]	87.4512 [0.0000]	68.3022 [0.00000]	48.5091 [0.0000]	89.3561 [0.0000]
ARCH(5)	0.2465 [0.9427]	0.2861 [0.9678]	0.2934 [0.9765]	0.2874 [0.9672]	0.2987 [0.9711]	0.267 [0.9700]
Q(30)	9.2578	8.3512	7.8091	8.5624	9.2357	9.3461
$Q^2(30)$	50.387***	89.357***	78.8094***	89.3722***	90.5372***	76.3891***

Source: Authors' (2024) estimation results from Eviews 13

Table 11. AFRIMA-FIGARCH model estimation results

Parameters	Return on Australia dollar/USD exchange rate			Return on Canadian dollar/USD exchange rate		
$(0,\ell,1)-(1,d,1)$	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution	EGARCH model with normal distribution	EGARCH model with skewed-GED distribution	EGARCH model with skewed-Student's t distribution
δ	0.0289*** [0.000]	0.0547*** [0.0000]	0.0189*** [0.0000]	0.0187** [0.0025]	0.0146*** [0.0000]	0.3745*** [0.0000]
φ	0.2389 [0.3487]	-0.2450*** [0.0000]	-0.3392 [0.268]	0.4633 [0.5745]	-0.2535*** [0.0000]	-0.458 [0.2347]
ℓ	0.0142 [0.2346]	0.0154*** [0.0000]	0.1179 [0.2463]	0.24556 [0.3328]	0.3102*** [0.0012]	0.0291** [0.0052]
ϕ	0.2673 [0.5614]	0.4609*** [0.0015]	-0.5688 [0.2366]	0.2567 [0.7823]	0.4568** [0.0052]	0.1368 [0.4721]
α	3.156 [0.000]	1.5873*** [0.0000]	1.3872*** [0.0000]	4.2872 [0.5566]	1.2879*** [0.0000]	2.3479 [0.4863]
η_1	-0.0193 [0.286]	0.0298 [0.2263]	0.0124 [0.2396]	0.0379 [0.5691]	0.5391** [0.0342]	0.3945 [0.2568]
η_2	0.2639 [0.6812]	0.3894*** [0.0003]	0.1295** [0.0053]	0.2879 [0.5467]	0.3874*** [0.0000]	0.0182 [0.2796]
d	0.3256 [0.2168]	0.4671*** [0.0000]	0.5482 [0.2873]	0.2130 [0.1457]	0.4673*** [0.0000]	0.3973 [0.4582]
υ	-	1.0259*** [0.0000]	3.5497** [0.0000]	-	1.2309*** [0.0000]	4.3879*** [0.0000]
$\log\gamma$	-	-	-	-	-	0.0018*** [0.0000]
JB	59.367	55.2870	56.3809	79.209	89.2571	105.3287
Skewness	-0.3621	-0.1873	-1.2897	-2.3489	3.0287	-1.2864
Kurtosis	3.3891	2.3409	2.1910	1.3792	3.2105	2.3189
SIC	3.147	5.3891	4.2982	2.4899	2.4870	3.2290
AIC	2.3099	3.2011	2.3001	3.2056	2.3476	2.2981

Parameters	Return on Australia dollar/USD exchange rate			Return on Canadian dollar/USD exchange rate		
Log-likelihood	-1345.891	-1908.171	-1972.372	-1921.380	-1890.742	-1685.109
Likelihood ratio test	1.2389	7.0943***	2.3409	4.5622	9.3477***	2.3411
P(20)	90.386 [0.0000]	67.387 [0.0000]	56.389 [0.0000]	76.5418 [0.0000]	56.3891 [0.0000]	77.3212 [0.0000]
P(30)	178.287 [0.0000]	155.289 [0.0000]	188.357 [0.0000]	123.287 [0.00000]	114.567 [0.0000]	109.367 [0.0000]
ARCH(5)	0.3879 [0.9568]	0.1387 [0.9235]	0.1294 [0.9999]	0.1952 [0.9568]	0.1038 [0.9345]	0.1873 [0.9156]
Q(30)	6.8990	5.3982	56.4801***	5.2769	6.9880	6.8002
$Q^2(30)$	78.365***	24.279	89.257***	67.890***	98.357***	75.389***

