Research Article

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Does Bitcoin Affect Term Deposits? Evidence from MINT Countries

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Abstract: This article examines the relationship between Bitcoin volume and term deposit investments in Mexico, Indonesia, Nigeria, and Turkey (MINT) from 2016 to 2021. We run cointegration and error-correction econometric models for each country, analyzing both the long-term and short-term interactions between Bitcoin volume and time deposits. Our findings indicate a negative association between Bitcoin volume and term deposits in all the MINT countries, except Mexico. This suggests that individual investors in economically and financially unstable nations are increasingly turning to Bitcoin as an alternative investment option. The observed effects, while currently modest, highlight the potential threats posed by decentralized cryptocurrencies to the monetary systems of emerging economies, impacting the stability of the banking industry and overall economic growth.

Keywords: Bitcoin, term deposits, MINT, currency substitution

1 Introduction

The global financial crisis of 2008 shook investors' confidence in traditional financial systems, leading them to seek alternative options. In response to this need, Bitcoin emerged in 2008 as a decentralized digital asset (Nakamoto, 2008). As a peer-to-peer electronic cash system, Bitcoin enables direct online payments between parties, eliminating the need for intermediaries such as financial institutions. This innovative approach uses blockchain technology and cryptography to ensure secure and anonymous monetary transactions, bypassing the need for banking system approval and regulatory interference (Schilling & Uhlig, 2019). Unlike traditional financial assets, Bitcoin has evolved beyond its initial role of providing speed and economic efficiency in global money transfers to become a highly versatile asset with a wide range of applications. With the growing demand for protection against inflation and currency crises, investors have increasingly turned to Bitcoin, recognizing its versatility as a hedge against economic uncertainties such as inflation and currency devaluation, and as a potential substitute currency in turbulent times (Dyhrberg, 2016; Gozgor et al., 2019; Marmora, 2021; Urquhart & Zhang, 2019).

Investors seeking protection against inflation and currency crises have increasingly turned to Bitcoin, favoring it over fiat currencies. For example, in 2018, when Donald Trump vowed to double metal tariffs on Turkey, the Turkish lira depreciated to such an extent that people in Turkey shifted their investments to cryptocurrencies, especially Bitcoin (Sharma, 2018). The same thing happened again in 2021, when the president of Turkey announced the adoption of the low-interest rate policy to fight the currency crisis; due to this announcement, BTC/TRY reached a record high (Suberg, 2021).

Given the challenges posed by currency crises in certain countries, the concept of currency substitution becomes relevant. Firms and households in these economies often seek alternatives to their fiat currencies to protect their investments, often turning to foreign currencies or commodities like gold. Interestingly, the emergence of Bitcoin as a deflationary asset raises the question of whether it could also serve as a substitute currency, posing various challenges for countries in implementing effective monetary, exchange rate, and fiscal policies (Bergstrand & Bundt, 1990; Miles, 1978).

The monetary policy effect can be observed through the money supply, as the introduction of Bitcoin reduces the fiat currency in circulation through its velocity and demand (Hazlett & Luther, 2020). Replacing fiat currency with Bitcoin causes money in circulation to move out of the traditional financial system, resulting in a decrease in the

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velocity and, consequently, money supply. Previous research confirms this effect. For example, Sarker and Wang (2022) examined the relationship between the price of Bitcoin and money supply, M2,[1] including inflation and economic policy uncertainty for the UK and Japan, while Wang et al. (2023) examined its impact on the US economy in both the short run and long run. Both studies find an inverse relation between Bitcoin and M2. Similarly, Narayan et al. (2019) investigated the association between Bitcoin price growth and M2 for Indonesia, confirming Bitcoin's destabilizing effect on the monetary system. In addition, Mert and Timur (2023) explored the same relationship for the USA but using M1[2] as the money supply. Their findings confirm a negative relationship, pointing to the hedging properties of Bitcoin.

Moreover, this phenomenon can have a significant impact on banks, in particular on their credit markets, as it can lead to fluctuations in deposit levels. As banks play a crucial role in providing liquidity to economies, any disruptions in their deposit positions can significantly impact a country's overall economic performance (Attila, 2022; Diamond & Dybvig, 1983). The stability of bank deposits is of paramount importance, as it directly affects the economy's ability to finance investments and stimulate growth (Mushtaq & Siddiqui, 2017). The adoption of Bitcoin, which involves the replacement of fiat currency, can have a direct effect on credit markets by influencing bank deposits. For instance, Othman et al. (2019) investigated the long-term relationship between the cryptocurrencies market capitalization and bank deposit variability for seven countries where cryptocurrencies are legal and used as a medium of exchange, while Othman et al. (2020) did the same for the Gulf countries. They find that bank deposit variability decreases in the sample countries as the market capitalization of the cryptocurrency market increases, suggesting that capital in bank deposits is transferred to cryptocurrencies. However, previous studies do not document this relationship between Bitcoin volume and term deposits. We believe that volume is a more accurate variable to measure the substitution effect, particularly for emerging countries.

The purpose of this article is to investigate whether Bitcoin will become another financial asset for currency substitution, and how this will affect term deposits. In particular, we examine the relationship between Bitcoin volume and term deposit nexus in Mexico, Indonesia, Nigeria, and Turkey (MINT) for the years 2016–2021. MINT countries have a young and growing population, and their geographical location is favorable due to the proximity of advanced and developing markets (Adebayo et al., 2020). They are fast-growing countries, but their economic and financial instability could lead individuals to invest in Bitcoin. In contrast to the previous studies, we include term deposit (M2–M1) and Bitcoin volume. Since M2 includes both fiat currency and financial assets, we use M2–M1 to compare the financial asset property of Bitcoin. Instead of the price of Bitcoin, we use the volume to measure the substitution effect. By applying cointegration and error correction models, we analyze how the monthly percentage change in Bitcoin volume affects the monthly percentage change in term deposit volume. We find an inverse relationship between Bitcoin volume and term deposits, suggesting that as Bitcoin investment increases, term deposits in MINT countries decrease.

The other sections of the article are organized as follows. Section 2 reviews the relevant literature and theoretical framework. Section 3 outlines the data and provides descriptive statistics. Section 4 presents the methodology used in this study. Section 5 discusses the empirical results of cointegration and error correction models. Section 6 concludes the article.

