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Flip the Coin: Heads, Tails or Cryptocurrencies?

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Abstract: This paper analysis and compares the volatility of seven cryptocurrencies – Bitcoin, Dogecoin, Ethereum, BitcoinCash, Ripple, Stellar and Litecoin – to the volatility of seven centralized currencies – Yuan, Yen, Canadian Dollar, Brazilian Real, Swiss Franc, Euro and British Pound. We estimate GARCH models to analyze their volatility. The results point to a considerably high volatility of cryptocurrencies when compared to that of centralized currencies. Therefore, we conclude that cryptocurrencies still fall far short of fulfilling all the requirements to be considered as a currency, specifically regarding the functions of store of value and unit of account.

Keywords: centralized currencies; cryptocurrencies; GARCH models; volatility.

JEL classification: E51; G12; G15; G17; G23.

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1. INTRODUCTION

Cryptocurrencies – especially the most famous one, the Bitcoin – are very popular and are a controversial topic in the economic literature nowadays (Kristoufek, 2013; Yermack, 2013; Baur *et al.*, 2018; Aalborg *et al.*, 2019; Cagli, 2019; Makarov & Schoar, 2020; BIS, 2021). Cryptocurrencies use to buy goods and services is increasing and they are becoming an important medium of exchange. However, they are far from assuming all the functions inherent to the centralized currencies, especially the unit of account and store of value. The main reasons for that is their high level of price volatility and their speculative nature (Cheah & Fry, 2015; Dyhrberg, 2016; Blau, 2017; Katsiampa, 2019a; Tiwari *et al.*, 2020) as well as the fact that the cryptocurrencies are associated with illegal activities (Aldridge & Askew, 2017; Durrant, 2018; Choi *et al.*, 2020; Cuervo *et al.*, 2020).

Since the creation of Bitcoin in 2008 (Nakamoto, 2008), cryptocurrencies are seen as an alternative investment, especially in periods of crisis, which can indicate that they may assume the function of store of value or even unit of account. However, the excessive price volatility is a problem and without its elimination, the fulfillment of these functions will be impossible.

This paper analyzes the volatility of seven cryptocurrencies (Bitcoin, Dogecoin, Ethereum, BitcoinCash, Ripple, Stellar and Litecoin), compared to the volatility of seven centralized currencies from different economic backgrounds (Yuan, Yen, Canadian Dollar, Brazilian Real, Swiss Franc, Euro, and Pound Sterling).

Regarding the methodology, we estimate Generalized AutoRegressive Conditional Heteroskedasticity (GARCH) models. Our results point to the existence of strong volatility cryptocurrencies' returns, in line with other papers (Yermack, 2013; Balcilar *et al.*, 2017; Yi *et al.*, 2018; Bouri *et al.*, 2019; Katsiampa, 2019b; Katsiampa *et al.*, 2019; Kumar & Anandarao, 2019; BIS, 2021). The volatility of cryptocurrencies is significantly higher than the volatility of currencies. For that reason, cryptocurrencies will have a hard time being considered a measure of value and a standard of value. For now, they can only fulfill the function of means of payment. This paper gives an additional value to the economic literature because it compares several cryptocurrencies against various currencies from different economic and geographic areas with distinct dynamics. To best of our knowledge this is the first time that the volatility of cryptocurrencies and currencies is compared. Therefore, we contribute empirically to the debate around the role of the cryptocurrencies, in the line of Eichengreen (2019).

The paper has five sections. Section 2 presents a brief literature review. Section 3 is dedicated to describing the data and the methodology. Section 4 presents and discusses the main results. Finally, Section 5 draws the conclusions.

2. LITERATURE REVIEW

We live in a world of fiat money since the development of societies led to an evolution of the concept of money, the most recent being digital money. Commodity money was the first concept in the primitive economies. Later, representative currency appeared. Nowadays, we have fiat money, which is legal and is issued and controlled by central banks – the euro, for example, issued by the European Central Bank (ECB). Fiat money exists in physical forms (banknotes and coins), and bank deposits (a computer record). There are even countries in Europe (e.g. Netherlands and Sweden) where electronic payments are superior to cash payments because they are more convenient, safer, and cheaper. Recently, cryptocurrencies appeared, the most famous being the Bitcoin. They are not supervised by any regular entity or central bank (Spahn, 2001; Helleiner, 2002; McLeay *et al.*, 2014; Eichengreen, 2019; BIS, 2021).

Jevons (1896) defined three functions that an asset must satisfy in order to be considered money. First, it must be means of payment. This function allows for saving time and reducing transaction costs. Another function is unit of account (it makes possible to compare prices of goods and services, as well as assign them a value). Last but not least, money need to be store of value over time. Economic agents should be able to use a currency for investments, as well as preserve their purchase power.

Despite these three functions that an asset must satisfy to be considered a currency, Hazlett and Luther (2020) are convinced that what matters is whether the asset is accepted by the economic agents. On this point, the world of cryptocurrencies, with an ascending acceptance and use, seems to be gaining ground in replacing currencies in the near future. Nevertheless, at best, cryptocurrencies are only an imperfect substitute for currencies.

