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Ayuba Napari[1]

CRYPTOIZATION AND VOLATILITY OF THE EXCHANGE RATE IN NIGERIA[2]

This study aims to examine the impact of the cryptocurrency market returns, measured by Bitcoin and stablecoin market index returns, on the volatility of the Nigerian Naira. Noting that cryptocurrency returns are positively related to cryptocurrency adoption, this amounts to testing the impact of cryptoization on the exchange rate volatility of the Nigerian Naira. The study adopts an E-GARCH-X model to test the volatility impact of cryptocurrency returns with several controls using daily data from December 2017 to December 2024. It was found that cryptocurrency returns represented by Bitcoin returns and Stablecoin returns, proxied by a weighted return of the major stablecoins, contribute positively to the volatility of the naira. This result is robust even after accounting for global risk sentiment, the dollar-naira interest rate differential and country risk using the VIX index, Naira NIBOR and SOFR rate difference and the Global X MSCI Nigeria ETF as controls.

Keyword: *Cryptoization; volatility; Naira; Stablecoins; Exchange Rates*
JEL: *C58; E44; G32; G01*

1. Introduction

Nakamoto (2008) bemoaned the role of third-party intermediation in commerce and created Bitcoin, the first cryptocurrency, and its underlying blockchain chiefly as a peer-to-peer payment system that would undo third-party intermediation. The usage of blockchain has since transcended the original purpose of its invention in money and finance to support data security and data sharing in fields as diverse as health, military, and defence (Krichen et al., 2022).

In the finance industry, blockchain has been used to design and replicate financial instruments from lending to derivatives trading. The approval of Spot Bitcoin Exchange-Traded products by the US Securities and Exchange Commission (SEC) on the 10th of January 2024 is the latest development in the crypto space that enthusiasts see as a validation and an important step towards making blockchain-based products mainstream. In the statement of approval, Gensler (2024) notes that the approval of certain Bitcoin EFTs does not amount to the approval of Bitcoin and, as a caveat, re-emphasises the speculative and volatile nature of

[1] *Ayuba Napari, Researcher, Department of Economics, Ibn Haldun University, Ordu Cad. F-05 Blok No 3, 34480 Başakşehir/Istanbul, Turkey, +9(0212) 692 02 12 ORCID: 0000-0002-1401-2016, e-mail: ayubanapari@ihu.edu.tr/napariayuba@gmail.com.*

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crypto assets and their use in illicit activities. Nonetheless, the enthusiasm preceding the approval sent the Bitcoin price soaring. The recent cryptocurrency price rally started on November 5th and was chiefly caused by renewed optimism among crypto-enthusiasts due to the re-election of Donald Trump as the US president.

In response to SEC approval for Bitcoin EFTs, Ramaswamy (2024) notes that it only entrenches one frivolous use case, as Bitcoin has no practical utility. This expression of contempt by Ramaswamy (2024) is commonplace among traditional finance agents and some sections of the public. However, several reports have documented differing but nonetheless significant and even increasing rates of cryptocurrency adoption, especially among fragile emerging and developing market economies. For example, Statista (2023) reports an increase in crypto adoption from 8% in 2020 to 19% in 2023 in Egypt, from 20% in 2019 to about 47% in 2023 in Turkey, 8% in 2019 to 27% in India and from 28% in 2019 to about 47% in Nigeria. Chainanalysis (2023) notes that globally, crypto adoption saw a marked decline in 2023. However, lower-middle-income (LMI) countries witnessed a marked increase in grassroots crypto adoption.

The IMF (2021) notes the increasing adoption of cryptocurrencies in emerging and developing countries. This increasing adoption, which results in citizens preferring cryptocurrency over the fiat currency of their country, akin to currency substitution, is termed cryptoization (IMF, 2021). In the context of Nigeria, that will mean the substitution of the Nigerian Naira holdings for cryptocurrency. IMF (2021) identifies returns from speculation, relative transaction costs, competitive financial products, and the convenience of on-chain custody as some of the pull factors driving cryptocurrency adoption in these markets (IMF, 2021).

While the pull factors may be common across countries, most of the drivers of cryptocurrency adoption in emerging and developing economies are push factors peculiar to (some of these) emerging and developing markets (IMF, 2021). One of these factors is financial exclusion. Agents in financially underdeveloped countries may adopt cryptocurrencies to benefit from financial services like the receipt of remittances. Beyond the need to be included, the public may also adopt cryptocurrencies to bypass capital controls. Chainanalysis (2023), for example, observes higher activities on P2P exchanges in countries with stricter capital controls. Alnasaa et al. (2022) found a significant correlation between cryptocurrency usage and capital controls and conjectured that cryptocurrencies could be used to circumvent capital controls and move corruption proceeds. Hu et al. (2021) studied the impact of cryptocurrencies on Chinese capital controls, which have long sought to limit the outbound remittance of citizens and capital flight. Cuen and Zhao (2018), in an editorial on CoinDesk, listed several crypto millionaires who have funnelled their wealth out of China by selling their cryptocurrencies abroad and using the proceeds to purchase real property in the US.

One other push factor for cryptocurrency adoption in emerging and developing countries is currency devaluation and inflation. Devaluations usually plunge the devaluing country into an inflation-cum-devaluation spiral. With devaluation and high domestic inflation, the public often resorts to alternatives to safeguard their earnings and purchasing power. In most cases, this often involves the substitution of local currency deposits for foreign currency deposits. The switching of local currency holdings for foreign currency holdings is termed currency substitution (De Freitas, Veiga, 2006), while the holding of residents' assets or liabilities in foreign currency has been termed financial dollarisation (Ize, Yeyati, 2003).