2 Related Literature and Theory

A growing number of studies have been conducted to examine various aspects of Bitcoin. These studies cover diverse areas, including price formation (Kristoufek, 2015; Ober et al., 2013), its classification as a currency or asset (Yermack, 2015), market efficiency (Bariviera, 2017; Urquhart, 2016), and the relationships between return and trading volume (Balcilar et al., 2017). In addition, several studies focus on investigating the role of Bitcoin as a potential hedge, safe haven, or diversifier relative to traditional assets, with the aim of protecting investments against uncertainty. For example, Bouri et al. (2017) discussed Bitcoin's safe haven property, suggesting its potential as a protective asset in times of market stress. Similarly, Dyhrberg (2016) and Urquhart and Zhang (2019) found that Bitcoin can be used as a hedge against fiat currency depreciation, providing investors with a means to mitigate currency-related risks. In addition, Gozgor et al. (2019) used the wavelet method to investigate Bitcoin's potential as a hedging instrument against inflation and exchange rate volatility. Their results document that Bitcoin's value is influenced by economic fluctuations, suggesting that it can act as an asset for investors seeking protection against inflationary pressures and currency market uncertainties. In line with these, Marmora (2021) examined the currency substitution between

1 M2 is M1 plus time deposits.

2 M1 is money in circulation plus demand deposits.

Bitcoin and fiat currency in the shadow markets of 28 emerging markets under varying inflation expectations. Their quasi-experimental specification model shows that inflation expectations play a crucial role in influencing Bitcoin trading volumes in these markets, reinforcing the notion of Bitcoin's currency substitution effect, particularly in inflationary environments. However, it is important to recognize that while currency substitution may protect individual investments, it can also have negative effects on countries' monetary and banking systems. Therefore, the aim of this article is to examine the effect of the impact of currency substitution on the monetary and banking systems of MINT countries.

The currency substitution effect of Bitcoin on money supply can be observed through two different channels due to its properties, such as fiat currency and financial asset channels. The fiat currency property of Bitcoin influences money supply through the velocity of money, which measures how quickly money is exchanged in an economy. This relationship is defined by the Equation of Exchange as $V = (P \times T)/M$, where V is the velocity of money, P is the price, T is the total value of transactions, and M is the money in circulation, derived from the quantity theory of money. The greater acceptance of Bitcoin as a substitute for fiat currency can lead to a reduction in the frequency and value of T, which subsequently leads to a reduction in the velocity of money while holding M and P constant. Consequently, this substitution effect leads to a reduction in the velocity of fiat currency, which in turn affects the money supply in the economy.

The financial asset property of Bitcoin affects the money supply by altering the demand for fiat currency by replacing it with Bitcoin. The impact of this effect can be explained by the demand for money equation as $M_\mathrm{d} = P \times L(r, Y)$, where M_d is the demand for money, P is the price, and $L(r, Y)$ is the preference for holding cash, where r is the nominal interest rate, and Y is the level of output. The lower interest rates reduce the demand for fiat money, leaving P and Y unchanged. When the return on financial assets is higher than the interest rate, investors prefer to invest in financial assets that offer higher returns. This attracts attention to Bitcoin as its unusual returns attract investors. Therefore, the increased investments in Bitcoin reduce the demand for fiat currency, which has an effect on the money supply.

Few studies examine the effect of Bitcoin price on money supply. Narayan et al. (2019) examined the effect of Bitcoin price growth on Indonesia's monetary system, including inflation, exchange rate, and velocity of money. Using GARCH models, they observe an increased effect of Bitcoin price growth on inflation and exchange rate, while the velocity of money decreases, suggesting that Bitcoin may have a destabilizing effect on the monetary system. Sarker and Wang (2022) and Wang et al. (2023) analyzed the relationship between Bitcoin price and money supply, inflation, and economic policy uncertainty, the former for the UK and Japan and the latter for the USA, using wavelet-based methods. Both articles conclude that Bitcoin price and money supply, M2, are inversely related, and there is a transmission effect from Bitcoin to money supply, inflation, and economic policy uncertainty across time and frequency. Instead of using M2 for money supply, Mert and Timur (2023) used M1 to examine the relationship between Bitcoin price and money supply for the USA, Eurozone, and Japan by applying Bayesian vector autoregressive (VAR) and Granger causality. Their findings suggest that Bitcoin has the potential to serve as a hedge against the inflationary effects of fiat currency.

A limited number of studies explore the association between cryptocurrencies and bank deposits. Othman et al. (2019) analyzed the impact of cryptocurrencies on bank deposit variability in seven countries where cryptocurrencies are legally used as a medium of exchange, using the VAR-VECM model. Their findings suggest that an increase in the market capitalization of cryptocurrencies reduces the variability of bank deposits in the long term. However, they also observe differences in the responsiveness of bank deposits to cryptocurrency market behavior based on trading days across these countries. In a subsequent study, Othman et al. (2020) examined the long- and short-term effects of cryptocurrency market capitalization on bank deposit variability in Gulf countries by applying causality and vector error correction model (VECM). Their results indicate that cryptocurrency market developments affect the capital in bank deposits. Therefore, this article aims to address the significant gap in the literature on the potential substitution impact of Bitcoin volume on the monetary and banking systems of emerging economies.

3 Data

The dataset includes the monthly transaction volume of Bitcoin, term deposits, and USD exchange rates of MINT countries from 2016 to 2021. We collected the Bitcoin volume (BTC) from coindance.com, term deposit (M2 minus M1) from Federal Reserve Economic Data (FRED), and exchange rates against USD from investing.com (Table 1). We prefer to use BTC to understand the nature of the flow of local currency between Bitcoin and M2–M1. Theoretically, M1 is money in circulation plus demand deposits, and M2 is M1 plus term deposits. Since we are focusing on Bitcoin as a financial asset, we use the difference

Table 1: Data and source

Symbol	Definition	Source
LVL_BTC	Bitcoin volume*	coin.dance
BTC	Return change of Bitcoin volume*	coin.dance
M2	Return change of "M1 money supply + Term deposits"*	fred.stlouisfed.org
M2_M1	Return change of "M2 minus M1 (proxies investment for term deposits)"*	fred.stlouisfed.org
EXC	USD exchange rate to local currency	investing.com

*All retrieved data are local currency of countries.

between M2 and M1, which serves as a proxy for local currency investment, to examine its relationship with term deposits. Term deposits are considered investment instruments where investors expect low risk and low return and are typically invested by individuals in traditional financial institutions using local currency. In addition, we include the value of the USD against local currencies (EXC) as a control variable in our model. All variables are differently transformed according to the following formula: ($\text{Volume}_t - \text{Volume}_{t-1}$).

