Research Article

Exchange Rates of Currencies, Volatility of Bitcoin Returns and Value at Risk (VaR) Analysis

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Abstract: There has been an increase in curiosity about the relationship between the returns on Bitcoins and returns on exchange rates in the last few years. This is especially important since Bitcoin is becoming more and more well-liked as a substitute for fiat money. This study therefore estimates the dynamic impact of exchange rates and their returns on Bitcoin return and also the value-at-risk (VaR) associated with each exchange rate and Bitcoin. The variance series derived from an estimation of the variations between the current and historical prices of Bitcoin using the exponential generalised autoregressive conditional heteroscedasticity (EGARCH) model was used to compute data on Bitcoin volatility. Accordingly, return on Bitcoins was modelled as the natural logarithm of the difference between current day Bitcoin price and previous day price. The joint ARMA-FIGARCH models were estimated in this study to model the returns on Bitcoins transactions and currency trading rates based on time series from February 1, 2010 to August 30, 2024. The research findings underscore the presence of a significant dynamic adjustment of Bitcoin returns to exchange rate returns across all countries. This goes to indicate that there is a high possibility of incurring losses when making investments with digital currencies like Bitcoin. The originality of the paper lies on the fact the research assessed the effect of returns on currency exchange rates of rich countries and also estimated the dynamic effect of Bitcoin returns on exchange rates of the selected countries. The study establishes a substantial volatility feedback effect for returns on Bitcoins, whereas for each of the currencies, the incidence of a less significant volatility feedback effect was made evident. Investors in the foreign exchange market who chose to maximize profits at a lower risk, trading with the pound sterling/US dollar rate, the Euro/US dollar rate, the Australian dollar/US dollar rate; Canadian dollar/US dollar rate, Swiss Franc/dollar rate, New Zealand dollar/US dollar rate, and Luxembourg Franc/US dollar rate are profitable options. In policy circles, monitoring volatility dynamics is crucial for promoting forex market stability and investor confidence. This research benefits policy makers and marketers of financial assets in OECD countries.

Keywords: long memory coefficient; returns; losses; GARCH effect; OECD; ARMA-FIGARCH model

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1. Introduction

The past few years have seen a rise in interest in understanding the nexus between Bitcoin demand and exchange rate movements. This is particularly relevant for emerging economies, where Bitcoin has gained popularity as an alternative to traditional currencies. A growing body of research suggests that there is a dynamic relationship between Bitcoin demand and exchange rates in emerging economies. Exchange rate movements represent significant dynamic adjustments that impact international trade. When a currency depreciates, it takes more units of that currency to buy a unit of another currency (Mankiw, 2020). This makes imported goods and services more expensive but makes exports cheaper for foreign buyers, potentially boosting a country's exports. For exporters, a depreciation of their home currency makes their goods cheaper and potentially more attractive to foreign buyers, leading to an increase in demand.

Here, we assessed the distribution of return on exchange rates of the currencies of Organization for Economic Co-operation and Development (OECD) countries and also estimated the dynamic effect of Bitcoin transaction prices on currency return in the selected OECD countries. The research is significant given that, in the burgeoning field of financial technology, the demand for cryptocurrency, particularly Bitcoin, has become revolutionary in the global space. This is because, as Bitcoin continues to integrate into mainstream financial systems, its interactions with economic indicators, especially the exchange rate, whose fluctuations do have the capability to influence and determine the direction of international transactions, warrant in-depth exploration. This research evaluates the rate of dynamic impact of exchange rate movements on Bitcoin returns and also estimates the value-at-risk (VaR) for returns on nine exchange rates. Bitcoin provides a rich context for examining the interaction between digital and fiat currencies.

Although a substantial body of research has been conducted to explore these interactions between exchange rates and Bitcoin returns, there are still gaps, especially in the context of VaR for each return on exchange rates and Bitcoin trading. Some studies (Umoru et al., 2024; Liu et al., 2024; Kao et al., 2024) have all examine connectivity between currencies, Bitcoin volatility, and/or gold. Kumar and Anandarao (2019) utilized the GARCH and wavelet models to ascertain volatility spillover in crypto-currency markets. BenSaïda (2023) established significant linkage between Bitcoin and foreign exchanges in developed and emerging market. This present research is highly desirous because it potentially takes into cognizance the unique dynamics present in both emerging and developed markets while simultaneously basing analysis on the intricate back-and-forth of depreciation and appreciation of the currency exchange rates of the OCED countries, and this could have a telling impact on the usage of Bitcoin and hence, its demand. Moreover, the literature tends to neglect how these spillover effects vary across different frequencies or behave under various market conditions. To address these gaps, this study proposes an extensive investigation into the persistence of volatility between the rate of demand for transactions with Bitcoin and exchange rate movements in the selected OECD markets using the FIGARCH regression method.

The research findings serve as a contribution to financial literacy and awareness. With the findings of this research, economic agents are positioned to make more insightful decisions regarding the use of digital currencies in their financial transactions. Accordingly, the findings of this research provide a guide on how investors rebalance their portfolios in response to changes in foreign exchange market conditions. The study found that exchange rate movements (devaluation) had a significant positive influence on the demand for Bitcoin. In sum, the study found that currency devaluation stimulates the demand for Bitcoin transactions by increasing its attractiveness as a safe haven asset. This could be explained by the fact that when a country's currency depreciates, it stimulates a higher inflation rate as imported goods become more expensive. In this circumstance, Bitcoin serves as a hedge against inflation due to its fixed supply. As a result, demand for Bitcoin rises. The scope of the study on the dynamic adjustments of Bitcoin demand to exchange rate movements in emerging economies encompasses various dimensions that collectively define the boundaries and parameters within which the research will be conducted. In the next section, we reviewed some relevant literature, followed by a discussion of the methodology. Results are reported and analyzed in Section 4, while in Section 5, we conclude the study.

2. Literature Review

2.1. Theory of Bitcoin Demand in Relation to Dynamic Exchange Rate Adjustments

This study analyzed the association between Bitcoin demand and exchange rate adjustment through the lens of the asset demand model. Due to its adjustment mechanism, the exchange rate, which is the worth of one currency when converted to another plays a critical role in determining the demand for Bitcoin (Antar, 2024; Al-Omoush et al., 2024; Lin et al., 2025). In the theory of finance, dynamic adjustment processes involve realignment of a portfolio's asset mix in response to shifts in market conditions, investment objectives, or risk tolerance and are crucial to portfolio management methods in the theory of finance (Firman et al., 2017; Kayal & Rohilla, 2021). Risk management and portfolio performance can be greatly impacted by the efficacy of this adjustment mechanism. Dynamic adjustment is fundamental to optimization problems, according to Hillier & Lieberman (2001) from the standpoint of operations research. It is defined as the procedure by which a system modifies its variables iteratively to enhance its functionality or make progress in finding the best answer. As a result, methods for dynamic adjustment support how markets react to shocks or changes in policy. This kind of adjustment regulates how quickly markets take in new information and return to normal, which affects economic development and stability (Mankiw, 2020). Theoretically, therefore, dynamic adjustment is a process by which markets move towards equilibrium after a shock or change in exchange rate, which could result in an appreciation or depreciation until a new equilibrium is reached.