Currency substitution and financial dollarisation are not benign. As such, governments often attempt to dissuade currency substitution and dollarisation by instituting capital and exchange rate controls. However, the public can often find means to circumvent these controls to transact and save in foreign currency (Calvo, Végh, 1993). In the age of blockchain, cryptocurrencies have become one such means, since, thus far, governments are not equipped to control the movement of cryptocurrencies. Chainanalysis (2023) documents the substitution of local currency for cryptocurrencies in Argentina in the recent currency crisis. They note that cryptocurrency purchases in Argentina spiked in the middle of April 2023, around the time Argentina's inflation crossed 100%. It is also observed that soon after the stabilisation of the Argentinian Peso, cryptocurrency purchases stabilised (Chainanalysis, 2023).

Among crypto assets, inflation and savings-induced cryptocurrency adoption is skewed towards stablecoins. Stablecoins are mostly US dollar-denominated tokens backed by financial assets held in reserves in traditional financial institutions. In Argentina, for example, stablecoins have been used tremendously, and ordinary Argentines have begun to convert their paycheques into stablecoins immediately (Chainanalysis, 2023). This trend of agents substituting their local currency for digital money has been termed cryptoization by Copestake et al. (2023), akin to currency substitution and financial dollarisation.

Given the new trend of cryptoization in places like Argentina, several authors have forewarned monetary and regulatory authorities about the implications of cryptoization on monetary (Benigno et al., 2022), exchange rate (He et al., 2022), contagion amplification (Copestake et al., 2023), macroprudential policy (IMF, 2021) and fiscal policy (Benigno et al., 2022).

Despite these apprehensions and forewarnings, empirical studies in the literature have often focused on the exchange rate hedging properties of cryptocurrencies (Cheong, 2019) and on the connectedness of advanced economies' equity markets and exchange rates with cryptocurrencies (Andrada-Félix et al., 2020). Thus far, not many studies have been conducted on the impact of cryptocurrencies on "troubled" emerging market economies like Nigeria.

Nigeria, the country with the second-highest cryptocurrency adoption rate globally (Chainanalysis, 2023), has gone through two devaluations since June 2023 (Onu, 2024). These devaluations, along with President Bola Tinubu's government's decision to remove subsidies on fuel prices, have caused inflation to accelerate (Alexander, 2024). These features make Nigeria a good case study for the impact of cryptoization on emerging market economies. Yet only two empirical studies on cryptocurrencies and their relationship with exchange rates have been observed. Joseph et al. (2022) estimated the volume and price elasticity of cryptocurrency demand in Nigeria and included the Naira exchange rate as a control variable. They found increasing cryptocurrency demand in times of Naira exchange rate depreciation. The other related study was done by Ajayi et al. (2022), who used a Vector Error Correction (VECM) on monthly data of Bitcoin, Ethereum, Litecoin, Ripple, Binance Coin and the Dollar-Naira exchange rate to examine the long-term and short-term impulse response among the variables. Thus far, no study has been conducted on the volatility impact of cryptocurrencies on the Naira exchange rate. As such, this study aims to fill this empirical gap. This is crucial because of the impact of exchange rate volatility on financial stability through its impact on banking performance (Keshtgar et al., 2020) and inflation (Musa, 2021).

GARCH-type models are the most widely used methodology in the literature on financial volatility. This is because of their ability to capture the stylised facts of financial time series. These stylised facts are, among other things, leptokurtic, volatility clustering and shock asymmetry (Babashova, 2020). A GARCH-type method has not been used to examine the cryptocurrency exchange rate nexus in Nigeria. This essay, by employing the E-GARCH-X model, contributes to the empirical literature by showing how the changes in the returns of cryptocurrency impact the volatility of the Naira and, as such, indirectly shows the impact of speculative crypto (asset) substitution on the volatility of the Naira.

The estimation results point to a significant and positive relationship and a significant negative relationship between Bitcoin and stablecoin returns and the Naira exchange rate volatility, respectively. This relationship is found to persist even after accounting for global risk sentiment, the dollar-naira interest rate differential and country risk.

The remainder of the articles is structured as follows. Section two briefly reviews the theoretical and empirical literature on currency substitution and dollarisation and their impact on exchange rate volatility. The third section presents the E-GARCH-X model and the data used in the study. Section four presents the results, and section five concludes.

2. Literature Review

Standard monetary theory assumes single money monopolies along sovereign borders (Girton, Roper, 1981). However, years of inflation, currency crisis and the liberalisation of capital markets have brought the monopoly of currencies within national borders into question. With liberalised capital markets, residents naturally switch to more stable foreign currency holdings (Özbilgin, 2012) for savings and/or transactions. Fischer (1982) also observes movement away from the local currencies in high inflation-prone countries. The switching of local currency holdings for foreign currency holdings for transactional services is termed currency substitution, while switching local currency for foreign currency holdings for savings purposes is termed dollarisation (De Freitas, Veiga, 2006). These two terms are, however, used interchangeably despite their difference (Calvo, Vegh, 1992).