The first cryptocurrency considered successful, with the highest capitalization index and the most users on social media and online exchange offices, was Bitcoin, created by Nakamoto (2008). This cryptocurrency resolves a potential problem associated with digital currencies, the double-spending problem. It consists of the lack of a mechanism that prevents the user from using the digital currency for more than one payment (Bação *et al.*, 2018). Bitcoin is a peer-to-peer mechanism and because of its algorithm and the cryptography used in Blockchain, this problem does not exist. This cryptocurrency is traded without the intermediation and supervision of any monetary authority. The transactions are verified by each user and, at the same time, are recorded on Blockchain, which is publicly available (Duarte *et al.*, 2018). Each transaction creates a new block that is connected to the previous transaction. In each block a new code that identifies the transaction is created, called hash, which is also connected to the previous code, called previous hash.

Compared to other cryptocurrencies, Bitcoin has a particularity, its offer is limited to 21 million units. Nowadays, 18 million Bitcoins are in circulation. While the Central Banks have the monopoly of creating money and can control their offer with monetary policies, this does not happen in the cryptocurrency world. This eliminates the possibility of inflationary processes. On the contrary, deflation is more likely.

Despite this advantage, the lack of monetary policy drives the cryptocurrencies out of the realm of currencies. Yermack (2013) highlights the high volatility of Bitcoin and cryptocurrency in general, which can jeopardize the possibility of their being affirmed as a currency. Other authors (Fink & Johann, 2014; Cheah & Fry, 2015; Dyhrberg, 2016; Blau, 2017; Katsiampa, 2019b; Tiwari *et al.*, 2020) empirically confirm this reality, as well as its speculative nature, which does not contribute to the possibility of cryptocurrencies fulfilling the functions of measure and standard of value.

Regarding the measure of value Wallace (2011) mentions the episode of the first purchase of goods through Bitcoin on the 21st of May 2010. Two pizzas were bought for 10,000 Bitcoins which equaled 25 dollars at the time. Today, at the current price of Bitcoin, this purchase would represent more than 500 million dollars. Therefore, cryptocurrencies will have a hard time functioning as a measure of value and standard of value, due to their price instability.

Recently, Hazlett and Luther (2020) point out that since Bitcoin is frequently used as a medium of exchange that can be enough to consider it a currency. Some countries have already accepted Bitcoin (e.g., El Salvador) as a medium of exchange.

The increase in the use of cryptocurrencies as a medium of exchange, with the lack of financial regulation, results in associating their use with criminal activities, such as money laundering, drug or gun trafficking[1]. Cryptocurrencies payments are similar to Cash payments. They use a decentralized system without visible intermediates and allow anonymous transactions, and for that reason, they are often related to illegal activities (Durrant, 2018; Swammy *et al.*, 2019; Choi *et al.*, 2020; Cuervo *et al.*, 2020; BIS, 2021; Hendrickson & Luther, 2021).

However, as Steinmetz *et al.* (2021) mentions, this association is made by those who know little about cryptocurrencies. The fact that every transaction is recorded in the Blockchain discourages or even prevents the use of cryptocurrencies for illicit activities since it is possible to know who is involved. According to Pacheco (2018), only 1% of all transactions of Bitcoin relate to illegal activities. However, about 3 to 5% of the fiat money economy results from illicit activities.

The impact that cryptocurrencies have been having on the global economy is high. Nowadays there are more than 6,500 cryptocurrencies in circulation, according to CoinMarketCap[2]. Most central banks have warned about the increase in using cryptocurrencies and their legality, in particular, for the possibility of using them for corruption. Gonzálvez-Gallego and Pérez-Cárceles (2021) believe that using cryptocurrencies should be promoted and not dismissed as long as there are policies that control their use. However, that is a bit ironic: if policies existed, it would no longer be a decentralized system. The authors also mention that the governments need to promote stable financial institutions, because that alone would prevent people from choosing cryptocurrencies instead of currencies. We must keep in mind that the cryptocurrency phenomenon began due to the instability caused by the financial crisis of 2008.

Another option is the creation of centralized cryptocurrencies (BIS, 2021; Auer *et al.*, 2022).This hypothesis is being considered by many central banks, such as the ECB, the Bank of England, and the Central Bank of Sweden, which propose their own digital coins, the Central Bank Digital Currencies (CBDC). The U.S. Federal Reserve is still considering how CBDC may fit into the U.S. money and payments landscape (Board of Governors of the Federal Reserve System, 2022).

The Central Bank of Sweden, Riksbank, although the oldest in Europe, is the first one in the race to create a CBDC, the eKrona. This project is still in a pilot phase, studying what effects this digital currency would have on the economy and Sweden's laws, as well as what the best model would be for its creation (Sveriges, 2021). The goal is that eKrona could work as a complement to physical money and have a system of use accessible to the entire population. It should be noted (Duarte, 2022) that the launch of this project was driven by the increasing dematerialization of money in Sweden, a fact that the central bank believes could result in situations of marginalization, with a user wanting to pay in physical money and the seller no longer accepting it.

Like Sweden's case, China is also in the race to develop a digital currency. According to the BBC[3], cryptocurrency transactions are forbidden in this country since 2019. Still, according to Forbes[4], China intends to create its own digital currency that is supervised and centralized, going against the initial concept of what a cryptocurrency is (BIS, 2021; Goodell & Al-Nakib, 2021; Lee *et al.*, 2021).