In an insightful theoretical explanation, Liu and Tsyvinski (2021) reported that adding a small proportion of Bitcoin to a broad portfolio of traditional assets can improve the portfolio's risk-return tradeoff, highlighting the potential role of Bitcoin as a portfolio diversifier. According to Bouri, Lucey, Saeed, and Vo (2020), during periods of economic uncertainty or currency depreciation, demand for Bitcoin often increases in emerging economies as investors look for ways to preserve their wealth. This was evident during the economic crises in countries like Argentina and Zimbabwe, where Bitcoin trading volumes surged amid hyperinflation. Accordingly, the dynamic modifications of Bitcoin demand can also be influenced by spillover effects from other asset classes. For example, volatility in the stock market or notable shifts in commodity prices may impact the demand for Bitcoin when investors modify their holdings in reaction to these events. Cheah and Fry (2020) highlighted the dynamic adjustments in Bitcoin demand in reaction to changes in currency rates, arguing that Bitcoin serves as a speculative asset and a potential haven during economic instability. According to Kwon (2020), these spillover effects can lead to intricate dynamic linkages that change over time and are difficult to accurately depict with simple models. This study's theoretical approach is based on Pilbeam's (1998) improvement of the portfolio balance model (PBM). The PBM advises investors to balance the trade-offs between projected returns and risks by maintaining a diversified portfolio that consists of both domestic and foreign assets. According to the model, shifts in exchange rates can impact how much risk and reward people associate with owning assets denominated in foreign currencies, which can impact demand for those assets. According to this model, an asset's demand is determined by its risk, projected return, and the returns on alternative assets (Yousaf et al., 2020; Kumar & Anandarao, 2019). The expected return is determined by factors such as the perceived likelihood of future price appreciation and the potential for Bitcoin demand as a conventional currency. The link between exchange rate movements and Bitcoin demand is not static but may vary over time in response to changing conditions (Tan et al., 2021). In the context of Bitcoin, this could mean that the impact of exchange rate movements on digital money demand varies depending on the time horizon considered (Rahman, & Khan Dawood, 2019).

The PBM indicates that several factors influence the demand for Bitcoin in emerging economies: Higher wealth increases the ability and likelihood of diversifying portfolios by including assets like Bitcoin. The difference between domestic (idf) interest rates can affect the attractiveness of holding Bitcoin. If domestic rates are lower, investors might seek higher returns in alternative assets, including Bitcoin, assuming it has the potential for high returns. If investors expect their domestic currency to depreciate, they might increase their holdings in Bitcoin as a hedge against currency risk. The riskiness of Bitcoin, including its price volatility and regulatory uncertainties in emerging economies, can impact its demand. Investors willing to tolerate higher risk for potentially higher returns might be more inclined to hold Bitcoin. This model allows for an understanding of how exchange rate movements in emerging economies could lead to dynamic adjustments in Bitcoin demand. Within the broader context of portfolio choices, influenced by exchange rates, interest rates, and risk perceptions, the PBM shows a structured way to analyze the factors driving the demand for Bitcoin as an alternative investment.

2.2. Nexus between Cryptocurrency Prices and Foreign Exchange Rates

The nexus between cryptocurrency prices and foreign exchange markets has been explored, revealing volatility spillover effects and the reaction of exchange rates and equities indexes to cryptocurrency prices. According to Lin, Liu, and Sheng (2025), who used quantile regression to analyse the influence of macroeconomic factors on digital currencies returns, discovered that both the US currency exchange rate and the price index of production have an enormous but detrimental effect. By using the asymmetrical two-state MS-MGARCH model, Kayal and Dutta (2024) found a regime shift in fluctuation dynamics, which served as a basis for investigating volatility spillovers before and after COVID-19. The study also uses the Windowed Scalogram Difference technique to evaluate the strength of the correlation between the cryptocurrencies and confirms a spillover using the BEKK-GARCH model.

Additionally, the findings highlight the interdependence between Bitcoin and Ethereum and Litecoin by revealing bilateral shock spread and volatility spillovers between them.

Kao, Zhao, Chuang, and Ku (2024) also documented considerable asymmetric nexus between the Bitcoin futures' return, volatility, and trading volume. Using unrestricted quantile regression, Dumitrescu, Obreja, Leonida, Mihai, and Trifu (2023) demonstrated an association between variations in nominal exchange rates and fluctuations in the price of Bitcoin. Under typical market circumstances, a rise in the price of Bitcoin can be linked to a rise in the value of the currencies in our sample; however, during the COVID-19 epidemic, the opposite was true. Furthermore, we discover that this connection exhibits heterogeneities based on the degree of change in the nominal exchange rate. The findings highlight how important changes in the price of Bitcoin are to the way monetary policy is implemented via the exchange rate channel. Related findings have been reported by research carried out by Liu, Julaiti, and Gou (2024).

Feng and Zhang (2023) used the autoregressive distributed lag methodology to empirically assess the regulating role of Bitcoin in currency exchange rate forecasting. Both forecasts from the error correction specification and the autoregressive distributed lag surpass benchmarks for some of the exchange rates. At the daily horizon, the ADL model's superior performance is most noticeable. Forex trading techniques based on Bitcoin produce considerable gains in the Sharpe ratio when compared to the carry trade and the US risk-free rate. Once lagged exchange rate changes have been adjusted for, Bitcoin returns take into account additional information about future interest rate variations.

Safiyanu, Haruna, Gurin, and Bayero (2022) investigated the impact of cryptocurrency on the Nigerian exchange rate using the autoregressive distributed lag model. According to their research, the price of Bitcoin has a major short- and long-term impact on the exchange rate. An increase in the price of Bitcoin indicates that the value of the home currency has increased. The volatility of the price of Bitcoin has a long-term detrimental impact on the Nigerian exchange rate. Given that local money must be translated to US dollar (USD) before purchasing Bitcoin on the cryptocurrency market, consumers are more inclined to buy and keep while the price is low. This drives up the exchange rate.

Research findings shared by Hsu (2022) using a diagonal BEKK model validate the fluctuating volatility of the connection between digital currency and exchange rates at various times, such as when the market faced multiple risk events like the Russian-Ukrainian war, the COVID-19 pandemic, and the US-China trade war. We use the diagonal BEKK model and discover that, except for Tether and the U.S. dollar index, the co-volatility spillover effects between the returns of cryptocurrencies and currencies changed substantially. Additionally, there are most significant impacts and changes from the co-volatility spillover effects between digital currencies and EUR. Bitcoin and Ethereum, two large-cap cryptocurrencies, have higher co-volatility spillover effects with other currencies. Ibikunle and Akutson (2022), Ibrahim and Ali Basah (2022) have all evaluated the volatility spillover effect of cryptocurrency prices and foreign exchange rates. Their findings reveal that spikes in Bitcoin transaction volumes and volatility are closely followed by volatility in the currency rates, particularly during periods of heightened geopolitical tensions in the region.

Li and Li (2021) analyzed the entire spread of volatility and paired fluctuation spillover in both the time and frequency domains using the risk spillover index model put forth by Barunik and Krehlik. They found a substantial asymmetric fluctuation spillover effect between China financial markets and Bitcoin, with Bitcoin being the recipient of the ripple effect. In the event of a market anomaly, particularly in the stock, foreign exchange, and copper futures markets, the relatively moderate spillover effects will become stronger. The empirical economics of the volatility of Bitcoin and its role as a medium of exchange and a store of value has also been analyzed by Baur and Dimpfl (2021). Liu and Tsyvinski (2021) also reported considerable relation between risks and returns of digital currencies.

The squared returns of three digital currencies have a notable long memory, according to the findings of Kaya Soylu, Okur, Çatıkkaş, and Altintig (2020), which supports the adoption of Fractional GARCH extensions as an appropriate modelling technique. According to our research, the model that seems to fit Bitcoin the best is the Hyperbolic GARCH model. With a skewed student distribution, however, the Fractional Integrated GARCH model yields more accurate Ethereum projections. The results also hold that the student distribution FIGARCH model seems to provide a decent fit for the ripple return. The Toda-Yamamoto approach was used by Yamak, Yamak, and Samut (2019) on data spanning from December 27, 2013, to March 3, 2019. Using the EGARCH model to generate price volatility series, the study discovered a strong causal connection between price volatility and Bitcoin trading volume. Simultaneously, price volatility to Bitcoin trading volume showed a substantial and beneficial concurrent connection.