De Freitas and Veiga (2006) concluded that the distinction between currency substitution and dollarisation is irrelevant if money demand is modelled by restricting foreign currency-denominated bonds. Thus, with a binding constraint on foreign bond holdings, foreign currency assumes a store of value alongside the means of payment, making currency substitution indistinguishable from dollarisation. Under such a scenario, speculative and risk-hedging considerations will influence the demand for domestic and foreign currency (De Freitas, Veiga, 2006). The hedging component minimises the portfolio purchasing power risks, while the speculative component is critically determined by the real return differential

(Thomas, 1985). Noting the negative effects of money demand volatility on exchange rate volatility (McGibany, Nourzad, 1995), currency substitution and/or dollarisation will necessarily impact exchange rate volatility through the demand for domestic currency function. Girton and Roper (1981) developed a two-currency model of the exchange rate, assuming an exogenous money supply. Their model showed that, in the presence of currency substitution, the exchange rate between monies is unstable due to the magnitude of exchange rate movements required to achieve equilibrium. They also note that with perfect currency substitution, exchange rates become indeterminate.

Empirically documented evidence shows that agents tend to substitute local currency savings for foreign currency savings (Demir, Sezgin, 2023) and occasionally even resort to transacting in foreign currency in times of excessive inflation and currency depreciation. Savastano (1992), for example, examined currency substitution episodes in Bolivia, Uruguay, Peru, and Mexico and concluded that allowing foreign currency deposits in the domestic financial system tends to aggravate the inflationary impact of fiscal imbalances and exchange rate adjustments. Ferrari Minesso (2019) found that a strong dollar caused by growth momentum and high interest rates in the US tends to trigger capital outflows from emerging markets to the US, which in turn causes emerging market currencies to depreciate. In Lay et al. (2012), the impact of dollarisation on the Cambodian Riel is examined. Dollarisation, as represented by foreign currency deposits to M2, was found to be a source of increasing exchange rate volatility of the Cambodian Riel. Akçay et al. (1997) also found currency substitution to contribute positively to exchange rate volatility in Türkiye. Yusif et al. (2023) examined the impact of currency substitution on the Ghanaian Cedi and documented a positive impact of currency substitution on the volatility of the Ghana Cedi.

3. Methodology

It is a stylised fact that price series of financial assets, including currencies, are non-stationary. As such, the log returns are often modelled instead. The percentage log returns are computed as in equation (1).

$$r_{i,t} = 100 \times log(\frac{p_{i,t}}{p_{i,t-1}}) \tag{1}$$

With $r_{i,t}$ representing the returns on asset i on period t, $p_{i,t}$ representing the price of asset i on period t and $p_{i,t-1}$ the price of asset i on period $t-1$.

Financial returns, as computed in equation (1), are also known to exhibit volatility clustering. In modelling volatility clustering, the Generalised Autoregressive Conditional Heteroscedastic (GARCH) and Stochastic Volatility (SV) models have been widely used (Ning et al., 2015).

The Generalised Conditional Heteroskedastic (GARCH) type models utilise a two-step procedure with a mean and conditional volatility equation. The mean equation is often modelled as a sum of the average return and a time-dependent prediction error term, ϵ_t, as in equation 2.

$$r_{fx} = \omega + \epsilon_t \tag{2}$$

The prediction error term, ϵ_t, can be decomposed multiplicatively as in Equation (3) with v_t being a real-valued standardised innovation with mean zero and unit variance, while σ_t is the standard deviation of ϵ_t.

$$\epsilon_t = \sigma_t v_t \tag{3}$$

The conditional variance of ϵ_t, σ_t^2, is widely modelled (Sucarrat, 2021) as a first-order Generalised Autoregressive Conditional Heteroskedasticity, GARCH (1,1) process as in Equation (4) following the classic formulation of Bollerslev (1986).

$$\sigma_t^2 = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \tag{4}$$

With restrictions on $\alpha_0 > 0, \alpha_1 \geq 0,$ and $\beta_1 \geq 0$. ϵ_{t-1}^2 and σ_{t-1}^2 are termed the ARCH (1) and GARCH (1) terms, respectively (Sucarrat, 2021).

As a developing country's currency, the Nigerian naira's exchange rate is susceptible to global shocks and policy inconsistencies, which can trigger extreme depreciation and volatility. This is bound to produce outliers. In line with Doornik and Ooms (2005), Sakarya and Ekinci (2020), Kur et al. (2021) and Napari and Parlaktuna (2022), we assumed that such outliers are generated by a different data generation process. This is catered for by including an outlier dummy in the conditional mean equation and a lag of the outlier dummy in the variance equation (Doornik & Ooms, 2005). Following the lead of Nelson (1991) and several other studies (Engle & Bollerslev, 1986), we also include the contemporaneous conditional volatility term in the mean equation to capture the risk premia. Thus, a mean equation of the form in Equation (5) is estimated.

$$r_{fx} = \omega + \beta_0 \sigma_t^2 + \gamma_0 dummy + \epsilon_t \tag{5}$$

Nelson (1991) raised three fundamental issues with the standard GARCH specification. For one, standard GARCH specifications are based on the assumption that only the size of lagged residuals, not the sign, is important in determining conditional variance. Thus, standard GARCH models contend symmetry. This has, however, been found to be questionable, beginning with Black (1976) and several authors after. Also, standard GARCH models impose nonnegativity restrictions on the constant, the ARCH and the GARCH parameters to ensure that the conditional variance term is always positive with probability one. These nonnegativity constraints can create computational problems. A third concern, raised by Nelson (1991) on the standard GARCH formulation, has to do with the degree and how to evaluate persistence.