Source: Authors' (2024) estimation results from Eviews 13

Table 12. EGARCH model results for currency returns with Bitcoin transaction value

Parameters	EGARCH model with skewed-GED Distribution					
$(0,\ell,1)-(1,d,1)$	EUR/dollar return	JPY/USD return	GBP/USD return	CHF/USD return	AUD/USD return	CAD/USD return
a	0.0527 [0.3426]	-0.0035 [1.0389]	0.0145 [0.0109]	0.0126** [2.4795]	0.0187*** [11.2835]	0.01389 [1.1240]
ϕ	0.2946*** [5.4820]	0.1025*** [7.3892]	0.1932*** [9.0211]	0.3561*** [8.4809]	0.4371** [2.3549]	0.5389** [2.6627]
λ	-1.02576*** [8.3922]	1.0192*** [9.3462]	1.2846** [2.3875]	1.3476** [2.0193]	1.1798*** [15.3120]	1.4962*** [16.1290]
b	-0.1037*** [17.290]	-0.1498*** [19.339]	-0.4320*** [15.1427]	-0.5682*** [19.4793]	-0.2368*** [40.2190]	-0.1173*** [20.3489]
α	-0.0786*** [29.3810]	-0.0114*** [14.582]	-0.0167 [6.3452]	-0.0126** [2.6790]	-0.0567*** [13.3092]	-0.0139*** [17.1422]
γ	0.1735*** [10.9912]	0.1394*** [7.3622]	0.4876** [2.1023]	0.5680*** [17.0245]	0.6910*** [14.5972]	0.1972*** [30.4875]
β	0.8962*** [24.1589]	0.9251** [2.309]	0.7955*** [14.3986]	0.9137*** [23.0482]	0.9915*** [25.0943]	0.7903*** [101.1290]

Parameters	EGARCH model with skewed-GED Distribution					
∂	-1.2904*** [250.7261]	1.1682*** [137.5091]	1.9925*** [146.4895]	1.5684*** [900.0062]	1.7829*** [122.3814]	1.4098*** [645.2713]
JB	123.348	187.4890	134.5895	122.3479	119.3873	112.3489
Skewness	3.2991	3.4982	3.4948	4.2671	2.3456	3.4892
Kurtosis	7.3893	2.3894	3.4580	5.3092	2.5891	3.3256
Likelihood test ratio	15.4899***	17.4804***	10.2387***	13.2894***	9.0372***	11.2387***
Log-likelihood	-4563.487	-5672.3489	-5209.4891	-5264.3973	-4286.4791	-5379.2803
P(20)	18.3497 [0.3678]	22.4596 [0.0165]	43.2894 [0.0000]	60.3892 [0.0156]	58.3489 [0.0000]	47.1592 [0.0002]
P(30)	123.4891 [0.7899]	23.9289 [0.0000]	46.2895 [0.0000]	79.4322 [0.0001]	80.345 [0.0078]	79.5933 [0.0012]
ARCH(5)	9.3677 [0.3267]	8.5687 [0.4982]	11.3582 [0.3423]	9.1568 [0.5672]	18.1324 [0.3372]	6.4673 [0.2794]
Q(30)	12.3479	11.3896	16.3809	20.3791	13.3897	14.2892
$Q^2(30)$	23.4490	97.3862	45.3922	66.4589	89.2672	50.5679

Source: Authors' (2024) estimation results from Eviews 13

4.1 Discussion

We took out time to estimate different ARFIMA (p,ℓ,q) models for (p,q) taking on zero, one, and two as values for return on Ghana/USD exchange rate, Ghana/USD exchange, Ghana/USD exchange, Ghana/USD exchange, and return on transactions with Bitcoin. The different models were subjected to the selection techniques of Akaike (AIC), Schwarz (SIC) Information Criteria, and log-likelihood. The best empirical model was chosen on the basis of the model with the lowest log-likelihoods, AIC and SIC, respectively, and the estimated results are reported in Tables 3, 4, and 5, respectively. As shown in the Tables, the ARFIMA model captures long memory in the exchange return of the EUR/USD for the skewed EGARCH-Student's t and skewed EGARCH-GED distributions. The long memory behaviour in the exchange rate returns of the JPY/USD and GBP/USD, respectively, was only supported by the skewed EGARCH-GED distribution, whereas for the exchange return of the CHF/USD, both the EGARCH-Skewed