2.3. Summary of review

The above literature highlights the interconnectedness of the Bitcoin market and the forex market, where Bitcoin's role as both an investment and a speculative asset becomes more pronounced. In this study, we are eager to further determine the impact of exchange rate movements on Bitcoin returns in the OECD countries. Hence, the broad objective of this research is to econometrically assess the distribution of returns on exchange rates of the currencies of OECD countries. Specific objectives are to: (1) estimate the dynamic effect of Bitcoin transaction prices on currency return in the selected OECD countries; (2) estimate the relationship between the returns on Bitcoin and currency trading rates of the selected OECD countries; (3) estimate the VaR associated with each exchange rate in the selected OECD countries and Bitcoin. The relevant research hypotheses include: (1) there is no dynamic effect of Bitcoin transaction prices on currency return in the selected OECD countries; (2) there is no relationship between the returns on Bitcoin and currency trading rates of the selected OECD countries; (3) there is no VaR associated with each exchange rate in the selected OECD countries and Bitcoin.

3. Materials and Methods

3.1. Model Specification

The econometric methodology of the research entails the maximum likelihood estimation of an autoregressive moving average (ARMA) of the conditional mean of the daily return series. This approach describes a combination of the autoregressive model with p lags and the moving average model with q lags. Additionally, the researchers are cognizant of the time-varying conditional volatility and autoregressive volatility clustering and applied the generalized autoregressive conditional heteroscedasticity (GARCH) model based on Bollerslev's (1986) works to the squared residuals of the ARMA model, with *p* and q lags, respectively. The ARMA(*p*,*q*)-GARCH(*g*,*h*) model is so specified as:

$$
\begin{aligned}
x_t &= \phi + \sum_{i=1}^{p} \rho_i x_{t-i} + \sum_{j=1}^{q} \gamma_j e_{t-j}, \quad e_t \sim iid(0,\sigma_t^2) \\
\sigma_t^2 &= \partial_0 + \partial_1 e_{t-1}^2 + \partial_2 e_{t-2}^2 + \ldots + \partial_g e_{t-g}^2 + \ell_1 \sigma_{t-1}^2 + \ell_2 \sigma_{t-2}^2 + \ldots + \partial_h \sigma_{t-h}^2
\end{aligned} \tag{1}
$$

where $\partial_i (i = 1, 2..., g)$ symbolize the GARCH coefficients, σ_{t-h}^2 demonstrates how the previous conditional variances have affected the current situation, and σ_t^2 is the recent conditional variance; e_t is white noise with zero average value, constant variance σ_t^2, and it is in no way correlated in time *t*, and the series xt represents the returns on transactions with Bitcoins and returns on currency trading rates at time *t*. The constraints that are satisfied by the ARMA-GARCH model's parameters include:

$$
\begin{aligned}
&\partial_0 > 0, \ \partial_i \ge 0 \ \ \forall (i = 1, 2..., g), \ \gamma_j \ge 0 \ \ \forall (j = 1, 2..., h), \\
&\sum_{i=1}^{\max(g,h)} (\partial_i + \gamma_i) < 1, \ \ or \ \ \sum_{i=1}^{g} \partial_i + \sum_{j=1}^{h} \gamma_j < 1
\end{aligned} \tag{2}
$$

Three types of *ARMA* models exist: autoregressive models of order p, given by *AR(p)*; moving average models of order q, given by *MA(q)*; and *ARMA(p,q)*. Hence, the *ARMA(p,q)* model combines models *AR(p)* and *MA(q)*. Thus, the general specification of the *ARMA* model is given by equations (3), (4), and (5) respectively.

$$AR(p): \ x_t = \mu + \sum_{j=1}^{p} \vartheta_j x_{t-j} = \mu + \vartheta_p(\Gamma) x_t \tag{3}$$

$$MA(q): \ x_t = \mu + \sum_{i=0}^{q} \partial_i e_{t-i} = \partial_q(\Gamma) e_t \tag{4}$$

$$ARMA(p,q): \ x_t = \mu + \sum_{j=1}^{p} \vartheta_j x_{t-j} + \sum_{i=1}^{q} \partial_i e_{t-i} \tag{5}$$

We also estimated the ARMA (*p*,*q*)-FIGARCH model in modeling returns on Bitcoin and currency trading rates. Accordingly, the specifications of the equation for Bitcoin return and its volatility are given in (6), (7) and (8) respectively:

$$RET_{(t)} = \beta_0 + \sum_{j=1}^{p} \phi_j RET_{(t-j)} + \sum_{j=1}^{p} \beta_j EXR_{t-j} + \sum_{i=1}^{q} \delta_i e_{t-i} + e_t \tag{6}$$

$$\begin{aligned} &\vartheta_p(\Gamma) RET_t = \partial_p(\Gamma) e_t \\ &[1-\vartheta_1\Gamma - \vartheta_2\Gamma - \ldots - \vartheta_p\Gamma^p] RET_{it} = [1-\partial_1\Gamma - \partial_2\Gamma - \ldots - \partial_q\Gamma^q] e_t \end{aligned} \tag{7}$$

where RET represents the log returns on Bitcoin and log returns on currency trading rates; ϑ_p is AR polynomial operator in Γ of degree p and δ_q is MA polynomial operator in Γ of degree q. The differencing of the ARMA model permits the polynomial to lie within the unit circle such that the solution to equation (7) is absolutely less than one for the ARMA model to be weakly stationary. By mathematical definition, $\vartheta(\Gamma)$ and $\partial(\Gamma)$ are lag polynomials with matching orders of q and p, and the definition of stochastic innovation is as follows:

$$\sigma_t^2 = Var[e_t \mid \Theta_{t-1}],\ e_t = \upsilon_t^2 - \sigma_t^2 \tag{8}$$

Specifying equation (8) as an $ARMA(p, q)$ process in v_t^2, we have equation (9) as follows:

$$[1-\vartheta(\Gamma)-\partial(\Gamma)]v_t^2 = \mu + [1-\vartheta(\Gamma)]v_t \tag{9}$$

Granger and Joyeux (1980) and Hosking (1981) individualistically developed the fractionally integrated ARMA model (ARFIMA) to measure the long-memory component in the mean equation of return.

$$\vartheta(L)(1-\Gamma)^{\tau}(RET_t - \partial_0) = \pi(\Gamma)e_t, \tag{10}$$

where τ is the ARFIMA long memory coefficient, $\emptyset(L) = 1 - \sum_{j=1}^{k} \emptyset_j \Gamma^j, \pi(\Gamma) = 1 + \sum_{j=1}^{z} \pi_j \Gamma^j, \partial_0$ is the mean of $return_t$ and e_t, is the white noise. Similarly, Baillie et al. (1996) reworked IGARCH model to arrive at the fractionally integrated GARCH (FIGARCH) model. The corresponding FIGARCH *(p,γ,q)* process is specified as follows:

$$[1-\vartheta(\Gamma)-\partial(\Gamma)](1-\Gamma)^{\gamma} e_t^2 = \mu + [1-\vartheta(\Gamma)]e_t \tag{11}$$

Hence, γ is the FIGARCH long memory coefficient; if $\gamma = 0$, the FIGARCH model reduces to a GARCH model; when $\gamma_{FIGARCH} = 1$, it reduces to an integrated-GARCH (IGARCH) process. The FIGARCH model's conditional variance can be expressed as follows:

$$\sigma_t^2 = \mu[1-\partial(\Gamma)]^{-1} + [1-\partial(\Gamma)]^{-1}[1-\vartheta(\Gamma)(1-\Gamma)^{\gamma}]\upsilon_t^2 \tag{12}$$