To remedy these situations, Nelson (1991) suggests modelling the ARCH term as a linear combination of two lags of the standardised innovation term, v_t, such as, $\alpha_1(|v_{t-1}| + \mathrm{E}|v_{t-1}|) + \alpha_2 v_t$, with $\alpha_1(|v_{t-1}| - E|v_{t-1}|)$ capturing the magnitude effect while $\alpha_2 v_{t-1}$ captures the asymmetry. Specifically, asymmetry is said to exist if $\alpha_2 \neq 0$ (McAleer & Hafner, 2014), while leverage is said to exist if $\alpha_2 < 0$ and $\alpha_2 < \alpha_1 < -\alpha_2$ (McAleer, 2014).

On the question of persistence, Nelson suggests taking the log of the conditional variance and its lags, which renders the stationarity and ergodicity of the conditional variance easily checkable and relaxes the nonnegativity restrictions on the parameters. Nelson's (1991) formulation of the standard GARCH (1,1) model has come to be termed the exponential GARCH (1,1) model. The standard E-GARCH model with the lag of the outlier dummy is depicted in Equation (6).

$$ln\sigma_t^2 = \alpha_0 + \alpha_1(|v_{t-1}| - E|v_{t-1}|) + \alpha_2 v_{t-1} + \beta_1 ln\sigma_{t-1}^2 + \gamma_1 dummy_{t-1} \quad (6)$$

The usefulness of exogenous covariates in volatility modelling and prediction has been underscored by Engle and Patton (2001). They contend that despite the proliferation of univariate GARCH models, no one actually believes that historical information in a series is the only relevant information for the prediction of the series' volatility. Engle and Patton (2001) also emphasise the structural and economic interpretational value of covariates in volatility models. Also, Sucarrat (2021) contend that the extension of the GARCH model to include exogenous covariates could help substantially in predicting and explaining volatility. In this regard, Melvin and Tan (1996) employed a GARCH model with exogenous covariates to test the impact of country risk factors, including social unrest and demonstrations, on the volatility of the foreign exchange bid-ask spread of the South African Rand and a cross-section of industrialised and developing countries. In line with this, we adopt an exponential GARCH (1,1) with exogenous covariates, as in Equation (7), to test the impact of cryptocurrency returns on the conditional volatility of the Nigerian Naira exchange rate.

$$ln\sigma_t^2 = \alpha_0 + \alpha_1(|v_{t-1}| - E|v_{t-1}|) + \alpha_2 v_{t-1} + \beta_1 ln\sigma_{t-1}^2 + \gamma_1 dummy_{t-1} + \rho X_{t-1} \quad (7)$$

From equation (8), X_{t-1} represents the lag of the cryptocurrency measure. In our model estimations, the generalised error distribution (GED) is assumed as in Nelson (1991).

As a robustness check, we estimate Equation (8), which includes several controls, including the CBOE volatility index, $V_{i,t-1}$, as in Sakarya and Ekinci (2020), the Global X MSCI Nigeria ETF returns, $ETF_{i,t-1}$, as in Sakarya and Ekinci (2020) and Napari and Parlaktuna (2022) and the differenced interest rate differential, $INTDIFF_{i,t-1}$ as in Effiong (2014) and Scott Hacker et al. (2012)

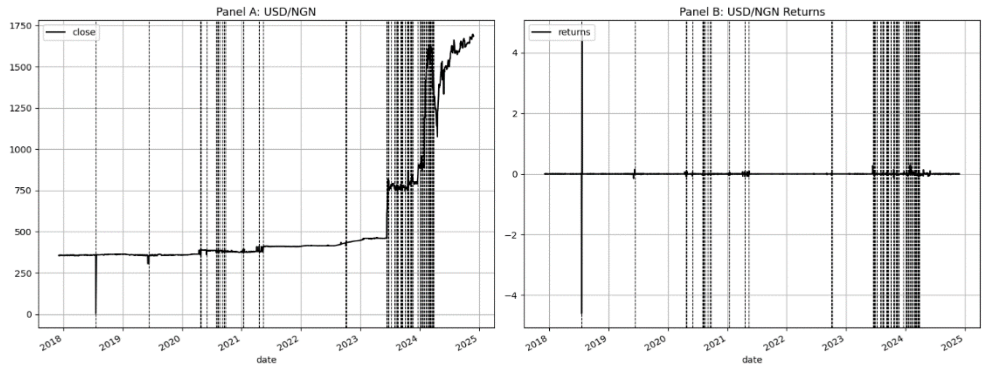
$$\begin{aligned} ln\sigma_t^2 = \alpha_0 + \alpha_1(|v_{t-1}| - E|v_{t-1}|) + \alpha_2 v_{t-1} + \beta_1 ln\sigma_{t-1}^2 + \gamma_1 dummy_{t-1} + \rho X_{t-1} \\ + \varphi_1 V_{t-1} + \varphi_2 ETF_{t-1} + \varphi_3 INTDIFF_{t-1} \end{aligned} \quad (8)$$

4. Data

The Dollar-Naira exchange rate was relatively stable until May 2021, trading below 400 Naira per dollar since December 2017. However, this changed following the devaluation of the currency in the official Nigerian Autonomous Foreign Exchange Fixing (NAFEX) on 14th May 2021, causing a plummet of the Naira to 419.8 Naira per dollar, as depicted in Panel A of Figure 1. This soon worsened, with the Naira trading at 896 per dollar on 25th December 2023 and over 1500 Naira per dollar as of February 2024.