Despite the announcement of these pilot projects, the Bahamas was the first country to effectively launch a global CBDC, called the “Sand dollar”, in October 2020. In February 2021, the United Arab Emirates joined China, Hong Kong, and Thailand in a joint cross-border CBDC to test the use of Distributed Ledger Technology (DLT) for foreign currency payments.

The UK, Japan and the ECB are also considering their entry into digital currencies. The digitization of central bank currencies is in fact a global rapidly growing process, particularly in the euro area. It is expected that the launch of a digital euro will revolutionize the lives of all European economic agents through the changes it will introduce in their lives, and in the way payments are made in the future (Duarte, 2022).

The digital euro project was announced by the ECB in July 2021, right in the middle of the Covid-19 pandemic. This does not mean, however, that the ECB will necessarily issue a digital euro immediately, but rather that it will get ready to possibly issue it in the near future, considering any changes in the European legislation that may have to be made. As mentioned by the ECB[5], a digital euro will guarantee that agents in the euro area can maintain cost-free access to a simple, universally accepted, safe and trusted means of payment. The digital euro will still be a euro, like banknotes and coins, but digital, turning the euro area into a global digital player. It will be an electronic form of money issued by the ECB and national central banks and accessible to all economic agents. A digital euro will not replace cash, but rather complement it. The Eurosystem will continue to ensure that European citizens would have access to cash across the euro area, giving them an additional option for making payments, thus contributing to greater accessibility and inclusion in the European financial space. Using a digital euro, agents could have the same level of confidence as with bank currencies, since they would be both backed by the monetary authority. A digital euro would consequently become a digital symbol of progress and integration in Europe[6].

3. DATA AND METHODOLOGY

This paper analyzes the volatility of seven cryptocurrencies (Bitcoin, Dogecoin, Ethereum, BitcoinCash, Ripple, Stellar and Litecoin), compared to the volatility associated with money, specifically Yuan (CNY), Yen (JPY), Canadian Dollar (CAD), Brazilian Real (BRL), Swiss Franc (CHF), Euro (EUR) and Pound Sterling (GBP). These currencies belong to different monetary and geographic areas, thereby allowing a more robust analysis. The data consists of the daily prices of both, cryptocurrencies and currencies.

The cryptocurrency data was collected from the Coindesk site (https://www.coindesk.com/, accessed November 6th, 2021), and refers to the closing prices in American dollars (USD). For each currency, we considered the daily exchange rates in USD. This data was collected from the Federal Reserve Bank of Saint Louis (https://www.stlouisfed.org/, accessed November 6th, 2021).

For each variable, we tried to collect the greatest number of observations possible. Table no. 1 shows the data available (initial observation and final) for the seven cryptocurrencies.

Table no. 1 – Cryptocurrencies (initial observation and final observation)

Criptocurrency	Initial Observation	Final Observation
Bitcoin (BTC)	03/11/2014	05/11/2021
Dogecoin (DOGE)	27/02/2019	05/11/2021
Ethereum (ETH)	16/12/2016	05/11/2021
BitcoinCash (BCH)	01/02/2018	05/11/2021
Ripple (XRP)	01/06/2018	05/11/2021
Stellar (XLM)	01/12/2018	05/11/2021
Litecoin (LTC)	01/02/2018	05/11/2021

Source: authors, using CoinDesk (2021, accessed November 6th, 2021)

The cryptocurrency with the lowest number of observations is Dogecoin (DOGE), with an initial observation only on 27/02/2019. For that reason, in this study the period of analysis starts in that date, in order to have a fair and comparative analysis. The period of the analysis extends from 27/02/2019 to 05/11/2021, which gives us a significant number of observations, since we are working with high-frequency data. It is important to note that the cryptocurrency market functions daily, while the currency market is only available on workdays. Figures no. 1 and no. 2 illustrate the evolution of the daily prices of cryptocurrencies and exchange rates in USD, respectively.

Looking at Figure no. 1, we observe a general growth in the prices of cryptocurrencies since the beginning of 2021. After May 2021, there was a significant increase in almost every cryptocurrency. Bitcoin (BTC) clearly has the highest prices compared to the other cryptocurrencies, presenting its highest value on October 26th, 2021, when one BTC was worth 63.081,80 dollars. In contrast, we have Dogecoin (DOGE), with the lowest prices. The highest price was reached on May 8th, 2021, with a value of 0.72 dollars per unit.

As for the seven currencies (Figure no. 2), they do not present significant changes in their exchange rate. Still, some currencies, for example, the Brazilian Real (BRL) show a high depreciation, in particular since January 2020. In contrast, we have the Yuan (CNY), which, since May 2020, has shown a significant trend of appreciation. In both cases, the relative volatility of these currencies is low, which naturally gives them an advantage compared to cryptocurrencies in being considered a measure of value and a standard of value.

Since the main focus of this paper is to analyze the volatility of the cryptocurrencies and comparing it with the volatility of the chosen currencies, following e.g., Bouri *et al.* (2019); Katsiampa (2019b); Kumar and Anandarao (2019) we started by computing the return (the first difference of the logarithm).

The econometric model that is used to study the volatility of the series of our study is the Generalized AutoRegressive Conditional Heteroskedasticity (GARCH), developed by Robert Engle (Engle, 1982; Bollerslev, 1986). The ARCH/GARCH models are frequently used to model financial time series that show clusters of volatility over time. There are periods with high instability alternating with stable periods.