Finally, we have the $ARMA(p,q) - FIGARCH(p,\gamma q)$ model given below:

$$[1-\vartheta(\Gamma)-\partial(\Gamma)]v_t^2 = \mu + [1-\vartheta(\Gamma)]v_t$$

$$\rightarrow \mu[1-\partial(\Gamma)]^{-1} + [1-\partial(\Gamma)]^{-1}[1-\vartheta(\Gamma)(1-\Gamma)^{\gamma}]\upsilon_t^2 \tag{13}$$

Both the ACF and PACF are used to test the fitness of the $ARMA(p,q) - FIGARCH(1,\gamma,1)$ models. We estimated the auto-correlation functions given by equation (14) where r_s are the sample correlations below:

$$r_s = \frac{\sum_{t=1}^{T-s}(x_t - \hat{x})(x_{t+s} - \hat{x})}{\sum_{t=1}^{T-s}(x_t - \hat{x})^2} \tag{14}$$

The coefficients of the ARMA- FIGARCH model and the long memory of the volatility of exchange rate and Bitcoin returns were all estimated using the maximum likelihood estimation (MLE). The $ARMA(p,q)-FIGARCH(p,\gamma,q)$ combining one-step-ahead history of the moving-average with the memory of the autoregressive ends up in smoother model results. By adjusting the (ϑ,∂) coefficients, we found an appropriate model that matches wide variety of recurring and asymmetrical financial data sets such as the return on exchange rate and Bitcoin.

3.2. Data Measurement, Description and Sources

The study made use of the following exchange rates: Swiss Franc (CHF)/dollar rate, Canadian dollar (CAD)/USD rate, Japanese Yen (JPY) /USD rate, New Zealand dollar (NZD) /USD rate, the pound sterling (GBP)/USD rate, the Australian dollar (AUD) /USD rate, the Euro (EUR)/USD rate, the Luxembourg Franc (LUF)/USD rate, and the Danish Kroner/USD rate. The currency pair shows that the worth of a currency is not measured in absolute terms. This comes from the fact that currencies are traded in pairs. When it comes to CAD/USD rate, the base currency is the CAD and the reference (quoted) currency is the USD; and is represented by the rate or amount of the U.S. dollar needed to exchange for one unit of the CAD. In effect, the decrease or increase of a rate corresponds to the depreciation or appreciation of the base currency, and the inverse corresponds to the quoted currency. The exchange rate for Austria is EUR/USD because Austria adopted the EUR as the common currency and is a member of the economic and currency unions as part of the European Community. The study used daily series from February 1, 2010 to August 30, 2024 to evaluate the rate of response for Bitcoin to fluctuations in the exchange rate of OECD currencies. The rationale behind the selection of OECD countries' currency exchange rates is that they are firmly governed by the intricate relationship between supply and demand in foreign exchange markets. Furthermore, the majority of currency rates are floating, which means that supply and demand determine how much they are worth. Data on Bitcoin volatility were calculated as the variance series obtained from an EGARCH model estimation of the differences between current and previous prices of Bitcoin. Accordingly, the return on Bitcoin was measured as the difference of the natural logarithm between the Bitcoin price of today and the price of yesterday, while the return on a currency trading rate was calculated as the difference between the logarithms of today's trading rate and the rate traded yesterday. The methodology for the calculation of returns is defined as $RET = \log[x_t / x_{t-1}]$. Trading values on Bitcoins were obtained from Blockchain.info as well as yahoo finance databases while exchange rates where sourced from country-specifics of the World Bank database.

4. Results and Discussion

First, the analysis of results was driven by the discussion of the descriptive statistics which were used to show the statistical properties of the variables. Next, the unit root tests were used to determine the order of integration of each variable. Next, the ARMA models were estimated for the log returns on Bitcoins in response to the OECD currency exchange rates. Finally, the FIGARCH model for the long memory effect of currency exchange rates and Bitcoins was estimated. After determining whether or not ARCH effects were present in Bitcoin returns and returns on each currency rate, we estimated the volatility models using the fractional difference coefficient for each exchange rate and Bitcoin return. For each exchange rate and Bitcoin return, we estimated the sample autocorrelation functions (ACF) and the corresponding partial autocorrelation function (PACF) as our next empirical step. This was necessitated in order to find the best volatility ARMA(p,q)-FIGARCH(p, γ, q) models. Finally, we conducted the VaR analysis for Bitcoin and all the currency exchange rates covered by the research. EViews 13.0 was used for the estimation. The statistical description information is shown in Table 1 for the exchange rate of currencies and Bitcoin returns.

Table 1. Descriptive statistics of Bitcoin and exchange rate returns.

Currency	Mean	Std. Deviation	Skewness	Kurtosis	Jarque-Bera	Observation
BTCNR	90.1065	197.5896	1.2863	5.4094	24609.1460	5289
GBP/USD	111.2389	26.3472	2.0387	5.3389	15871.4953	5289
EUR/USD	130.5472	53.4481	0.5419	4.5680	15639.5891	5289

AUD/USD	132.4892	10.3875	1.2809	2.3467	31678.3892	5289
CAD/USD	140.5873	25.6892	2.5940	3.3848	18792.3893	5289
JPY/USD	178.3487	110.4641	0.1730	5.3891	18934.5487	5289
CHE/USD	160.2380	13.4548	3.3793	3.3491	12890.3487	5289
NZD/USD	123.1954	11.3348	1.4870	10.2893	15678.3891	5289
DKK/USD	101.3879	14.5792	1.3479	2.0892	27489.4329	5289
LUF/USD	122.1074	16.3892	2.5473	16.2893	19872.3879	5289

Source: Authors' results from EViews software.

As reported in Table 1, the average value of the variables across the observed period is represented by the mean, while the standard deviation shows how the data points are distributed around it. Daily Bitcoins return had an average value of 90.1065. The standard deviation is 197.5896 for daily returns on Bitcoins, which is on the high side. This signifies the presence of high fluctuations in the number of transactions done with Bitcoin per day. This support the result of Mignot and Westerhoff (2025) where it was accentuated that daily Bitcoin returns are characterized by higher volatility. The positive values of the standard deviation for the exchange rates indicate some level of variability in the exchange rates of the currency of each country in our sample for this study, while the positive mean exchange rates signifies the average rate within the study. For GDP growth, the mean exchange rates are 111.2389, 130.5472, 132.4892, 140.5873, 178.3487, 160.2380, 123.1954, 101.3879, and 122.1074, with a skewness of about 2.0387, 0.5419, 1.2809, 2.5940, 0.1730, 3.3793, 1.4870, 1.3479, and 2.5473.

According to the skewness statistics, every variable had a positive skewness. Statistically, the positive values of skewness signify a distribution of Bitcoin trading and exchange rates with an asymmetric tail. Economically speaking, the positive skewness of the exchange rates implies the possibility of earning positive returns on the exchange rates of all the countries. Also, apart from Austria and Denmark, whose kurtosis coefficients are 2.3467 and 5.0892 for their exchange rates, respectively, the kurtosis coefficients of other countries all exceed 3. By implication, the distribution of exchange rates in Austria and Denmark is platykurtic (narrower and shorter than that of normal value), while the distribution of exchange rates with respect to other currencies is leptokurtic (fat tails) as opposed to a Gaussian distribution. The kurtosis value of Bitcoin transaction price is 5.4094, which implies that the distribution of the log returns for Bitcoins transactions per day has heavy tails, suggestive of a leptokurtic distribution. The Jarque Bera probability for both exchange rates and daily Bitcoin returns is large, implying significance at the 1% level. This further confirms a non-Gaussian distribution type. Specifically, daily Bitcoin returns and currency exchange rates do not obey a normal distribution.

Table 2. Unit root results.