4 Methodology

First, we looked at the descriptive statistics and characteristics of the data before building the model. We observed whether there was a historical structural break in the BTC data using the figures and then detected the structural break using the Chow test (Chow, 1960) test. Thus, we selected the appropriate data range for econometric modeling and then applied unit root tests to the data. To determine the presence of cointegration between the variables using the maximum Eigenvalue test and the Trace test, we first found the appropriate lags using VAR models. Finally, we built appropriate VECM models to see the direction of the relationship between the variables.

4.1 Time Series Diagnostics

First, from a broad perspective, we looked at Bitcoin volume data for Turkey (TRY), Nigeria (NGN), Indonesia (IDR), and Mexico (MXN) to see if there are structural breaks that exist between the series. Detecting structural breaks statistically among these series, we applied the Chow structural breakpoint test. The Chow test (Chow, 1960) is used to determine whether there are distinct regression coefficients for divided data sets. In essence, it tests whether a single regression line or two separate regression lines better fit a split dataset. The Chow test identifies the presence of a structural break if it shows significant differences in the regression coefficients. Once breaks have been identified, the data from the early period that caused the structural break are removed from the dataset, and the stable dataset is used.

In most time series models, it is essential to carry out unit root tests to ensure that there are no spurious regressions. Therefore, unit root tests are applied to the variables. The absence of unit roots, indicating stationarity in the time series, is crucial for the robustness of the models. We apply Augmented Dickey and Fuller (1979) and Phillips and Perron (1988) unit root tests to the series and find out whether the variables do not have a unit root.

4.2 Cointegration Analysis

Cointegration can be briefly defined as a co-movement between economic variables in the long term. It is necessary to apply cointegration analysis to determine whether there is a long-term equilibrium relationship between the series. This article uses the test developed by Johansen (1988) and Johansen and Juselius (1990). The Johansen–Juselius (JJ) method appears to be superior in the literature to the two-stage procedure developed by Engle and Granger (1987).

Since the two-stage Engle–Granger cointegration test only shows the relationship between two variables and is therefore not a systematic model for predicting the multiple cointegration vector, we use the Johansen cointegration test to predict the long-run relationship. The Johansen procedure (1988) is based on the relationship between the rank of a matrix and its characteristic roots. This method is used to determine the cointegration relationship for more than two variables.

This approach reveals the cointegrated relationships between non-static variables by estimating the number of cointegration relationships and the parameters of these relationships using the maximum likelihood method. In this method, each variable is modeled as a VAR model that is a function of the lagged values of all intrinsic variables in the system. Equation (1) shows the VAR model with n variables and k lags.

$$Z_t = \sum_{i=1}^{k} A_i Z_{t-i} + \varepsilon_t, \tag{1}$$

where Z_t is the vector consisting of the observation values at t, A_i is the coefficient matrix for the ith delay, and ε_t is the error term vector for the variable.

Assume that all variables in the model expressed in equation (1) are equally cointegrated. In equation (1), some transformations are made to arrive at the model expressed by the following equation:

$$\Delta Z_t = \Pi Z_{t-k} + \sum_{i=1}^{k-1} \Gamma_i \Delta Z_{t-i} + \ \varepsilon_t k \geq 2. \tag{2}$$

The transformation used to obtain equation (2) is called the "cointegration transformation." The model expressed in equation (1) can also be constructed in the form of a known error-correction model:

$$\Delta Z_t = \Pi Z_{t-1} + \sum_{i=1}^{k-1} \Gamma_i^{*} \Delta Z_{t-i} + \varepsilon_t. \tag{3}$$

The matrix Π of equation (3) contains error correction coefficients and cointegration vectors. Thus, when Π is expressed in two parts, the following equality is obtained:

$$\Pi = \alpha\beta', \tag{4}$$

where α shows the vector of error correction coefficients and β presents the cointegration matrix. The rank of the matrix Π expressed in equation (4) shall be equal to $r(\prod) = \min\{r(\alpha),\ r(\beta)\}$. If $r(\prod) = 0$ or $r(\prod) = n$, it is concluded that the variables are not cointegrated, $1 \leq \ r(\prod) \ \leq n - 1$ while they are grain cointegrated vectors if $r(\prod) = r$. Thus, when the rank of the matrix Π is determined, it can be decided whether there is a cointegrated relationship between the variables, and if so, how many cointegrated vectors there are.

Johansen (1988) proposed two different likelihood tests to reveal the cointegration relationship. The first is the maximum Eigenvalue test, and the second is the Trace test. In the maximum Eigenvalue test, the existence of at most r cointegration vectors is tested against the alternative hypothesis of the existence of the $r + 1$ cointegration vector. The Trace test tests the presence of at most r cointegration vectors against the alternative hypothesis that there are at least $r + 1$ cointegration vectors.

According to Engle and Granger (1987), if there is cointegration between variables, there is at least a one-way causality between the variables, and the VECM can be used. If the set of $I(1)$ static first-order variables is cointegrated, failure to include the error correction term (ECT) estimated in the VAR model in the VECM may lead to specification errors in causality tests. Therefore, it would be useful to include ECTs in the VECM model, where each of the variables is used as an argument to determine the direction of possible causality in the VAR structure.

4.3 Error Correction Model (VECM)

In this approach, Engle and Granger (1987) showed that if cointegration is found between two variables, there is a vector error correction model (VECM) that removes short-term disequilibria. In general, causality tests recommend a long-term equilibrium model and a short-term error correction model. These models allow the integration of both long-term relationships (equilibrium relationships) between variables and short-term adjustment behavior (disequilibrium).