Student's t and EGARCH-Skewed GED distributions supported the long memory property in the return behavior. The long-term memory behaviour in the exchange rate returns of the AUD/USD and CAD/USD, respectively, was supported only by the EGARCH-skewed GED distribution. The significance of the long memory property was determined on the basis of the significance of the coefficient. Diagnostically speaking, the tail (shape) and asymmetry parameters are significant for both the skewed-GED and skewed-student's t distributions. Besides, JB estimates show a non-normal error distribution, which satisfies the skew-GED type of distribution.

Tables 6, 7, and 8 give the results of the FIGARCH model estimation. The results clearly uphold the hypothesis of declining conditional volatility at a hyperbolic rate since d lies within the interval of zero and unity. In other words, the effect of a volatility shock on the exchange rate and Bitcoin returns dies off slowly. This follows from the significance of the long memory *d* parameter, indicated as *d* for all the countries and also for the Bitcoin return. By implication, the return on exchange rates for Bitcoin is highly persistent. This is supported by the previous findings obtained by Umoru *et al.* (2024). The volatility of returns on exchange rates of all the currencies in the study and returns on Bitcoin transaction prices exhibit a long memory process. The Ljung-Box test statistics show that the returns are devoid of serial correlation. The Pearson test values indicate that all the distributions are well fitted for the return series. The asymmetry coefficient was only significant for the student's t distribution, whereas for all distributions, the tail parameter was found to be statistically different from zero. Tables 9, 10, and 11 report the results for the chosen ARFIMA-FIGARCH model having undergone the selection process. According to the results of the ARFIMA-FIGARCH model, the long memory coefficient in the conditional mean return is significant for exchange rate returns on the EUR/USD, JPY/USD, GBP/USD, CHF/USD, and AUD/USD, respectively, for only the GED distribution, while the mean return on transactions with Biotin is significant for both the GED and Student's t distributions for the CAD/USD. Similarly, the long-term memory coefficient in the conditional variance of return on the EUR/USD, GBP/USD, CAD/USD, and AUD/USD is significant for only the EGARCH-skewed-GED distribution. The long-term memory is significant for both the EGARCH-skewed student's t distributions with respect to the return on JPY/USD and CHF/USD, respectively.

The diagnostic results are highly satisfactory, especially the ARCH-LM test result, which shows the absence of ARCH effects in the returns' residuals for all the distributions. Furthermore, the tail parameter is considerably well behaved for all the distributions, while the asymmetry coefficient was also significant for t distribution. Hence, the EGARCH skewed-GED distribution is the most appropriate distribution for evaluating the volatility behaviour of returns on exchange rates and returns on transactions with Bitcoin in Europe, Japan, the UK, France, Australia, and Canada. Nevertheless, we have chosen the EGARCH-SGED model for estimation as the best that outperforms the GARCH skewed-student-t distribution and EGARCH-normal distribution models because it produces the smallest AIC and SIC values, and the long memory in the volatility was significant for all the EGARCH-SGED models with a skewed-GED distribution. Our outcomes agree with the conclusions of Samuel Ampadu, Mensah, Aidoo, Boateng, and Maposa (2024); Song *et al.* (2023); Dinga, Claver, Cletus, & Che (2023); Li *et al.* (2023); Godfrey and Ismail (2022); Cerqueti, Giacalone, and Mattera (2020); Neethling, Ferreira, Bakker, & Naderi (2020); Samson, Enang, & Onwukwe's (2020) research findings; and Yen-Hsien & Tung-Yueh (2010). Ampadu *et al.* (2024) reported that the SGED outscored the Normal, Student's t, GED, and skewed Student's t distributions, leading these authors to conclude that it is the most effective and reliable distribution for simulating financial returns. According to Song *et al.* (2023), the quantile regression QR-SGED-EGARCH (1, 1) model produces VaR values that are superior to other models when tested using the Kupiec test at various confidence levels. Additionally, the QR-SGED-EGARCH (1, 1) model's ES values are more effective in times of crisis, as seen by its higher accuracy and robustness for the Chinese economy.