Currency	5% Critical values	ADF t-statistic	Probability values	Order of stationary
BTCNR	-2.977544	-23.27892	0.0000	I(1)
GBP/USD	-2.977544	-16.87714	0.0000	I(1)
EUR/USD	-2.977544	-27.10010	0.0000	I(1)
AUD/USD	-2.977544	-26.85920	0.0000	I(1)
CAD/USD	-2.977544	-14.34569	0.0000	I(1)
JPY/USD	-2.977544	-23.27892	0.0000	I(1)
CHE/USD	-2.977544	-37.15432	0.0000	I(1)
NZD/USD	-2.977544	-26.87756	0.0000	I(1)
DKK/USD	-2.977544	-36.91333	0.0000	I(1)
LUF/USD	-2.977544	-26.12435	0.0000	I(1)

Source: Authors' results from EViews software.

Table 2 reports the unit roots test results on the variables involved in the analysis. This was deem fit in order to prevent misleading results and align with economic theory. Therefore, we evaluated for the order of integration among the variables using the ADF. It is clear from the results that both Bitcoin returns and exchange rates were stationary after the first difference. At level 1, none of the series was stationary. As such, we do not report such insignificant ADF statistics. Since the variables show the same integrated order, the possibility of a co-integrating link between the variables was not in doubt.

4.1. ARMA Results for Log Returns on Bitcoins in Response to Exchange Rates of OECD Currencies

The information criteria, namely, AIC, SIC, HQIC, and BIC, were estimated for different ARMA models. The best model was the one with the least prediction error as detected by AIC. Hence, the ARMA (0, 0) model, where both the Bitcoin returns and the error terms are significant at levels, was chosen as the best model. Hence, ARMA (0, 0) is our reference model, and this signifies AR coefficients and MA coefficients. In this case, the ARMA (0, 0) model takes values of 0 for 'p' (autoregression) and 0 for 'q' (moving average). Daily log returns of major trading assets are likely to behave like a white noise. This laid credence to the possibility that the best model to describe log returns for Bitcoin is ARMA (0, 0). Similarly, the daily log returns of the exchange rates follow ARMA (0, 0) process. This indicates that these returns are also white noises. Hence, there are no AR(1), MA(1) and so on. Results are presented in Table 3.

Table 3. ARMA results for log returns on Bitcoins in response to exchange rates of global currencies.

Currency	Equation: ARMA (0,0); Dependent variable: BTCNR [Log Returns for Bitcoins]			Conclusion	
	Coefficient	**z-Statistic**	**P > |z|**		
D(GBP/USD)	-0.8965	-10.3786	0.0000	Significant	
D(EUR/USD)	-0.9031	-90.8645	0.0000	Significant	
D(AUD/USD)	0.2368	66.9386	0.0000	Significant	
D(CAD/USD)	-0.1245	-809.765	0.0000	Significant	
D(JPY/USD)	-1.1038	-30.3761	0.0000	Significant	
D(CHE/USD)	-0.1374	-50.0614	0.0000	Significant	
D(NZD/USD)	0.2519	2947.289	0.0000	Significant	
D(DKK/USD)	0.1463	7.133049	0.0000	Significant	
D(LUF/USD)	0.2910	2947.289	0.0000	Significant	
			Ljung-Box test statistic(s)		
Q(20) Bitcoin returns	11.9532	0.3466**	0.3466	Q(20) USD/JPY	0.3568**
Q^2(20) Bitcoin returns	10.5462	0.7890**	0.7890	Q^2(20) USD/JPY	0.5742**
Q(20) GBP/USD	10.6928	0.4677**	0.4677	Q(20) USD/CHE	0.1978**
Q^2(20) GBP/USD	10.0345	0.2569**	0.2569	Q^2(20) USD/CHE	0.6730**
Q(20) EUR/USD	14.3799	0.2533**	0.2533	Q(20) NZD/USD	0.3089**
Q^2(20) EUR/USD	20.5671	0.6980**	0.6980	Q^2(20) NZD/USD	0.2546**
Q(20) AUD/USD	21.8930	0.5879**	0.5879	Q(20) DKK/USD	0.4851**
Q^2(20) AUD/USD	30.2690	0.3456**	0.3456	Q^2(20) DKK/USD	0.5192
Q(20) CAD/USD	43.3940	0.4788**	0.4788	Q(20) LUF/USD	0.4221**
Q^2(20) CAD/USD	26.4781	0.5678**	0.5678	Q^2(20) LUF/USD	0.6793**

Source: Authors' results from EViews software.

The results of Table 3 show a negative and significant effect of the GBP/USD rate exchange rate on Bitcoin returns. The causal effect is of the magnitude of -0.8965 for GBP/USD. The implication of these results is that with a stronger currency like the GBP, investors still prefer to trade and diversify their portfolio investments in the forex market rather than trade much in the digital market with the Bitcoin. Similarly, we observed a significant negative nexus between the EUR/USD exchange rate and Bitcoin transaction earnings. In particular, the coefficient of the EUR/USD exchange rate is -0.9031. By implication, if one EUR buys 0.9031 units of the USD by way of EUR currency appreciation, financial traders and crypto currency users will engage in forex trading rather than engage in Bitcoin transactions. This is suggestive of the fact that when the EUR appreciates in comparison to the USD, the return on Bitcoin drops. This result aligns with those of Kang, Yoon, Bekiros, and Uddin (2020), and BenSaïda (2023).

Also, the ARMA estimates reveal a positive coefficient of 0.2368 for the Australia dollar (AD)/USD exchange rate. This goes to show that a percentage rise in the AUD in relation to the USD will attract investors who trade with the AUD or whose financial assets are denominated in the AD to still prefer to invest in Bitcoin. Specifically, even if one AUD buys 0.2368 units of the USD by way of exchange rate appreciation, investors in Bitcoin and various financial assets denominated in the AUD will still not diversify their investments away from Bitcoin trading. This can be liken to the findings reported by Aalborg, Molnár, and de Vries (2019) where it was noted that exchange rate volatility in emerging economies can increase the demand for Bitcoin as a form of digital gold. Their study showed that during periods of high exchange rate volatility, individuals and businesses in these economies tend to convert their local currency into Bitcoin to preserve their wealth and purchasing power. Since the economic environment in most economies is often characterized by currency volatility, inflation, and capital controls, Bitcoin's decentralized nature and global accessibility make it a potential tool for economic stability. In effect, the value of a Bitcoin is not directly linked to the economic policies or performance of any single country. This makes it a potential hedge against local economic instability (El Hajj & Farran, 2024; Eichengreen, 2019). The relationship between exchange rate changes and Bitcoin demand could be non-linear. This means that the effect of exchange rate changes on Bitcoin demand can vary depending on the magnitude and direction of the exchange rate change.

For the CAD/USD, JPY/USD, and GBP, CHF/USD with estimated coefficients of -0.1245, -1.1038, and -0.1374, respectively, the implication of the results differs, with the indication that an appreciation of the USD in relation to the CAD, JPY, and CHF is an attraction for investors to diversify their portfolios away from digital currency trading and rather invest in the conventional foreign exchange market. Accordingly, an appreciation of the USD drives currency traders and financial investors to prefer trading with the dollar rather than investing in Bitcoin. This in turn produces a decline in bitcion returns. An appreciation in the USD does not attract Bitcoin users to diversify into Bitcoin. This could be attributed to the recent drop in the Bitcoin/USD exchange value to USD 53,991.46 as of August 5, 2024, from USD 73,000 in March 2024 due to the FTX crypto exchange filing for bankruptcy. Our results support the finding obtained by Palazzi, de Souza Raimundo Jr, Klotzle (2021), who observed that an increase in the value of the EUR induces a fall in Bitcoin returns.