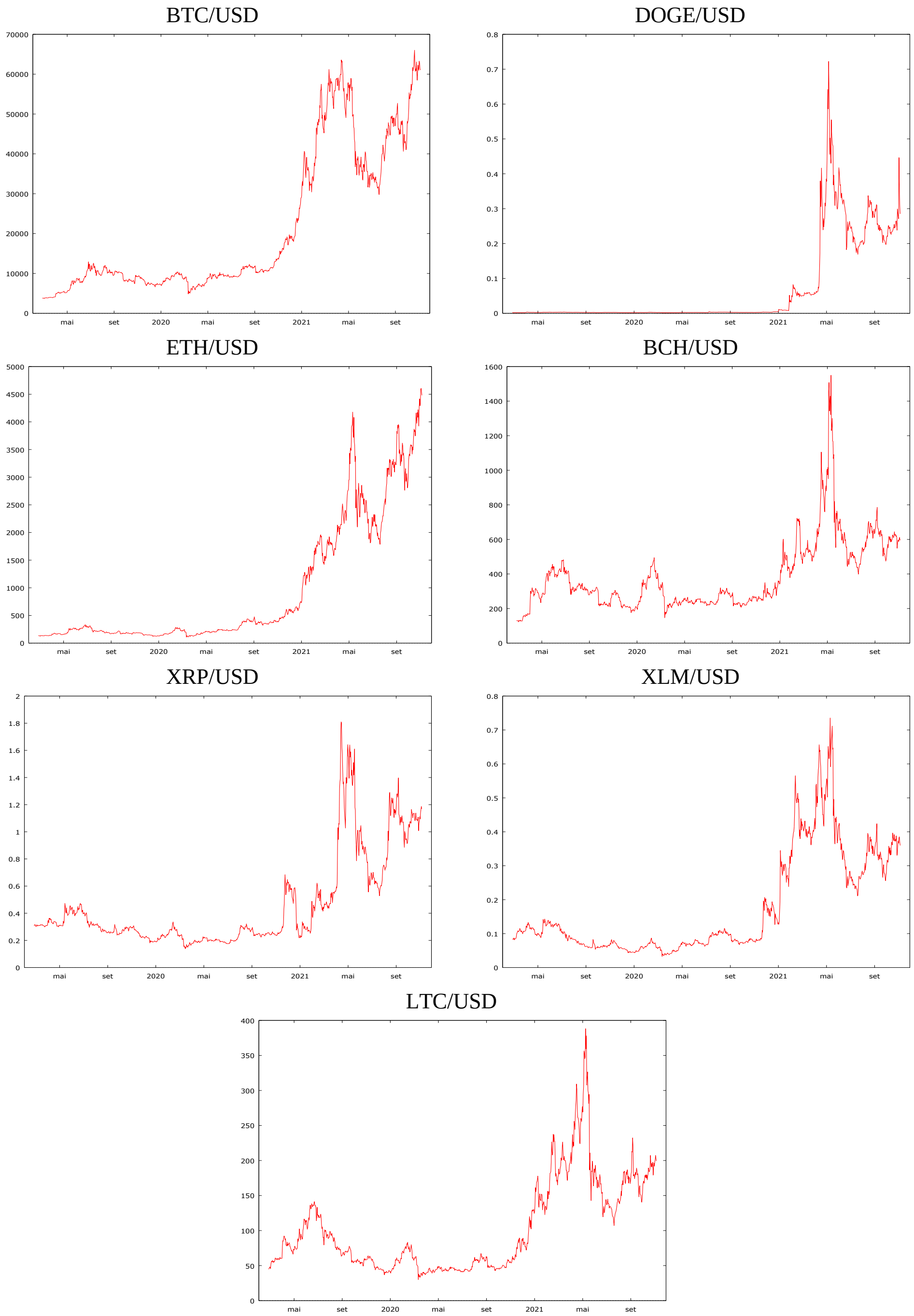

Figure no. 1 – Cryptocurrency daily prices in USD
Source: authors, using CoinDesk (2021, accessed November 6th, 2021)