Dinga et al. (2023) establish that GJRGARCH (1,1)-SGED and GJRGARCH (2,2)-SGED models that work best for estimating the volatility of the returns on the USD/XAF and CNY/XAF exchange rates, respectively, based on selecting the model with the lowest AIC. Additionally, the authors discovered that the models with the highest predictive ability for the USD/XAF and CNY/XAF exchange rate returns were GARCH (1,1)-SGED and GJR (2,2)-SGED, respectively, basing selection on MAE and RMSE. The smooth transition GARCH-MIDAS model was found by Li et al. (2023) to perform the best in forecasting stock volatility in the presence of economic policy uncertainty. Additionally, Godfrey and Ismail (2022) discovered that for the DSEI All-Share stock data, the three-state heterogeneous regime MS-GARCH and mixture of the chosen GARCH type models give the greatest fit and dynamic feedback between components. Cerqueti *et al.* (2020) investigated how to simulate crypto currency volatility using skewed non-Gaussian GARCH models. As stated in the study's conclusions, the GARCH-type model with skewed GED enhances the prediction accuracy and volatility of the Bitcoin/USD and Litecoin/USD exchange rate specifications. According to Neethling *et al.* (2020), time series variables with kurtosis and asymmetry are best explained by autoregressive skewed generalized innovation distributed models. Samson *et al.*'s (2020) estimated results further demonstrate that the SGED surpassed other non-

Gaussian innovation distributions among those taken into consideration. Yen-Hsien & Tung-Yueh (2010) discovered that the GARCH-SGED model performs better in forecasting REIT volatility in the US than the GARCH-N and GARCH-ST models for all prediction horizons when model selection is based on MSE or MAE. Furthermore, the DM-tests offer more proof that volatility projections given by the GARCH-SGED model are in general more accurate than those produced by the GARCH-N and GARCH-ST models.

Having verified that the EGARCH model with skewed GED was the best distribution to model returns, we deployed the EGARCH model as invented by Nelson (1991) to estimate the dynamic impact of Bitcoin trading values on exchange rate returns. Table 12 reports the EGARCH results of returns with Bitcoin transaction value for G7 currency rates. The volatility persistence coefficients given by β are significant for all G7 currency rates at the 1% level, an indication that the stationary persistence of shocks is related to conditional volatility. We estimated a significant EGARCH effect for the returns on all currencies. The coefficient of asymmetric effect given is significant at the 5% level. These coefficients are -0.0786 for the Euro/dollar return; -0.0114 for the JPY/USD return; -0.0167 for the GBP/USD return; -0.0126 for the CHF/USD return; -0.0567 for the AUD/USD return; and -0.0139 for the CAD/USD return. A closer look at the sign effects shows that they are negative and hence less than zero (0). By implication, the impact of a negative shock on current volatility exceeds the impact of a positive volatility shock for all the G7 currency exchange rates. The size effects of a positive shock on conditional volatility were measured. All the γ's coefficients, namely, 0.1735; 0.1394; 0.4876; 0.5680; 0.6910; and 0.1972 for the EUR/USD, JPY/USD, GBP/USD, CHF/USD, AUD/USD, and CAD/USD, respectively, are positive and significantly different from zero at the 1% level. By implication, shocks increase volatility.