On the contrary, we obtained significant positive coefficients of 0.1245, 1.1038, and 0.1374 for the exchange rates of the NZD, the Danish Kroner (DKK), and the LUF with respect to the USD respectively. The implication of these estimates is that an appreciation in the NZD, the LUF, and the DKK exchange rate causes financial traders to prefer to hold their assets and investments in Bitcoin. This is suggestive of the fact that when the exchange rates of the NZ dollar, the DKK, and the LUF with respect to the USD appreciate in response to the USD, the return on Bitcoin rises. By implication, if one unit of the NZD buys 0.1245 units of the USD, the LUF buys 1.1038 units of the USD, and the DKK purchases 0.1374 units of the USD by way of currency appreciation, financial traders and crypto currency users will diversify their portfolios to Bitcoin trading rather than the conventional forex markets of New Zealand, Luxembourg, and Denmark. Twenty lags were used in the calculation of the Ljung-Box (LB) test statistic(s) and the results indicate very clearly at the 5% level of significance (**) that the data do not exhibit serial correlation and is distributed on its own.

Table 4. Diagnostic results for ARMA (0, 0) model.

Number of Observations	Values
AIC	2678.4809
SIC	2879.4790
HQIC	2934.3810
BIC	2895.3873

Log-likelihood	-287054.1863
R^2	79.366%
F-statistic (p-value)	135.3897(0.0000)
S.D. of innovation	0.012793

Source: Authors' results from EViews software.

The results of Table 4 show that the overall ARMA model is robust, given a significant F-value of 135.3897 and a significant zero probability value. The estimated R2 is 79.366% significantly high with a coefficient of 0.79367, which indicates that the variations in Bitcoin earnings can be attributed to the variations in the exchange rates of selected OECD currencies. The log-likelihood value is -287054.1863. It is significantly large. This portrays a considerable goodness of fit for the ARMA (1, 1) model. The information criteria, especially the AIC, all show a low prediction error, which explains the relative good fit of the ARMA model.

4.2. FIGARCH Results for Long Memory Effect of Currency Exchange Rates and Bitcoin

Using the methodology of Geweke and Porter-Hudak (1983), we tested for the presence or otherwise of the long memory coefficient ($\gamma_{FIGARCH}$) of the FIGARCH model. This entails a fractional differentiation of ($\gamma_{FIGARCH}$) with respect to the residuals series of the Bitcoin return and the return for the exchange rates of all the currencies in our mean equation. The underlying test hypothesis is stated as: $H_0 : \gamma_{FIGARCH} = 0$ vs. $H_1 : \gamma_{FIGARCH} \neq 0$. Results are reported in Table 5 below:

Table 5. FIGARCH results for long memory effect of currency exchange rates and Bitcoin returns.

Exchange rate	$\gamma_{FIGARCH}$	$SE(\gamma_{FIGARCH})$	**z-statistic**	**Confidence interval**	**Long memory**
BTCNR	-0.3291	0.0173	-30.5838	-0.6314<γ<0.1357	Present
GBP/USD	-0.0127	0.0037	-3.4324	-0.2357<d<0.1357	Present
EUR/USD	-0.3861	0.0189	-32.4726	-0.3749<d<0.1458	Present
AUD/USD	-0.0592	0.0127	-4.6614	-0.4265<d<0.2274	Present
CAD/USD	-0.0679	0.0134	-5.0672	-0.2609<d<0.1651	Present
JPY/USD	-0.3452	0.0016	-215.750	-0.4923<d<0.1937	Present
CHE/USD	-0.6073	0.1793	-1.1562	-0.5524<d<0.7256	Absent
NZD/USD	0.0467	0.0122	3.8279	-0.3419<d<0.2489	Present
DKK/USD	0.1963	0.0119	50.1092	-0.5392<d<0.3092	Present
LUF/USD	0.1045	0.0235	4.4468	-0.3496<d<0.2935	Present

Source: Authors' results from EViews software.

Table 5 reports the FIGARCH results for the long-term memory effect of returns on Bitcoin and the currency exchange rates. A thorough look at the results shows significant z-statistics for the returns on Bitcoin, returns on CAD/USD rate, JPY/USD rate, NZD/USD rate, the GBP/USD rate, the AUD/USD rate, the EUR/USD rate, the LUF/USD rate, and the Kroner/USD rate. Only the return on the CHF/USD rate had no significant z-statistic at the 5% level of statistical significance with a 95% level of confidence for all coefficient estimates. Besides, all estimated fractional difference parameters lie within the confident interval $[-0.5 < \gamma_{FIGARCH} < 0.5]$. Accordingly, the returns on Bitcoin and exchange rates of the GBP, the EUR, AUD, CAD, JPY, NZD, DKK, and LUF all have a long-term memory effect. We could not account for the presence of long-term memory in the volatility of the USD/CHF rate, even with a significant z-statistic. The reason is that the estimated coefficient lies outside the confident interval.

4.3. ARCH Results

We proceed to estimate the volatility models using the fractional difference coefficient for each exchange rate and Bitcoin returns. First and foremost, we tested for the presence or otherwise of ARCH effects in Bitcoin returns and the returns on each of the currency rates. Accordingly, the ARCH effect was found in the dynamic adjustment of the Bitcoin returns. This was made evident by the significant F-statistics. The results are as shown in Table 6.

Table 6. Test results for ARCH effects.

Currency	F-Statistics
BTCNR	178.19**(0.0000)
GBP/USD	123.4**(0.0000)
EUR/USD	286.4**(0.0000)
AUD/USD	683.49**(0.0000)
CAD/USD	365.5**(0.0000)
JPY/USD	135.4**(0.0000)
CHE/USD	627.2**(0.0000)
NZD/USD	293.2**(0.0000)
DKK/USD	271.2**(0.0000)
LUF/USD	244.5**(0.0000)

Source: Authors' results from EViews software.

The calculated F as measured by the product of the number of observations and the pseudo-R2, that is, of each return as reported in Table 6, is significantly different from zero, with a zero probability value at 1%. What this suggests is the ARCH effect. Hence, the condition for further ARMA-FIGARCH analysis was fulfilled. In sum, Bitcoin and all the currency exchange rates exhibit ARCH effects in all the countries covered by the study.

4.4. Results of the Chosen Volatility ARMA(p,q)-FIGARCH(p, γ , q) Model

The next empirical step we took was the estimation of the sample autocorrelation functions (ACF) given by equation (12) and the associated partial autocorrelation function (PACF). Based on the configurations and the correlograms of ACF and PACF for each exchange rate and Bitcoin return, we found the best models to include ARMA (0,0)-FIGARCH (1,0.3291, 1) for BTCNR; ARMA (1,1)-FIGARCH (1, 0.0127, 1) for GBP/USD; ARMA (1,1)-FIGARCH (1, 0.3861, 1) for the EUR/USD rate; ARMA (1,1)-FIGARCH (1, 0.0592, 1) for AUD/USD rate; ARMA (1,1)-FIGARCH (1, 0.0679, 1) for CAD/USD rate; ARMA (1,1)-FIGARCH (1, 0.3452, 1) for the JPY/USD rate; ARMA (1,1)-FIGARCH (1, 0.6073, 1) for the CHF/USD rate; ARMA (0,1)-FIGARCH (1, 0.467, 1) for the NZD /USD rate; ARMA (1,1)-FIGARCH (1, 0.1963, 1) for the DKK/USD rate; ARMA (0,1)-FIGARCH (1, 0.1045, 1) for the LUF/USD rate, respectively. Table 7 displays the findings from the estimated volatility model.

The FIGARCH results depict that an appreciation in the exchange rates yielded positive returns for all exchange rates. The ARMA-FIGARCH model results validated the theory that with a stronger currency, the demand for Bitcoin falls. There is a notable persistence with implications for long-lasting volatility dynamics for the return on Bitcoin transactions. We found a long-term memory effect for the returns on Bitcoin and exchange rates of the GBP, the EUR, AUD, CAD, JPY, NZD, DKK, and LUF. We could not account for long-term memory's existence in the volatility of the USD/CHF rate.

Table 7. Results of the chosen volatility model.