For example, suppose there are two variables, Y and E, to express the explanation of error correction equations. Accordingly, if the two variables are static and cointegrated, causality tests can be established according to VECM. The error correction model to be built for the two variables is as follows:

$$\Delta Y_t = \alpha_1 + \sum_{i=1}^{m} \beta_{1i} \Delta E_{t-i} + \sum_{i=1}^{n} \gamma_{1i} \Delta Y_{t-i} + \sum_{i=1}^{r} \delta_{1i} \mathrm{ECM}_{r,t-i} + u_t, \tag{5}$$

$$\Delta E_t = \alpha_2 + \sum_{i=1}^{m} \beta_{2i} \Delta E_{t-i} + \sum_{i=1}^{n} \gamma_{2i} \Delta Y_{t-i} + \sum_{i=1}^{r} \delta_{2i} \mathrm{ECM}_{r,t-i} + u_t. \tag{6}$$

In the error correction model, the delayed error terms $\mathrm{ECM}_{r,t-i}$ are accepted as velocity adjustment parameters. ECM means that for Y, ΔE_t has two sources of causality delayed terms or delayed error terms. If one or more of these sources affect Y, i.e., if the parameters are statistically different from zero, then the empty hypothesis that "Y is the data, while the variable E is not the Granger cause of Y" is rejected. This hypothesis is tested using the t-test for the ECTs and the F-test for the lagged values of explanatory variables. In at least one of the VECM systems, the speed setting parameter must be statistically different from zero. If the speed setting parameters in the entire system of equations are zero, the long-run equilibrium relationship does not occur, and the model does not have the nature of error correction (Charemza & Deadman, 1997).

Since our objective is to investigate the long-run relationship of the BTC variable with the M2_M1 and EXC variables within the VEC models, we focus specifically on analyzing the cointegrated equations where BTC serves as the dependent variable in the models for all four countries (Models 7, 8, 9, and 10). To check the autocorrelation of the residuals, we

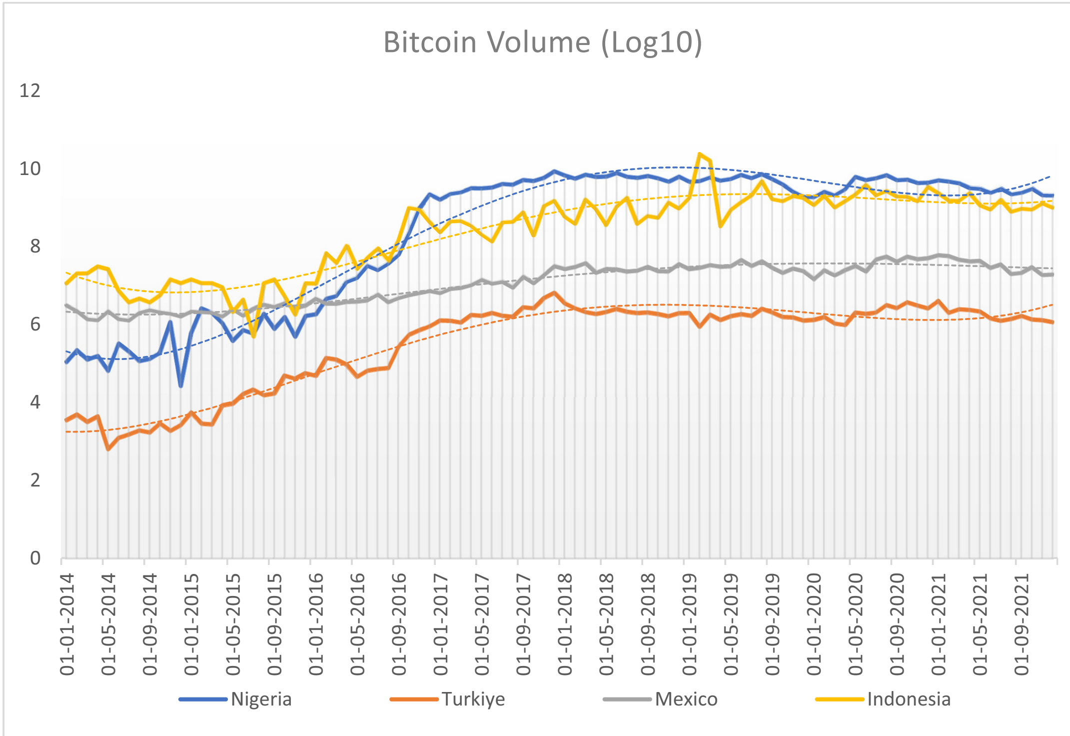

Figure 1: Bitcoin volume data (logarithmic).