Along with the now repetitive devaluation and depreciation of the Naira, the percentage returns on the Naira, as shown in Panel B of Figure 1, have gone through several spikes. The daily returns on the Naira touched a minimum of -4.61 on the 19th of July 2018. The worsening exchange rate produced several outliers both in the rate and the returns series, with the Rosner (1975) test detecting 73 outliers in the Naira return series, as indicated in the rate and returns plots in Figure 1 (with vertical dash lines).

Figure 1. US Dollar/Naira Daily Rates and Returns



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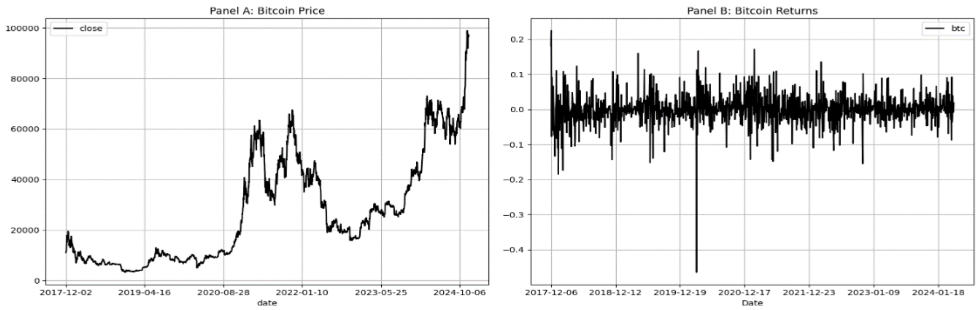
Currency substitution is often measured as the ratio of foreign currency deposits to M2 in the local banking industry (Akçay et al., 1997; Lay et al., 2012; Yusif et al., 2023). The anonymous and global nature of cryptocurrencies, however, makes it impossible to know the amount of cryptocurrency holdings within the borders of a country. Noting that currency substitution (Girton, Roper, 1981) and dollarisation (Civcir, 2005) are intricately determined and modelled as dependent on the relative rate of returns between the domestic and foreign currency, it is reasonable to assume a linear relationship between currency substitution/dollarisation and the change in the rate of returns.

This is particularly valid for cryptocurrencies, considering the role of speculation in cryptocurrency demand and transaction volumes. For example, Di Casola et al. (2023) modelled the transaction volume of Bitcoin on peer-to-peer platforms and found a positive association between returns and trading volumes. Jermann (2021) studied the money demand sensitivity to expected changes in the price of Bitcoin and Ethereum and found the money demand sensitivity parameter to be close to one. This implies that Bitcoin demand is very sensitive to price changes. We employ the percentage log returns of the cryptocurrencies to proxy cryptoization.

Bitcoin is the oldest cryptocurrency, having been implemented by the pseudonymous Satoshi Nakamoto in 2009. Since then, Bitcoin has been the undisputed leader in the cryptocurrency market, with unparalleled dominance in spillover transmission to other cryptocurrencies. Figure 2 depicts the evolution of Bitcoin's price since December 2017 and the computed daily returns of Bitcoin over the period.

As can be seen in Panel A of Figure 2, Bitcoin started 2018 trending downward and traded below 10000 dollars per coin throughout 2019. From July 2020, however, Bitcoin gained momentum, rising to as high as 65,466.840 dollars per coin in November 2021 before plummeting to 16,444.627 dollars in November 2022. The percentage returns associated with these price oscillations are depicted in Panel B of Figure 2.

Figure 2. Bitcoin Price and Returns



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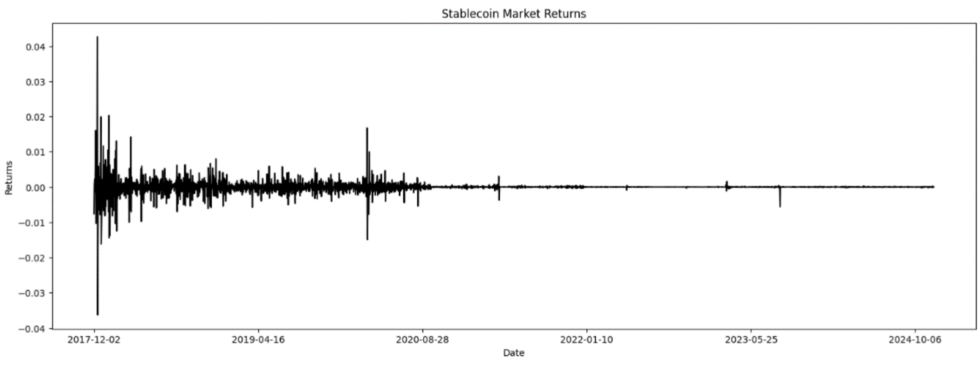
As a measure of the developments in the stablecoin market, we computed a stablecoin index following the methodology of the Coindesk Stablecoin Index for the period. The Coindesk Stablecoin Index is designed as a capitalisation-weighted index of the key coins in the stablecoin market3. In computing the index, four stablecoins are used. These are USD Tether, USD Coin, Dai, and PayPal Stablecoin. Tether is the oldest stablecoin and the stablecoin with the largest market share and capitalisation. As of 27th February 2024, Tether had a stablecoin market dominance of 70.07% according to DeFillama[4]. In calculating the index, Coindesk assigns weights of 0.7525, 0.2030, 0.042, and 0.0024 to USD Tether, USD Coin, Dai, and PayPal Stablecoin, respectively. Figure 3 presents the percentage returns of the stablecoin market, as represented by the computed stablecoin index.