Currency	ARMA (0,0)-FIGARCH (1,0.3291, 1)	Variable	Coefficient	z-Statistic	Pr
$RET(BTCN)_{(t)}$	Mean Equation	C	0.0027	124.089	0.0000
		$BTCNprc(t)$	0.4112	409.129	0.0000
		$RET(BTCN_{t-1})$	0.0183	123.465	0.0000
	Variance Equation	C	0.2379	2039.89	0.0000
		$e_{t-1}^{2}(arch)$	0.0561	1.4102	0.0965
		$\sigma_{t-1}^{2}(garch)$	0.7256	16.0866	0.0000
		$vol[RET(BTCN)]$	-0.1032	-113.4102	0.0000
Currency rate	ARMA (0,1)-FIGARCH (1,0.0127, 1)	Variable	Coefficient	z-Statistic	Pr
$GBP/USD_{(t)}$	Mean Equation	C	0.01342	567.123	0.0000
		$RET(GBP/USD(t))$	-0.5624	200.7676	0.0000
		$RET(BTCN(t))$	0.0325	123.8934	0.0000
	AR(1)	$GBP/USD_{(t-1)}$	0.1780	50.4182	0.0000
	MA(1)	e_{t-1}	0.5980	289.56	0.0000
	Variance Equation	C	-0.4386	-565.860	0.000
		$e_{t-1}^{2}(arch)$	0.2862	11.0361	0.0000
		$\sigma_{t-1}^{2}(garch)$	0.5563	1.07992	0.7625
		$vol[RET(BTCN)]$	-0.1027	-100.3861	0.0000
Currency Rate	ARMA (0,0)-FIGARCH (1,0.3861, 1)	Variable	Coefficient	z-Statistic	Pr
$EUR/USD_{(t)}$	Mean Equation	C	0.6724	566.991	0.0000
		$RET(EUR/USD(t))$	0.1654	500.368	0.0000
		$RET(BTCN(t))$	0.0149	114.2711	0.0000
	AR(1)	$EUR/USD(t-1)$	1.2896	1.0493	0.5699
	MA(1)	e_{t-1}	0.6891	130.766	0.0000
	Variance Equation	C	1.2083	1829.28	0.0000
		$e_{t-1}^{2}(arch)$	0.5124	226.459	0.0000
		$\sigma_{t-1}^{2}(garch)$	0.5930	1.0781	0.6378
		$vol[RET(BTCN)]$	-0.5930	-13.489	0.0000
Currency Rate	ARMA (0,0)-FIGARCH	Variable	Coefficient	z-Statistic	Pr

	(1,0.0592, 1)				
$AUD/USD_{(t)}$	Mean Equation	C	1.0892	109.6824	0.0000
		$RET(AUD/USD(t))$	0.1793	118.9265	0.0000
		$RET(BTCN(t))$	-0.0112	-156.2097	0.0000
	AR(1)	$AUD/USD_{(t-1)}$	0.0362	114.0158	0.0000
	MA(1)	e_{t-1}	0.0.025	130.1762	0.000
	Variance Equation	C	0.2369	190.368	0.0000
		$e_{t-1}^2(arch)$	0.3157	627.313	0.0000
		$\sigma_{t-1}^2(garch)$	0.5489	1.4592	0.8376
		$vol[RET(BTCN)]$	-0.2136	-19.3673	0.0000
Currency rate	ARMA (0,0)-FIGARCH (1,0.0679, 1)	Variable	Coefficient	z-Statistic	Pr
$CAD/USD_{(t)}$	Mean Equation	C	0.2198	167.298	0.0000
		$RET(CAD/USD(t))$	1.0725	306.276	0.0000
		$RET(BTCN(t))$	-0.0015	-120.1834	0.0000
	AR(1)	$CAD/USD_{(t-1)}$	0.7891	1.2685	0.1462
	MA(1)	e_{t-1}	0.0146	124.9402	0.0000
	Variance Equation	C	0.1089	234.767	0.0000
		$e_{t-1}^2(arch)$	0.2560	13.79468	0.0000
		$\sigma_{t-1}^2(garch)$	0.6542	1.09521	0.6973
		$vol[RET(BTCN)]$	-0.1093	-189.3267	0.0000

Source: Authors' results from EViews software.

A close investigation of the results of Table 7 shows that the coefficients for the log return for Bitcoin and the currency exchange rates are all significant at the 1% level. The baseline volatilities are high. In particular, the ARCH and GARCH coefficients are different from zero at the 1% level. The finding from the results is that previous appreciation of the exchange rates of each currency stimulates significant positive returns. The GARCH effects are insignificant at the 5% level. This means that in rich countries, previous days' currency rate volatility caused negligible volatility in the exchange rate of the same currency in the current period. There is no significant persistence in volatility for all the exchange rates as well as the digital currency, with the implication that volatility shocks with respect to the exchange rates of those currencies will be felt further in the future, but to a smaller extent.

Table 7. Results of the chosen volatility model.

Currency rate	**ARMA (1,0)-FIGARCH (1,0.3452, 1)**	**Variable**	**Coefficient**	**z-Statistic**	**Pr**
		D-FIGARCH	0.7926	17083.52	0.0000
$JPY / USD_{(t)}$	Mean Equation	C	1.0237	91.73611	0.0000
		$RET(JPY / USD(t))$	0.8610	410.5624	0.0000
		$RET(BTCN(t))$	-0.0162	-138.4092	0.0000
	AR(1)	$JPY / USD_{(t-1)}$	0.1895	156.780	0.0000
	MA(1)	e_{t-1}	0.0198	102.3895	0.0000
	Variance Equation	C	0.5721	1.36812	0.7631
		$e_{t-1}^{2}(arch)$	0.2693	7.1049	0.0000
		$\sigma_{t-1}^{2}(garch)$	0.4560	1.3728	0.5879
		$vol[RET(BTCN)]$	-0.2547	-17.0562	0.0000
Currency rate	ARMA (1,0)-FIGARCH (1,0.6073, 1)	Variable	Coefficient	z-Statistic	Pr
$CHE / USD_{(t)}$	Mean Equation	C	-1.9372	105.2260	0.0000
		$RET(CHE / USD(t))$	0.4269	802.1165	0.0000
		$RET(BTCN(t))$	-0.1045	-114.2892	0.0000
	AR(1)	$CHE / USD_{(t-1)}$	0.2951	1.257357	0.1892
	MA(1)	e_{t-1}	0.0143	112.3967	0.0000
	Variance Equation	C	1.3168	30.4159	0.0000
		$e_{t-1}^{2}(arch)$	0.2456	900.126	0.0000
		$\sigma_{t-1}^{2}(garch)$	0.6390	1.7362	0.5889
		$vol[RET(BTCN)]$	-0.0156	-24.3892	0.0000
Currency rate	ARMA (0,0)-FIGARCH (1,0.467, 1)	Variable	Coefficient	z-Statistic	Pr
$NZD / USD(t)$	Mean	C	0.5729	120.36545	0.0000
		$RET(NZD / USD(t))$	0.2960	612.0780	0.0000
		$RET(BTCN(t))$	-0.0144	-123.1873	0.0000
	MA(1)	e_{t-1}	-0.5723	-180.2768	0.0000
	Variance	C	1.4836	234.486	0.0000
		$e_{t-1}^{2}(arch)$	0.3910	540.110	0.0000
		$\sigma_{t-1}^{2}(garch)$	0. 6880	0.2689	0.7780