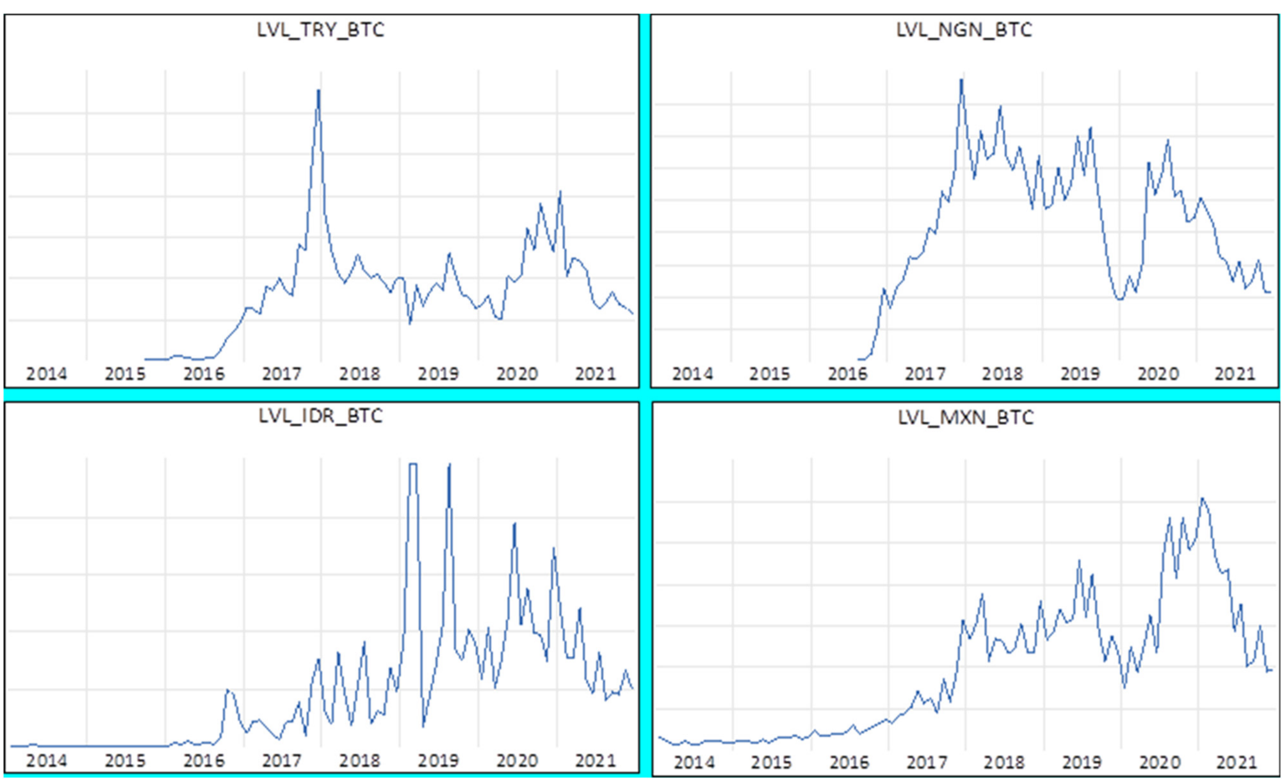

Figure 2: Bitcoin volume data country based.

Table 2: Chow breakpoint test

Bitcoin volume series	Breakpoint date	*F*-statistic	Prob.
LVL_TRY_BTC	2016-10	135.82	0.00***
LVL_NGN_BTC	2016-10	185.00	0.00***
LVL_IDR_BTC	2016-10	529.30	0.00***
LVL_MXN_BTC	2017-11	238.27	0.00***

Note: ***, **, * indicate the statistical significance at 1, 5, and 10%, respectively.

apply the Portmanteau (Box & Pierce, 1970) test to the residuals of the VEC models.

$$\text{TRY\_BTC} = \text{TRY\_BTC}(-1) + \alpha^*\text{TRY\_M2\_M1}(-1) + \beta^*\text{TRY\_EXC}(-1), \tag{7}$$

$$\text{NGN\_BTC} = \text{NGN\_BTC}(-1) + \alpha^*\text{NGN\_M2\_M1}(-1) + \beta^*\text{NGN\_EXC}(-1), \tag{8}$$

$$\text{IDR\_BTC} = \text{IDR\_BTC}(-1) + \alpha^*\text{IDR\_M2\_M1}(-1) + \beta^*\text{IDR\_EXC}(-1), \tag{9}$$

$$\text{MXN\_BTC} = \text{MXN\_BTC}(-1) + \alpha^*\text{MXN\_M2\_M1}(-1) + \beta^*\text{MXN\_EXC}(-1). \tag{10}$$

5 Empirical Results

5.1 Diagnostics

First, we looked at logarithmic Bitcoin volume data for TRY, NGN, IDR, and MXN from January 2014 to December 2021 (Figure 1). We observed apparent breaks in the data around the end of 2016 for all mentioned series.

Figure 2 displays the graphs for each country, and to identify structural breaks, we used the Chow (1960) structural breakpoint test, as presented in Table 2. The results reveal that the structural break date for TRY, NGN, and IDR is October 2016, while for Mexico, it is November 2017. Consequently, the sample period commences in 2016 due to the observed structural breaks.

Table 3 presents the descriptive statistics. The average percentage change in Bitcoin volume is 7.51% for Turkey, 14.28% for Nigeria, 35.75% for Indonesia, and 6.85% for Mexico. On the other hand, the percentage change in term deposits (M2_M1) exhibits lower volatility in comparison to Bitcoin volume. The average percentage change in term deposits is 1.87% for Turkey, 1.11% for Nigeria, 0.6% for Indonesia, and 0.48% for Mexico. Similarly, the average exchange rate is less volatile than Bitcoin volume with values of 2.64% for Turkey, 0.59% for Nigeria, 0.17% for Indonesia, and 0.18% for Mexico.

Next, we apply Augmented Dickey–Fuller (ADF) and Phillips and Perron (PP) unit root tests to identify the variables without a unit root, as presented in Table 4.

5.2 Cointegration Analysis

To assess the presence of cointegration among the series, we established the VAR models and determined the VECM lag lengths. The results for the optimal lag lengths for VAR are presented in Table 5. Typically, the VEC modeling requires one less lag than the optimum lag length of the

Table 3: Descriptive statistics of variables

	Mean	Median	Maximum	Minimum	Std. Dev.
TRY_BTC	0.0751	−0.0478	1.0510	−0.5544	0.3542
TRY_M2	0.0225	0.0172	0.1846	−0.0374	0.0334
TRY_M2_M1	0.0187	0.0147	0.1449	−0.0298	0.0286
TRY_EXC	0.0264	0.0146	0.4030	−0.0786	0.0762
NGN_BTC	0.1428	0.0300	3.4255	−0.3408	0.6089
NGN_M2	0.0114	0.0098	0.0820	−0.0383	0.0211
NGN_M2_M1	0.0111	0.0120	0.0852	−0.1146	0.0360
NGN_EXC	0.0059	0.0001	0.1090	−0.0819	0.0377
IDR_BTC	0.3575	−0.0170	5.6875	−0.9790	1.1842
IDR_M2	0.0082	0.0079	0.0528	−0.0318	0.0140
IDR_M2_M1	0.0060	0.0075	0.0423	−0.0374	0.0134
IDR_EXC	0.0017	0.0003	0.1367	−0.0905	0.0268
MXN_BTC	0.0685	0.0564	1.0206	−0.4269	0.3236
MXN_M2	0.0073	0.0053	0.0412	−0.0187	0.0125
MXN_M2_M1	0.0048	0.0033	0.0256	−0.0220	0.0106
MXN_EXC	0.0018	−0.0038	0.2092	−0.0821	0.0440