Figure 3. Stablecoin Index Returns



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[3] https://www.coindesk.com/indices/csc
[4] https://defillama.com/stablecoins

As can be seen, the price oscillations in the stablecoin market were immense prior to 2020. Stablecoin returns have since stabilised and are indicative of market maturity.

Aside from the money demand volatility (instigated by currency substitution), the interest rate differential is found to be a significant determinant of exchange rate volatility in the literature. Effiong (2014) documented a significant impact of the interest rate differential on exchange rates in Nigeria. Scott Hacker et al. (2012) studied the relationship between the interest rate differential and spot exchange rates between the Swedish Krona and the British Pound, the American Dollar, the Japanese Yen, the Euro, the Norwegian Krona, the South Korean Won and the Swiss Franc using a wavelet approach. They found a negative relationship between the interest rate differential and the value of the Swedish Krona for four of the currency pairs, especially in the short run.

In determining the interest rate differential between the Nigerian Naira and the US dollar, the Secured Overnight Financing Rate (SOFR) and the Naira Overnight Interbank Offer Rate (NIBOR)are used. The SOFR is the reference rate for US dollar-denominated loans since 3rd April 2018. Prior to this date, the London Interbank Offered Rate (LIBOR) was the reference rate for dollar-denominated loans. This reference series was formally discontinued in June 2023[5], paving the way for the SOFR to become the main interest benchmark for the US dollar. In this study, the LIBOR rates from December 2017 to April 2018 are used for the period prior to the SOFR. The SOFR and LIBOR data are obtained from the Federal Reserve Bank of St. Louis Economic Data[6]. As depicted in Panel A of Figure 8, the reference rates on US dollar loans started to rise beyond 1% from April 2022 in response to rising federal funds rates to combat inflation momentum post-COVID-19. Currently, the SOFR is hovering around 5%.

The Naira Overnight Interbank Offer Rate (NIBOR) rate is obtained from Refinitiv Eikon Datastream. The daily rate of the Naira NIBOR is depicted in Panel B of Figure 4. As depicted in Panel B of Figure 4, the Naira NIBOR dropped from around 20% in 2017 to about 3% in 2020 before the currency and inflation crisis forced interest rates back to about 19.33% by February 23rd, 2024.

The interest differential between the Naira and the dollar is depicted in Panel C of Figure 4. The insignificance in the magnitude of SOFR made the interest rate differential behaviour mimic the NIBOR.

Also, Shank and Vianna (2016) contend that passive investment instruments like Exchange Traded Funds (ETFs) may have become a source of exchange rate volatility. Sakarya and Ekinci (2020) empirically tested this and found an asymmetric relationship between exchange rate movements and ETF flows in Türkiye. As such, we include the returns of the Global MSCI Nigeria ETF index percentage daily returns as controls. The prices and percentage returns of the Nigeria ETF are presented in Panel A of Figure 5.

[5] https://www.newyorkfed.org/arrc/sofr-transition#:~:text=June%2030%2C%202023%20then%20 marked,U.S.%20dollar%20interest%20rate%20benchmark.
[6] https://fred.stlouisfed.org/series/SOFR

Figure 4. NIBOR, SOFR and Interest Rate Differential

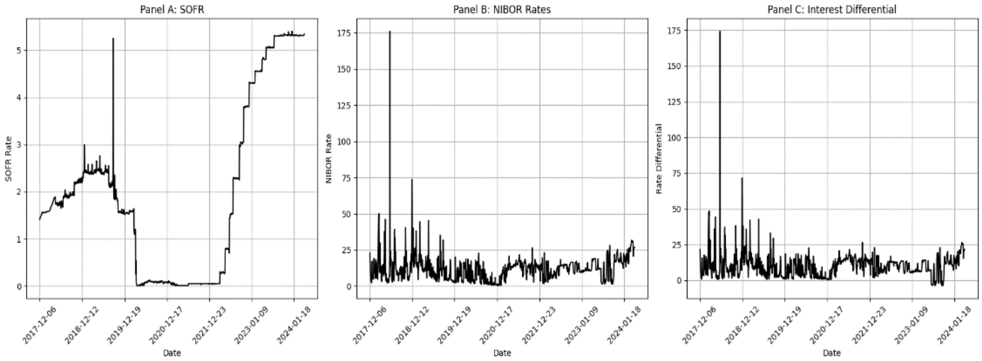

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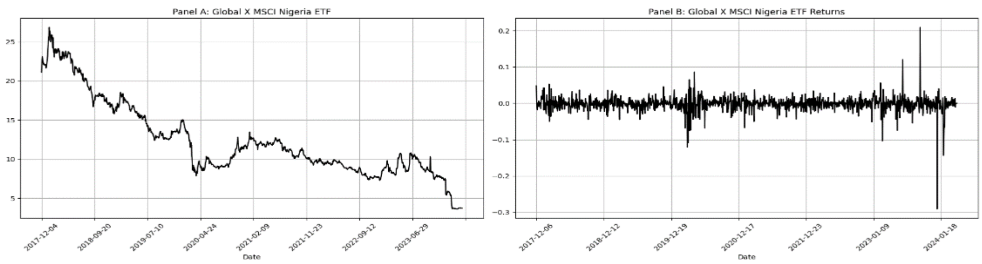
Figure 5. Global X MSCI Nigeria ETF Price and Returns