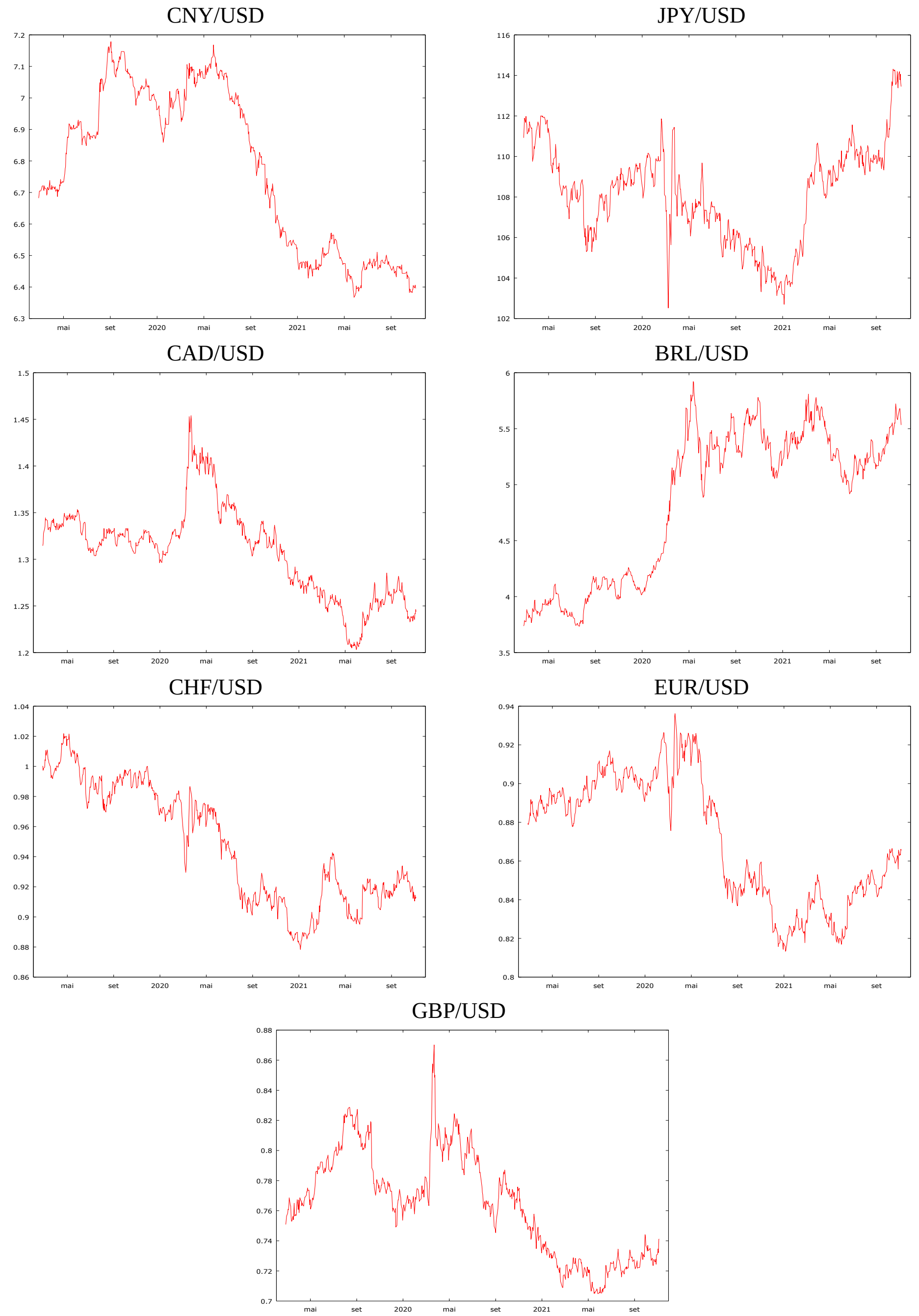

Figure no. 2 – Daily exchange rates in USD

Source: authors, using Federal Reserve Bank of Saint Louis (2021, accessed November 6th, 2021)

The estimated models (using the program GRETL) follow the formulation:

$$Y_t = a_0 + \varepsilon_t \tag{1}$$

where Y_t represents each series of volume and return and ε_t follows a process of type:

$$\varepsilon_t = z_t \sigma_t \tag{2}$$

with $z_t \sim i.i.d.(0,1)$ and σ_t follows a process of type $GARCH(p,q)$:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 \tag{3}$$

where $\omega \geq 0, \alpha_i \geq 0$ e $\beta_i \geq 0$.

The selection of the GARCH model aims to determine the autoregressive component (p) and the coefficient of the error terms (q). Next, we present the results of the estimation of GARCH models for the series of both cryptocurrencies and currencies.

4. MONEY AND CRYPTOCURRENCIES: A VOLATILITY ANALYSIS

We will analyze the descriptive statistics, the stationarity, and the volatility of the returns of cryptocurrencies and currencies. Figures no. 3 and no. 4 show the behavior of the returns of cryptocurrencies and the seven currencies in USD, respectively. The figures presented suggest the existence of periods with high and persistent volatility, alternating with periods with low volatility. In the particular case of cryptocurrencies, there are clearly peaks that can translate into phases of high instability.

Tables no. 2 and no. 3 document the descriptive statistics and statistical tests for cryptocurrency and exchange rate daily returns for the entire sample period[7].

Table no. 2 – Descriptive statistics and statistical tests for cryptocurrency daily returns for the entire sample period

	d_l_BTC	**d_l_DOGE**	**d_l_ETH**	**d_l_BCH**	**d_l_XRP**	**d_l_XLM**	**d_l_LTC**
Mean (%)	0.2828	0.508	0.3573	0.1551	0.136	0.1487	0.1518
Median (%)	0.2265	-0.0502	0.2702	0.2024	-0.0438	0.1545	0.0777
Minimum (%)	-49.03	-47.206	-58.166	-60.055	-45.028	-42.347	-47.592
Maximum (%)	17.775	115.28	23.407	42.553	36.964	57.835	25.931
Std. Dev. (%)	4.1432	8.6672	5.2698	6.2305	5.793	6.1894	5.5944
C.V.	14.653	17.063	14.751	40.163	42.609	41.648	36.861
Skewness	-1.5664	4.7489	-1.5658	-0.6481	0.066	0.7796	-1.0985
Excess kurtosis	21.67	52.986	18.026	16.957	10.871	13.967	11.493
ADF Test Statistics							
Without Constant	-14.55***	-16.28***	9.19***	-14.38***	-22.42***	-32.87***	-14.41***
With Constant	-14.73***	-16.38***	-9.44***	-14.39***	-22.43***	-32.87***	-14.43***
KPSS Tests Statistics							
Without Trend	0.09	0.27	0.19	0.05	0.11	0.11	0.08
With Trend	0.09	0.09	0.05	0.05	0.02	0.06	0.07
ARCH-LM Test Statistics (various lags)							
LM (5)	8.55	122.96***	24.16***	17.04***	46.99***	22.85***	35.91***
LM (10)	12.55	127.79***	27.54***	26.07***	48.33***	25.66***	48.11***