Table 4: Unit root tests statistics

	ADF (Cons)	ADF (Cons + Trend)	ADF (None)	PP (Cons + Trend)	PP (Cons)
IDR_BTC	−10.95***	−10.97***	−10.03***	−10.97***	−10.95***
IDR_M2	−13.34***	−13.29***	−0.69	−13.39***	−13.45***
IDR_M2_M1	−10.35***	−10.37***	−82.08***	−10.39***	−10.37***
IDR_EXC	−10.56***	−10.52***	−10.56***	−13.76***	−12.47***
MXN_BTC	−5.60***	−5.69***	−4.62***	−14.21***	−14.22***
MXN_M2	−9.64***	−9.61***	−7.34***	−9.77***	−9.81***
MXN_M2_M1	−9.26***	−9.21***	−8.45***	−9.22***	−9.26***
MXN_EXC	−9.66***	−9.69***	−9.54***	−10.34***	−9.98***
NGN_BTC	−3.87***	−6.69***	−3.75***	−6.77***	−6.09***
NGN_M2	−10.67***	−10.89***	−45.43***	−10.86***	−10.61***
NGN_M2_M1	−5.30***	−5.34***	−4.90***	−9.92***	−9.86***
NGN_EXC	−7.74***	−7.74***	−7.61***	−7.73***	−7.73***
TRY_BTC	−8.44***	−8.95***	−8.03***	−8.95***	−8.45***
TRY_M2	−7.29***	−7.72***	−5.49***	−7.68***	−7.27***
TRY_M2_M1	−8.44***	−8.73***	−6.23***	−9.28***	−8.58***
TRY_EXC	−7.23***	−7.25***	−6.58***	−7.22***	−7.20***

Note: ***, **, * indicate the statistical significance at 1, 5, and 10%, respectively.

VAR model. For NGN and MXN, the optimal lags for the VAR are more than 1, so their VEC model lag lengths are selected as 1 and 3, respectively. For TRY and IDR, the optimal lag length for the VAR model is 1. Hence, for TRY and IDR, the lags for cointegration testing and VECM are taken as 1.

We applied the Johansen (1988) cointegration test for stationary series BTC, M2_M1, and EXC for each country. Table 6 presents the cointegration test results, indicating that at least three cointegration equations are found in TRY, NGN, and IDR, and at least one cointegration equation is found for MXN.

5.3 Error Correction Model

We applied the VEC models to observe the long-term and short-term cointegration relationship between the variables. Figure 3 shows the graph of the unit root circle. We observed that all variables are within the unit root circle. We also performed a Portmanteau test to check the autocorrelation of the residuals, and the results show that the residuals of the IDR model are not autocorrelated. The test result is significant at 1%. Furthermore, the models for the other countries are also not autocorrelated, and the test results are significant at the 5% level. Since we aimed

Table 5: Optimal lag length select

	Lag/Crit.	0	1	2	3	4	Selected Lag
TRY	FPE	0.0000	0.0000*	0.0000	0.0000	0.0000	1
	AIC	−7.7968	−7.8693*	−7.6703	−7.6990	−7.4860	
	SC	−7.6947*	−7.4611	−6.9559	−6.6784	−6.1593	
NGN	FPE	0.0000	0.0000	0.0000*	0.0000	0.0000	2
	AIC	−5.6806	−5.8237	−5.9355*	−5.8013	−5.6644	
	SC	−5.5785*	−5.4155	−5.2212	−4.7808	−4.3377	
IDR	FPE	0.0000*	0.0000	0.0000	0.0000	0.0000	1
	AIC	−7.2702*	−7.1494	−6.9937	−7.0265	−7.0043	
	SC	−7.1681*	−6.7411	−6.2793	−6.0060	−5.6776	
MXN	FPE	0.0000	0.0000	0.0000	0.0000	0.0000*	4
	AIC	−9.2324	−9.2016	−9.0981	−9.1565	−9.2716*	
	SC	−9.1249*	−8.7715	−8.3454	−8.0812	−7.8737	

Note: ***, **, * indicates the statistical significance at 1, 5, and 10%, respectively.

Table 6: Johansen cointegration test statistics results

	Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical value	Prob.	Max-Eigen Statistic	0.05 Critical value	Prob.
TRY	None*	0.4654	94.9213	35.1928	0.0000	39.4494	22.2996	0.0001
	At most 1*	0.4280	55.4719	20.2618	0.0000	35.1907	15.8921	0.0000
	At most 2*	0.2752	20.2812	9.1645	0.0003	20.2812	9.1645	0.0003
NGN	None*	0.4034	66.1762	29.7971	0.0000	32.5380	21.1316	0.0008
	At most 1*	0.2969	33.6382	15.4947	0.0000	22.1886	14.2646	0.0023
	At most 2*	0.1662	11.4496	3.8415	0.0007	11.4496	3.8415	0.0007
IDR	None*	0.4969	110.3775	29.7971	0.0000	43.2759	21.1316	0.0000
	At most 1*	0.4639	67.1016	15.4947	0.0000	39.2815	14.2646	0.0000
	At most 2*	0.3570	27.8201	3.8415	0.0000	27.8201	3.8415	0.0000
MXN	None*	0.3682	39.7593	29.7971	0.0026	22.9560	21.1316	0.0274
	At most 1*	0.2008	16.8033	15.4947	0.0316	11.2075	14.2646	0.1441
	At most 2*	0.1059	55.9580	3.8415	0.0180	55.9580	3.8415	0.0180

*Rejection of the hypothesis No. of CE(s) at the 0.05 level.

to observe the long-run relationship of the BTC variable in the VEC models with the M2_M1 and EXC variables, we examined in particular the cointegrated equations in which the BTC is the dependent variable for all four countries' models (Tables 7 and 8).