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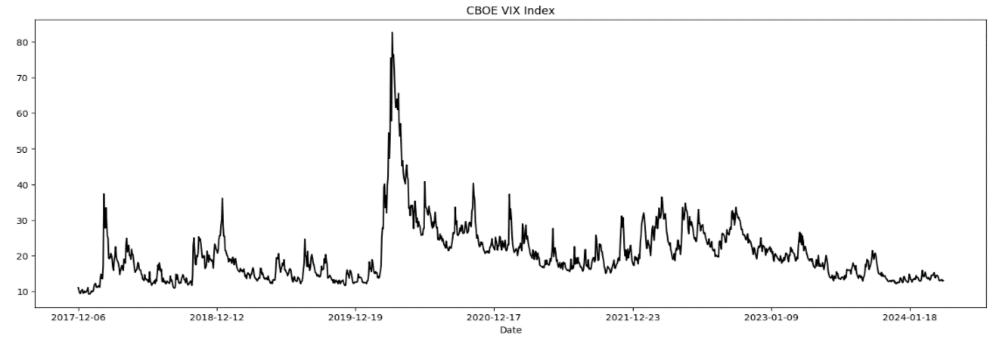
The Global X MSCI Nigeria ETF was trending downward as of December 2017, following the Recession in 2016. The recovery was further stalled by the COVID-19 pandemic and its associated uncertainties, resulting in further price declines. From a price of 63.24 in June 2014, the MSCI Nigeria ETF was trading at about 5.36 as of December 2023.

Global uncertainty is also one of the main determinants of exchange rate volatility (Ferrari Minesso, 2019) and one of the most recognisable measures of global uncertainty is the Chicago Board of Exchanges implied volatility index (CBOE VIX. This has been used by Sakarya and Ekinci (2020) to capture global risk while modelling exchange rate volatility. As such, we include the CBOE VIX to capture the impact of global risk as an additional control. Figure 6 presents the price movement of the CBOE VIX index from December 2017 to December 2023.

As can be seen, global uncertainty, as represented by the VIX index, was moderate, hovering below 30% prior to the COVID-19 pandemic in 2019. Thereafter, the index climbed to about 70% in March 2020 before trending downwards. It has since been hovering just within the pre-pandemic levels of below 30%.

Figure 6. CBOE VIX Index



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As a pre-estimation analysis, we test for the presence of ARCH effects with the Lagrange Multiplier (LM) test developed by Engle (1982) and implemented in Graves (2024). This is a popular diagnostic test in regression analysis (Hatemi, Hacker, 2005) and pre-empts the appropriateness of conditional volatility modelling (Chand et al., 2012). The existence of ARCH effects implies that the conditional variance of the time t prediction error is a function of time. Also, the stationarity of the datasets is examined.

Except for the interest rates, all other data series are obtained from Yahoo Finance7. Table 1 presents the descriptive statistics of the data used.

Table 1. Descriptive Statistics

Variable	r_{ngn}	r_{btc}	r_{sci}	vix	r_{etf}	$intdiff$
obs	1249	1249	1249	1249	1249	1249
Mean	0.00	0.00	0.00	20.28	0.00	9.95
Median	0.00	0.00	0.00	18.71	0.00	9.45
Maximum	0.29	0.23	0.04	82.69	0.21	174.25
Minimum	-4.61	-0.46	-0.04	9.15	-0.29	-3.68
Standard Deviation	0.13	0.04	0.00	8.32	0.02	8.64
Skewness	-34.40	-0.94	1.59	2.66	-2.10	6.46
Kurtoisis	1205.69	13.26	103.87	12.13	45.41	107.49
ADF Test	-10.72***	-11.13***	-12.30***	-4.14***	-10.47***	-7.26
ARCH-LM	454.46***					

Source: Created by Author.

As depicted in Table 1, the percentage daily returns of the Nigerian Naira averaged 0.00% with a minimum and maximum of -4.61% and 0.29%, respectively. As in most financial return series, the percentage of daily returns on the Naira is stationary and leptokurtic, with evidence of heteroscedasticity as evidenced by the ARCH-LM test. Over the period of the study, Bitcoin daily returns had a minimum of -0.46% and a maximum of 0.23%. Since the

[7] https://finance.yahoo.com/

CBOE volatility index (vix) and the interest rate differential are percentage indices, we utilised their level data in the analysis. The CBOE volatility index is a volatility index of the S&P 500 index, while the interest rate differential is the difference between the daily Nigerian Naira Interbank Offer Rate (NIBOR) and the Secured Overnight Offer Rate (SOFR).

5. Results

This section presents the estimation results of equations (5), (8) and (9). Model 1 and Model 2 are the estimation results of equations (5) and (8) and equations (5) and (9) with Bitcoin returns. Models 3 and 4 are the estimations of equations (5) and (8), and equations (5) and (9) with the stablecoin index returns are presented. The results for models 1 and 2 are presented in Table 2.