		$vol[RET(BTCN)]$	-0.3872	-10.3875	0.0000
Currency rate	ARMA (0,0)-FIGARCH (1,0.1963, 1)	Variable	Coefficient	z-Statistic	Pr
$DKK/USD_{(t)}$	Mean Equation	C	0.2974	129.3683	0.0000
		$RDKK/USD(t)$	0.2356	234.5791	0.0000
		$RET(BTCN(t))$	-0.0183	-197.2613	0.0000
	AR(1)	$DKK/USD(t-1)$	1.1038	18.7922	0.0000
	MA(1)	e_{t-1}	0.0015	193.1026	0.0000
	Variance Equation	C	0.2532	44.1964	0.0000
		$e_{t-1}^2(arch)$	0.5291	101.7901	0.0000
		$\sigma_{t-1}^2(garch)$	0.3260	1.0985	0.0879
		$vol[RET(BTCN)]$	-0.1065	-20.3876	0.0000
Currency rate	ARMA (0,0)-FIGARCH (1,0.1045, 1)	Variable	Coefficient	z-Statistic	Pr
$LUF/USD_{(t)}$	Mean Equation	C	0.2790	113.793	0.0000
		$RLUF/USD(t)$	1.4532	260.007	0.0000
		$RET(BTCN(t))$	-0.0103	-156.1982	0.0000
	MA(1)	e_{t-1}	0.2572	11.6100	0.0000
	Variance Equation	C	1.7683	0.89178	0.7562
		$e_{t-1}^2(arch)$	0.4278	7.3483	0.0000
		$\sigma_{t-1}^2(garch)$	0.5320	1.5196	0.3276
		$vol[RET(BTCN)]$	-0.1396	-140.3672	0.0000

Source: Authors' results from EViews software.

The GARCH effect for Bitcoin returns is highly significant. This further confirms the highly volatile behaviour of the digital currency. The ARCH effect is rather significant for all currencies, including digital currency. This suggests a substantial correlation between volatility in returns and previous innovations in returns. In other words, previous innovations in returns cause substantial volatility in the current days. By inference, the volatility of the return series is not constant over time. The variance equation coefficients further characterized the volatility dynamics between Bitcoin returns and exchange rates of currencies. The volatility of Bitcoin returns on currency rates is negative and significant, suggesting a negative dynamism on the relationship between the volatility of the return on Bitcoin and currency rates. A very high level of volatility induces depreciation in currency rates. This confirms that currency depreciation stimulates the desire to trade with Bitcoin. The volatility shocks from the return on Bitcoin had persisted over time in influencing currency exchange rates. The dynamic changes in Bitcoin demand in response to fluctuations in exchange rates in both emerging and advanced nations have significant implications for these economies. For example, importers find that a depreciating home currency makes foreign goods more expensive, potentially reducing demand.

These results agreed with the results reported by Joseph, Jahanger, Onwe, and Balsalobre-Lorente (2024), Thies and Molnár (2018), and Koutmos (2018). In contrast, when a currency appreciates, it takes fewer units of that currency to buy a unit of another currency.

This makes imported goods and services cheaper but makes exports more expensive for foreign buyers, and this hurts a country's exports.

4.5. VaR Analysis

The mean-variance analyses and the conditional VaR are among the tests that have been utilized to document evidence supporting the diversification benefits of cryptocurrencies (Letho et al., 2022). Table 8 below reports the estimates of the VaR. Considering the extremely low values of the quadratic probability score (QPS) tending towards zero as against the values-at-risk, it is obvious that the performance of the ARMA (*p,q*)-FIGARCH (1, γ, 1,) models in the measurement of risk is relatively sound. Accordingly, the results and findings from the study are reliable. According to the results at the 5% z-score or significance level, the risk associated with the transactions based on each of the currencies is very small, whereas the quantity of risk associated with the Bitcoin transactions or trading is on the high side. This goes to indicate that there is a high possibility of incurring losses when making investments with digital currencies like Bitcoin.

Specifically, the VaR for the Bitcoin returns is 0.22558104. This further ratifies the highly volatile behaviour of the digital currency. This goes to indicate that there is a high possibility of incurring losses when making investments with digital currencies like Bitcoin. An investor might be willing to invest in Bitcoin despite this finding on the premise that the larger the risk connected to a portfolio, the higher the expected returns. However, for a risk-averse currency trader, the result could be valuable when making investment decisions concerning cryptocurrencies. The JPY/USD rate, was next to exhibit a high risk coefficient of 0.2108365. For investors in the foreign exchange market who choose to maximize profits at a lower risk, trading with CHF/USD rate, CAD/USD rate, NZD/USD rate, the GBP/USD rate, the AUD/USD rate, the EUR/USD rate, the LUF/USD rate, and the DKK/USD rate is a better option. Our findings in this study are in line with those earlier obtained by Sukono, Lesmana, Susanti, Napitupulu, and Hidayat (2017) for stocks on the Indonesian capital market. Aside from the USD/JPY rate that was the next to exhibit a high risk return, the VaRs for the other rates include 0.0146225, 0.0254192, 0.0391164, 0.0139482, 0.0112675, 0.0659133, 0.0136154, 0.0123489, and 0.0418662. The corresponding QPS are 0.0159682, 0.0034216, 0.0251973, 0.0162453, 0.0025788, 0.0053499, 0.0086472, 0.0134956, and 0.0159822, respectively.

In terms of policy benefits, policymakers of the countries researched stand to profoundly benefit from this research in the formulation of effective regulatory policies. Ideas about how digital currencies interact with traditional economic indicators can guide the improvement of supervisory frameworks that foster advancement while moderating impending risks. The aforementioned nations often experience higher exchange rate volatility compared to developed economies, which can influence the expected return and risk of different assets, including Bitcoin. Policymakers can use the findings to design measures that promote financial stability and ensure the responsible integration of Bitcoin within the broader economic landscape. Additionally, investors, both local and international, as well as financial institutions operating in the aforementioned nations, can derive practical benefits from this research. An empirical exposition of the relationship between exchange rates and Bitcoin demand provides investors with an understanding of potential investment opportunities and risks. With this study, financial institutions can develop more informed strategies for incorporating digital assets into their portfolios, adjusting risk management practices based on the identified patterns and trends. Besides, businesses and entrepreneurs operating in researched countries can benefit from the research by gaining an understanding of consumer behaviour related to Bitcoin demand. Understanding how exchange rate movements influence Bitcoin demand can be valuable for businesses considering cryptocurrency transactions, guiding them in making knowledgeable decisions about payment methods, pricing strategies, and risk management.

5. Conclusions

In this research, an attempt has been made by the researchers to investigate the effect of exchange rates of nine currencies on Bitcoin returns and also compute the VaR for returns on nine exchange rates of OECD countries and Bitcoin. The study estimated the joint model of ARMA and FIGARCH by fitting the squared residuals of the time series and the conditional variance to an autoregressive term. The GARCH effect is less significant for all exchange rates, while for the return on Bitcoin trading, it was highly significant. Accordingly, the study establishes a substantial volatility feedback effect for Bitcoin, while for each of the currencies; volatility persistence is negligible, with the implication that volatility shocks with respect to the exchange rates of those currencies will be felt further in the future, but to a lesser extent. An appreciation of the USD in relation to the CAD, JPY, and CHF is an attraction for investors to diversify their portfolio away from digital currency trading and rather invest in the conventional foreign exchange market. More so, whenever there was an appreciation of the exchange rates of each currency in the previous days, a considerable positive return was stimulated. In contrast, we found a significant volatility feedback effect for the cyrptocurrency. Largely, the research findings adequately accentuate the significance of spillover effects of past Bitcoin transactions for investors navigating the growing space of the market for cryptocurrencies. Policymakers may use a use a VaR trend when formulating policies related to investment in currency trading and diversification strategies. Additionally, policymakers should recognize the influence of currency dynamics on digital asset markets and consider the implications for exchange rate policies and capital controls. By leveraging insights from the empirical findings reported in this study, policymakers should implement measures to maintain stable exchange rates through prudent monetary policies and effective capital flow management for the purpose of boosting investors' assurance and reducing currency risk. Also, there is an absolute need for policymakers to monitor volatility dynamics closely and implement regulatory measures to manage excessive volatility in the exchange rate, including risk management tools.

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