The results obtained from the VEC models of Turkish Lira (TRY), Nigerian Naira (NGN), and Indian Rupee (IDR) indicate that the cointegration vector coefficients are significant, implying a long-term causal relationship between BTC, M2_M1, and EXC in these countries. This finding aligns

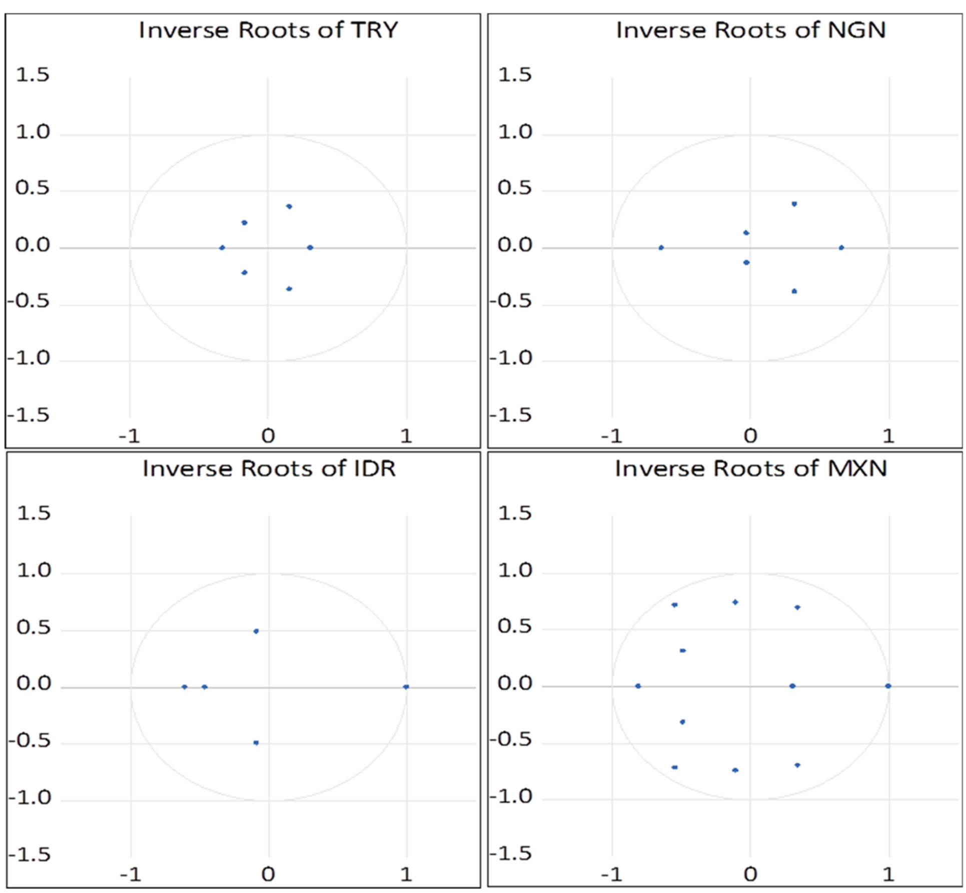

Figure 3: Unit root circle of AR.

Table 7: VECM statistics for TRY_BTC and NGN_BTC

VECM model for TRY (dependent: TRY_BTC)				VECM model for NGN (dependent: NGN_BTC)			
Cointegrating equation				**Cointegrating equation**			
Coint Eq.	Coefficient	*t*-statistics		Coint Eq.	Coefficient	*t*-statistics	
TRY_BTC(−1)	1.0000			NGN_BTC(−1)	1.0000		
TRY_M2_M1(−1)	85.6116	[6.2640]	***	NGN_M2_M1(−1)	30.9079	[2.5653]	**
TRY_EXC(−1)	−25.3352	[−5.1447]	***	NGN_EXC(−1)	−56.5631	[−4.8898]	***
C	−1.0076			C	−0.1622		
Error correction				**Error correction**			
Variables	**Coefficient**	***t*-statistics**		**Variables**	**Coefficient**	***t*-statistics**	
Coint Eq.	−0.1842	[−1.9579]	**	Coint Eq.	−0.0719	[−1.9519]	*
D(TRY_BTC(−1))	−0.3962	[−3.8600]	***	D(NGN_BTC(−1))	−0.0696	[−0.5511]	
D(TRY_M2_M1(−1))	11.4797	[2.2087]	**	D(NGN_M2_M1(−1))	2.4784	[1.6893]	*
D(TRY_EXC(−1))	−2.7571	[−1.6274]		D(NGN_EXC(−1))	−2.1499	[−1.2497]	
				C	−0.0144		
Model statistics				**Model statistics**			
R-squared	0.3923			*R*-squared	0.0872		
F-statistic	12.6934			*F*-statistic	1.3849		
Log likelihood	−37.9312			Log likelihood	−50.3377		
Akaike AIC	1.3312			Akaike AIC	1.7568		
Schwarz SC	1.4672			Schwarz SC	1.9268		
VEC residual portmanteau tests for autocorrelations				**VEC residual portmanteau tests for autocorrelations**			
Lags	*Q*-Stat	Prob.*		Lags	*Q*-Stat	Prob.*	
1	8.4069	—		1	7.4978	—	
2	18.0194	0.3228		2	18.6514	0.2300	

Note: ***, **, * indicate the statistical significance at 1, 5, and 10%, respectively.

with the existing literature on Bitcoin price, which also supports our findings. For example, Wang et al. (2023) found that Bitcoin price has a long-term effect on US money supply, Sarker and Wang (2022) established a co-movement between Bitcoin price and M2, and Othman et al. (2019) documented a long-run equilibrium relationship between cryptocurrency market capitalization and bank deposits. In the case of TRY, NGN, and IDR models, both the M2_M1 and EXC variables are significant. We observed a negative relationship between BTC and M2_M1, suggesting that investors shift between these two variables. This observation is consistent with previous literature findings for Bitcoin price; Sarker and Wang (2022) documented a unidirectional causal effect between Bitcoin price and money supply in the UK, while Narayan et al. (2019) and Wang et al. (2023) showed a negative interaction between Bitcoin price and money supply. Furthermore, the BTC and EXC appear to interact in the same direction. The depreciation of the US dollar in the world leads to an increase in Bitcoin yield; consequently, driving an increase in Bitcoin volume. However, the cointegration vector coefficient for MXN is found to be insignificant, suggesting that there is no long-term relationship between the variables for MXN.

Looking at the short-term interactions in Table 7, we observe the cointegration equation coefficient for TRY is −0.18, which is statistically significant. This indicates that a shock to the Turkish system reaches equilibrium after approximately 5.5 months. For NGN, the cointegration coefficient is −0.07, also statistically significant, suggesting that the system attains equilibrium after about 1 year for Nigeria. In the case of IDR, the cointegration coefficient is −1.1129 and statistically significant, indicating that the system finds its equilibrium in less than a month. However, the cointegration equation coefficient of MXN is not significant, implying the absence of a long-term relationship between the variables for Mexico.