Notes: "Std. Dev." is the standard deviation. "C.V." is the coefficient of variation. For the ADF and KPSS tests, the number of lags is defined according to the Akaike (AIC) information criteria. "*", "**" and "***" stand for the 10%, 5% and 1% statistical significance levels, respectively; "d" identifies the first difference of the series. "l" is the logarithm of the variable.

Source: authors, using CoinDesk (2021, accessed November 6th, 2021)

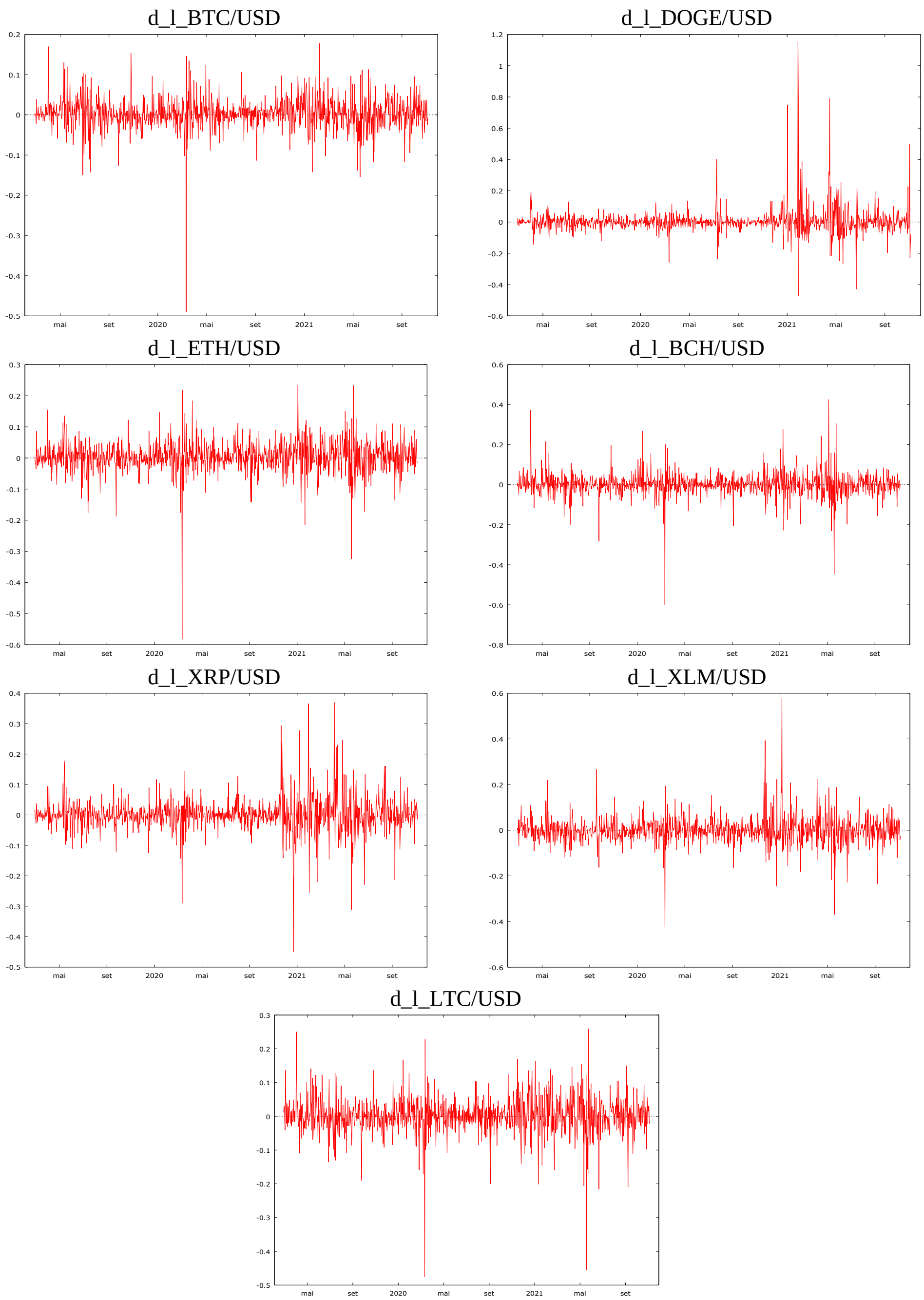

Figure no. 3 – Cryptocurrency daily returns in USD

Notes: "d" identifies the first difference of the series. "l" is the logarithm of the variable

Source: authors, using CoinDesk (2021, accessed November 6th, 2021)