While the λ coefficient measures the impact of Bitcoin transaction values on returns, the coefficient ∂ measures the dynamic impact of Bitcoin transaction values on the conditional variance of returns with a lag. The coefficients of lagged trading or transaction values of Bitcoin in the conditional variance equation of the EGARCH model estimation for all currencies are 1.2904 for the Euro/dollar return; 1.1682 for the JPY/dollar return; 1.9925 for the GBP/dollar return; 1.5684 for the CHF/dollar return; 1.7829 for the AUD/dollar return; and 1.4098 for the CAD/dollar return. These effects are significantly different from zero at both the 5% and 1% levels and are also all positive. Our estimates show a significant negative effect of Bitcoin trading values on the Euro/dollar return at the 1% level. This connection emphasizes how cryptocurrencies are becoming more and more important as substitute financial assets in periods of upheaval in the established financial system. The results of Patel & Morris (2024), who explored the spillover effects between Bitcoin investment returns and the Euro (EUR/USD) during times of stress on European banks, align with this finding. They surveyed data from 2022 to 2024 using a spillover index technique, paying particular attention to how the banking crises affect the relationship between Bitcoin and the Euro. Their findings show that investors may turn to Bitcoin as a hedge against standard banking risks, as Bitcoin trading profits tend to correlate negatively with changes in the EUR/USD during banking crises.

For the return on other currency rates, JPY/USD, GBP/USD, CHF/USD, AUD/USD, and CAD/USD, there is a significant positive nexus between the variance of returns, that is, the conditional volatility of returns on G7 currencies and Bitcoin transaction prices, but with a lag. By and large, the study established a positive link between return and lagged Bitcoin trading values. This particular result highlights the sensitivity of exchange rates to cryptocurrency market dynamics. By implication, Bitcoin is increasingly influencing traditional financial markets. This was substantiated by the estimated return equation for all G7 currencies. Even the return equation shows that Bitcoin trading values had a considerable positive effect on the level of return. This agrees with the results of Andersen & Kumar (2024), Fischer & Martinez (2024), Thompson & Zhao (2024), Martins & Rodriguez (2024), Brooks & Chen (2023), Zhao & Liu (2023), and Chen & Nakamura (2022). Andersen & Kumar (2024) focused their study on the volatility spillover between Bitcoin transactions and multiple exchange rates involving the Euro, British Pound, and Japanese Yen. Using the Dynamic Conditional Correlation (DCC) model, they analyzed data from 2020 to 2023 to capture the dynamic interrelationships. Their results demonstrated that the volatility spillover is most pronounced with the Euro, followed by the British Pound and the Japanese Yen. The study also revealed that news related to cryptocurrency regulation and technological advancements in blockchain significantly enhance the volatility spillover effects. Fischer & Martinez (2024) investigated the interactions between Bitcoin transactions and the Mexican Peso (MXN). They applied a structural break GARCH model to discern patterns of volatility transmission under different economic conditions from 2020 to 2024. Their results reveal that Bitcoin has a significant spillover effect on the MXN, particularly during periods of U.S. dollar strength or weakness, which traditionally affects the MXN due to close economic ties between Mexico and the United States.

The study suggests that Bitcoin's influence on the MXN becomes particularly pronounced during times of pronounced USD fluctuations, offering a potential diversification strategy for investors. The British Pound (GBP) and US Dollar (USD) exchange rate fluctuations are related to each other, according to Thompson & Zhao's (2024) research. By implementing a multivariate GARCH model, they assessed data spanning from 2022 to 2024 in an attempt to quantify the ripple effects of volatility among these markets. Based to their research, when it comes to the GBP/USD exchange rate, a greater variability in Bitcoin returns matters a lot, especially considering the economic concerns surrounding Brexit. In accordance to the study, there is an intense connection between the dynamics of the Bitcoin market and the local economic events in the UK, as seen by the noticeable impact of Bitcoin on the GBP during periods of political or economic news that directly affect the UK economy. Martins & Rodriguez (2024) conducted an analysis on the volatility spillover between Bitcoin transactions and the British Pound (GBP/USD). Using a multivariate GARCH-DCC model, they analyzed the data spanning from 2021 to 2024. Their research highlights a strong correlation between Bitcoin volatility and GBP fluctuations, especially considering the economic uncertainty associated with Brexit. This correlation suggests that, in addition to economic policies and global events, political decisions within countries can also significantly influence the relationship between digital and fiat currencies. Brooks and Chen (2023) investigated the volatility spillover between Bitcoin transactions and the Chinese Yuan (CNY/USD) exchange rate. Using daily transaction data of Bitcoin alongside the exchange rate fluctuations from 2020 to 2023; their analysis highlighted an increasing trend in the volatility transmission from Bitcoin to the Yuan, particularly during periods of policy shifts in China regarding cryptocurrency trading and mining. This study underscores the influence of regulatory environments on the extent of volatility spillover and illustrates how national policy decisions in major economies can affect global cryptocurrency markets.