5.4 Robustness Test

As part of the robustness test for TRY, NGN, and IDR, we also investigated the relationship between BTC and M2 with VEC models. Table 9 presents the results. The variables BTC and M2 are found to be cointegrated in the long

Table 8: VECM statistics for IDR_BTC and MXN_BTC

VECM model for IDR (dependent: IDR_BTC)				**VECM model for MXN (dependent: MXN_BTC)**			
Cointegrating equation				**Cointegrating equation**			
Coint Eq.	**Coefficient**	***t*-statistics**		**Coint Eq.**	**Coefficient**	***t*-statistics**	
IDR_BTC(−1)	1.0000			MXN_BTC(−1)	1.0000		
IDR_M2_M1(−1)	67.5786	[3.9470]	***	MXN_M2_M1(−1)	−34.8685	[−1.2533]	
IDR_EXC(−1)	−18.4980	[−2.3268]	**	MXN_EXC(−1)	43.4716	[4.7732]	***
C	−0.7371			C	−0.0668		
Error correction				**Error correction**			
Variables	**Coefficient**	***t*-statistics**		**Variables**	**Coefficient**	***t*-statistics**	
Coint Eq.	−1.1129	[−6.5410]	***	*Coint Eq.*	*0.0788*	*[1.3392]*	
D(IDR_BTC(−1))	0.1195	[0.9802]		D(MXN_BTC(−1))	−1.1570	[−6.5473]	***
D(IDR_M2_M1(−1))	35.6965	[3.3768]	***	D(MXN_BTC(−2))	−0.8236	[−3.9770]	***
D(IDR_EXC(−1))	−7.6637	[−1.6534]	*	D(MXN_BTC(−3))	−0.0844	[−0.5465]	
				D(MXN_M2_M1(−1))	4.8489	[1.0716]	
				D(MXN_M2_M1(−2))	−2.7602	[−0.5591]	
Model statistics				D(MXN_M2_M1(−3))	−1.5853	[−0.4112]	
R-squared	0.5300			D(MXN_EXC(−1))	−1.1543	[−0.5236]	
F-statistic	22.1798			D(MXN_EXC(−2))	−1.0903	[−0.6544]	
Log likelihood	−99.9535			D(MXN_EXC(−3))	−0.5412	[−0.4927]	
Akaike AIC	3.3001			C	−0.0107	[−0.2799]	
Schwarz SC	3.4362						
VEC residual portmanteau tests for autocorrelations				**Model statistics**			
Lags	*Q*-Stat	Prob.*		*R*-squared	0.7993		
1	7.4968	—		*F*-statistic	15.5277		
2	26.5073	0.0473		Log likelihood	0.6566		
				Akaike AIC	0.4137		
				Schwarz SC	0.8344		
				VEC residual portmanteau tests for autocorrelations			
				Lags	*Q*-Stat	Prob.*	
				1	1.4571	—	
				2	3.3497	—	
				3	7.9825	—	
				4	1.2018	0.6777	

Note: ***, **, * indicate the statistical significance at 1, 5, and 10%, respectively.

Table 9: BTC and M2 VECM robust statistics

VECM model BTC and M2 for TRY				**VECM model BTC and M2 for NGN**				**VECM model BTC and M2 for IDR**			
Cointegrating equation				**Cointegrating equation**				**Cointegrating equation**			
Coint Eq.	**Coef.**	***t*-statistics**		**Coint Eq.**	**Coef.**	***t*-statistics**		**Coint Eq.**	**Coef.**	***t*-statistics**	
BTC(−1)	1.0000			BTC(−1)	1.0000			BTC(−1)	1.0000		
TRY_M2(−1)	1.1594	[0.4930]		NGN_M2(−1)	79.1301	[4.6520]	***	IDR_M2(−1)	87.2433	[4.9471]	***
C	−0.1440			C	−1.0018			C	−1.0562		
Error correction				**Error correction**				**Error correction**			
Variables	**Coef.**	***t*-statistics**		**Variables**	**Coef.**	***t*-statistics**		**Variables**	**Coef.**	***t*-statistics**	
Coint Eq.	−0.8597	[−6.4637]	***	Coint Eq.	−0.1557	[−2.8086]	***	Coint Eq.	−0.9191	[−5.6799]	***

Note: ***, **, * indicate the statistical significance at 1, 5, and 10%, respectively.

run. For the three countries mentioned, the cointegration coefficient is significant and negative, indicating a long-run relationship between the variables. For NGN and IDR, there is a significant long-run inverse relationship between BTC and M2. For TRY, the coefficient becomes statistically insignificant, although the direction of the relationship is reversed. Thus, our results are robust.

6 Conclusion

This study provides valuable insights into the understanding of the role of Bitcoin as a potential substitute currency and its impact on the monetary and banking systems of MINT countries. The study investigates the correlation between Bitcoin volume and term deposits from 2016 to 2021, using cointegration and error correction models to analyze both long- and short-term relationships. Our findings indicate a negative relationship between Bitcoin volume and term deposits in all the MINT countries, except Mexico. This suggests that individual investors in economically and financially unstable countries are increasingly turning to Bitcoin as an alternative investment option.

While the observed effects may be modest at present, the rise of decentralized cryptocurrencies poses potential threats to the monetary systems of emerging markets. The shift of investments from traditional term deposits to Bitcoin may affect the stability of the banking industry, as deposits are an important source of income for banks. As a result, their ability to lend may be constrained, affecting overall economic growth.

In terms of policy implications, we recommend that monetary policymakers explore strategies to integrate cryptocurrencies into the financial system. This integration could help mitigate the risks posed by decentralized digital assets and contribute to a more stable and resilient monetary framework. Another significant implication of this research is for the banking industry itself. With the emergence of cryptocurrencies and central bank digital currencies, the traditional concept of financial intermediation may need to be redefined. The growing presence of cryptocurrencies could reshape the landscape of the banking industry, requiring innovative approaches and adaptations to remain relevant and competitive. Future research could explore the currency substitution effect of alternative cryptocurrencies and investigate the integration of cryptocurrencies into the quantity theory of money to gain a deeper understanding of their role in the monetary system.

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