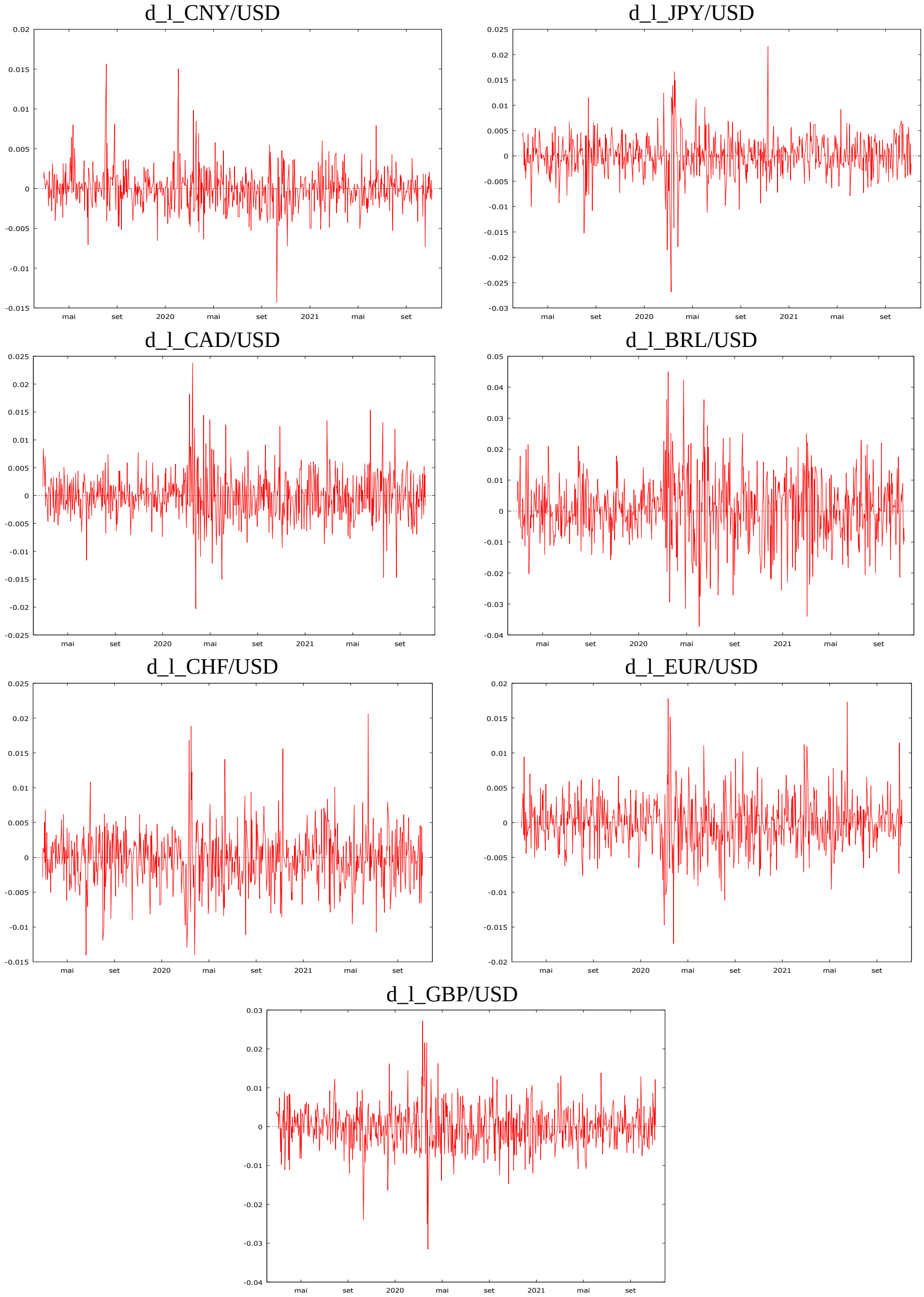

Figure no. 4 – Exchange rate daily returns in USD

Notes: "d" identifies the first difference of the series. "l" is the logarithm of the variable

Source: authors, using Federal Reserve Bank of Saint Louis (2021, accessed November 6th, 2021)

Analyzing the descriptive statistics of the logarithmic rates of change of the cryptocurrencies (Table no. 2), DOGE presents the highest average return, followed by ETH and BTC. This result was not expected. Due to the popularity of the BTC, it was expected that among the seven cryptocurrencies, it would present the highest average return, which does not happen. This may be explained by the low variation in prices of BTC compared to the other cryptocurrencies. Nevertheless, BTC presents an average return twice as high as XRP and XLM, which is something to keep in mind when looking at cryptocurrencies as speculative investments. BitcoinCash (BCH) and Litecoin (LTC) are the cryptocurrencies with the lowest average return, presenting almost the same results.