Zhao & Liu (2023) examined the volatility spillover effects between Bitcoin transactions and exchange rate movements, particularly focusing on the USD/CNY exchange rate. Utilizing a BEKK-GARCH model to capture the bidirectional spillovers, they analyzed extensive transaction data from 2019 to 2022. The findings indicate significant volatility transmission from Bitcoin transactions to exchange rate fluctuations, especially during periods of economic uncertainty. This research demonstrates the increasing impact of virtual currencies on conventional financial markets and suggests that Bitcoin's market activities can serve as a leading indicator for exchange rate volatility in certain economic contexts. Chen & Nakamura (2022) conducted an extensive study examining the volatility spillover between Bitcoin transactions and the USD/JPY exchange rate. They employed a multivariate GARCH (MGARCH) model, which allowed them to capture the dynamic correlation between these markets. The study focused on analyzing data from 2019 to 2021, a period marked by significant fluctuations in both the cryptocurrency market and international exchange rates. Their results indicated a substantial increase in volatility transmission from Bitcoin to the USD/JPY exchange rate, particularly during periods of high market uncertainty or significant cryptocurrency market events, such as regulatory changes or major security breaches.

The diagnostic results had no significant serial correlation as adjudged on the basis of the estimated Ljung-Box test statistics for 30th order autocorrelation in both the level and squared standardized residuals for the returns on all currencies. Therefore, the estimated EGARCH models fit the return data accurately. Besides, the likelihood ratio test statistics are significant, and the corresponding log-likelihood statistics are precisely huge. This is a further confirmation of the superiority of the EGARCH model with GED distribution over the EGARCH model with normal and GARCH with student's t distributions in modeling the trend in the daily return of currency rates. This could be traced to its ability to capture the temporal dependence of the conditional volatility of returns. The model findings are in line with those estimated by Hatice, Aweng, & Adire (2020), who recommended the EGARCH (1,1) model under the GED distributed errors model for modelingand predicting the USD/UGX rate's volatility. Also, our results are in line with those previously reported by Almarashi, & Khan (2019) who discovered that GARCH (1, 1) with GED is the best model for capturing the volatility of stock returns in the flying cement industry.

5. Conclusion

An attempt has been made in this study to investigate the distribution of the return on exchange rates of the currencies of the G7 countries. As well, we empirically estimated the dynamic effect of bitcoin transaction values on currency returns in the selected G7 countries. We found that the appropriate distribution of returns was the GED. The study invalidates the hypothesis of a normal distribution of returns and rather implies that returns exhibit fat tails. Hence, we agreed with Cerqueti *et al.* (2020) that it was a reliable decision to use normally distributed error for the GARCH model in volatility modeling. The policy implication is that, particularly when the underlying error distribution is heavier-tailed, the typical GARCH model may not always be able to produce reliable estimates of volatility persistence. By implication, the error distribution for return on G7 currencies, the euro, Swiss franc, British pound, Australian dollar, Canadian dollar, and Japanese yen, respectively, is beyond the normal distribution. Accordingly, there are extreme return values that exceed the expectations of a normal distribution in terms of frequency. Our findings show that Bitcoin trading values have sizeable predictive power for returns on exchange rates in G7 nations. The significance and large positive value of the shape parameter, otherwise called the tail coefficient, signifies heavier tails, while a lower value of the asymmetric coefficient signifies slower decay, allowing the distribution to capture extreme return series more effectively. Our study established a significant EGARCH-GED model effect with substantial asymmetric responsiveness and persistence of conditional volatility of return on foreign exchange rates for the six G7 currencies researched in this study. We therefore recommend a downward adjustment of the monetary policy rate to curtail the impact of the negative shocks, bad market news, that snowball volatility in returns. In general, there is a need for overall macroeconomic stabilization.

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