Table 2. Results of Models 1 and 2

Parameter	Model 1	Model 2
Mean Equation		
ω	0.00	-0.00
β_0	-0.10	0.03
γ_0	0.03***	0.03***
Variance Equation		
α_0	-7.62***	-14.68***
α_1	0.10***	0.08***
α_2	0.10***	0.08***
β_1	0.26***	-0.51***
γ_1	-0.77***	-0.65***
ρ	2.13**	3.51***
φ_1		-0.04***
φ_2		-14.81***
φ_3		-0.01
Diagnostics		
ARCH-LM	0.00	0.00
Log-likelihood	3881.53	4490.78

Source: Created by Author.

From Table 2, the risk premia are significant for both Models 1 and 2. In the variance equation, the asymmetric term $\boldsymbol{\alpha_2}$ is found to be positive and significant in Models 1 and 2. The ARCH term, α_1, the GARCH term β_1 and dummy variable terms are all found to be significant, with the dummy variable, indicating the lag of outliers having a negative effect on the volatility of the Naira. The parameter for cryptoization, Bitcoin returns, is found to have a positive and statistically significant impact on the conditional volatility of the Naira, with a magnitude of about 2.13 in Model 1 and 3.51 in Model 2. This implies that the Naira becomes more volatile as Bitcoin returns trend upward.

This is in line with the literature on currency substitution. For example, Ajibola et al.(2020) document a positive relationship between currency substitution and exchange rate volatility in Nigeria using an ARDL model. Akçay et al. (1997) used an E-GARCH model to test the volatility impact of currency substitution on the exchange rate of the Turkish lira and found a positive impact of currency substitution on exchange rate volatility. The result also parallels the findings of Yusif et al. (2023), who documented an exchange rate volatility-accelerating impact of currency substitution.

All control variables are significant in the estimations except the interest rate differential. Specifically, the ETF parameter is found to be a negative contributor to Naira volatility. This implies that positive All Nigeria Select 25/50 Index market returns, tracked by the Global MSCI Nigeria ETF, decrease the Naira return volatility. This result contradicts the findings of Sakarya and Ekinci (2020), who concluded that the outflows of exchange-traded funds, which will necessarily correlate positively with returns, result in a decrease in exchange rate uncertainty and, thus, volatility. The results on the interest rate differential also corroborate the findings of Scott Hacker et al. (2012), who found a positive relationship between the interest rate differential and the exchange rate.

Table 3 also presents the results of Models 3 and 4, which estimate equations (5), (8) and equation (9) with stablecoin index returns.

Table 3. Results of Model 3 and Model 4

Parameter	Model 3	Model 4
Mean Equation		
ω	-0.00	0.00
β_0	1.03	-0.01
γ_0	0.03***	0.04***
Variance Equation		
α_0	-8.36***	-13.72***
α_1	0.08***	0.09***
α_2	0.08***	0.09***
β_1	0.21***	-0.43***
γ_1	-0.68***	-0.66***
ρ	50.54**	93.58***
φ_1		-0.04***
φ_2		-16.62***
φ_3		-0.01
Diagnostics		
ARCH-LM	0.00	0.00
Log-likelihood	3475.84	4460.01

Source: Created by Author.

As in Models 1 and 2, evidence of asymmetry in the volatility of the Naira is found for both Models. The ARCH, α_1, and GARCH, β_1, terms are also positive and statistically significant in both Models 3 and 4.

The Stablecoin index parameter, ρ, is found to have a magnitude of 50.54 when only stablecoin index returns are included as a covariate and a magnitude of 93.58 when the VIX index, the MSCI Nigeria ETF and the interest rate differential are included in Model 4. All the control variables maintained their signs and were significant across the models. The findings on the interest rate differential again contradict the findings of Effiong (2014), who studied the monetary exchange rate model for the case of Nigeria and concluded that the interest rate differential is a significant predictor of exchange rate volatility in Nigeria.

6. Conclusion

It is established in the literature that episodes of devaluation and high inflation are known to trigger currency and asset substitution, with the public often resorting to saving and transacting in relatively stable foreign currencies. Governments often try to remedy this by instituting capital and exchange rate controls. Economic agents, however, are always able to find means to circumvent the controls. The advent and wide adoption of cryptocurrencies have made cryptocurrencies the obvious tool for such circumventions, with evidence of macroeconomic factors like currency depreciation and inflation being key drivers of cryptocurrency adoption.

In this study, we conjecture that the shift to cryptocurrency might feed into currency woes by making the currency demand unstable and increasing the volatility of the exchange rate, which is in line with the literature on currency substitution and dollarisation. We test this conjecture for Nigeria, the country with the second-highest cryptocurrency penetration rate globally as of 2023. This is done by testing the volatility impact of cryptocurrency returns on the return volatility of the exchange rate. We used an exponential GARCH model with exogenous covariates and the daily data from December 2017 to December 2024. Our findings confirm the conjecture with both measures of cryptocurrency returns, Bitcoin and the Stablecoin Index returns positively contributing to the volatility of the naira, even after accounting for global risk sentiment, the dollar-naira interest rate differential and country risk using the VIX index, Naira NIBOR and SOFR rate difference and the Global X MSCI Nigeria ETF as controls.

The implication is that monetary and macroeconomic policymakers, businesses, and individuals who are wary of exchange rate volatility should include cryptoization and the returns of the cryptocurrency market in their reaction function. For future researchers, a more detailed dataset on cryptocurrency holdings within a country's borders could be used.

Declaration

This work is derived from the author's doctoral dissertation. Portions of the text resemble or may replicate the original text from the unpublished PhD dissertation submitted for the award of a PhD degree at Ibn Haldun University, Istanbul, Turkey.

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