Table no. 3 – Descriptive statistics and statistical tests for exchange rate daily returns for the entire sample period

	d_l_CNY	d_l_JPY	d_l_CAD	d_l_BRL	d_l_CHF	d_l_EUR	d_l_GBP
Mean (%)	-0.0062	0.0032	-0.0079	0.0559	-0.013	-0.0023	0.0018
Median (%)	0	0.0091	-0.0076	0.0632	-0.0103	-0.0089	-0.0093
Minimum (%)	-1.4285	-2.685	-2.0298	-3.7261	-1.4054	-1.7384	-2.7216
Maximum (%)	1.5644	2.1638	2.375	4.4981	2.0597	1.7799	3.1547
Std. Dev. (%)	0.2409	0.3988	0.4172	1.0307	0.3938	0.3673	0.549
C.V.	38.643	124.12	53.055	18.439	30.385	160.62	298.61
Skewness	0.653	-0.4011	0.3871	0.0016	0.3289	0.298	0.0911
Excess kurtosis	6.9366	6.232	3.6961	1.369	2.8159	2.9889	3.8641
ADF Test Statistics							
Without Constant	-28.52***	-8.21***	-14.93***	-17.34***	-12.31***	-23.06***	-11.35***
With Constant	-28.52***	-8.22***	-14.93***	-17.39***	-12.36***	-23.04***	-11.35***
KPSS Tests Statistics							
Without Trend	0.51**	0.15	0.11	0.11	0.05	0.1	0.09
With Trend	0.15**	0.02	0.05	0.05	0.03	0.1	0.06
ARCH-LM Test Statistics (various lags)							
LM (5)	4.83	101.77***	43.77***	81.04***	21.62***	51.65***	114.36***
LM (10)	5.22	147.28***	135.19***	94.21***	35.6***	84.21***	138.77***

Notes: "Std. Dev." is the standard deviation. "C.V." is the coefficient of variation. For the ADF and KPSS tests, the number of lags is defined according to the Akaike (AIC) information criteria. "*", "**" and "***" stand for the 10%, 5% and 1% statistical significance levels, respectively; "d" identifies the first difference of the series. "l" is the logarithm of the variable.

Source: authors, using Federal Reserve Bank of Saint Louis (2021, accessed November 6th, 2021)

Focusing on the standard deviation, it points out the high level of volatility of the returns (Table no. 2) connected to cryptocurrencies, with particular emphasis on the volatility of DOGE, BCH e XLM. Bitcoin is the cryptocurrency with the lowest level of volatility.

On the other hand, analyzing the descriptive statistics of the logarithmic rates of change in the exchange rates (Table no. 3), we can see with some surprise that the highest medium return belongs to BRL. This result can be explained by the high volatility of this currency during the period in analysis, which is still significantly lower when compared to the volatility of the other seven cryptocurrencies mentioned earlier. In contrast, the Swiss franc (CHF), the Canadian dollar (CAD), and the yuan (CNY) have the lowest medium returns, even presenting negative values. CNY, EUR, CFH, and JPY have the most stable behavior (the lowest standard deviations), which was expected, since they have such an important role as international reserve currencies. Curiously, of the seven currencies that were studied and belonged to different monetary and geographic areas, the Pound Sterling (GBP), after BRL, is the one that shows the highest volatility. We can interpret this result by the loss of importance of the Britain currency as a unit of account and international store of value, due to the BREXIT.

Comparing Tables no. 2 and no. 3, we observe that the mean of returns of all currencies is significantly lower than the mean of returns of cryptocurrencies. We can also clearly see the high discrepancy of their standard deviation values, with cryptocurrencies presenting much higher volatility than currencies. Even the highest standard deviation value of currencies (1.0307 of BRL) is significantly lower than the lowest standard deviation value of cryptocurrencies (4.1432 of BTC). This result empirically confirms the difficulty that cryptocurrencies will have in assuming the functions of unit of account and store of value in the near future.

For the analysis of the stationary characteristics of the series, we ran two tests, a test of unit root, the Augmented Dickey-Fuller (Dickey & Fuller, 1979) - ADF - and a stationary one, Kwiatkowski-Phillips-Schmidt-Shin (Kwiatkowski *et al.*, 1992) - KPSS. As we can see, every series are I(0). We can proceed with the study of volatility.

The methodology used to study the volatility of the cryptocurrency returns and exchange rates was the GARCH model. The LM test does not reject the null hypothesis of ARCH effects on Bitcoin and Yuan (see again Tables no. 2 and no. 3). In this case, we expect that the optimum model only has variance lags. For the remaining cases, it will be a GARCH model. In the process of choosing the best model, the information criteria of Schwarz-BIC (Schwarz, 1978) was used, as we can see in Table no. 4.

The numbers in bold in Table no. 4 identify the chosen model. After selecting the most appropriate GARCH model for each series, we analyzed the unconditional variance of each model. Tables no. 5 and no. 6 present the results of the estimates of the selected models for the cryptocurrencies and the exchange rates, respectively.

Table no. 4 – (G)ARCH model selection

(G)ARCH (*p*,*q*) model selection Schwarz (BIC) information criteria						
	(0,1)	(0,2)	(1,1)	(1,2)	(2,1)	(2,2)
d_l_BTC	-3450.232	-3446.625	-3489.033	-3491.084	a	**-3509.871**
d_l_DOGE	b	**-2678.794**	b	b	b	b
d_l_ETH	-2982.069	-2986.311	-3075.275	-3074.848	a	**-3082.319**
d_l_BCH	-2659.053	-2668.585	**-2745.068**	-2738.418	a	a
d_l_XRP	-2998.355	-3027.558	-3086.216	b	**-3094.440**	a
d_l_XLM	-2784.267	-2816.023	**-2849.884**	-2840.674	-2844.176	-2836.228
d_l_LTC	-2879.011	-2875.415	**-2935.018**	-2929.011	a	-2926.342
	(0,1)	(0,2)	(1,1)	(1,2)	(2,1)	(2,2)
d_l_CNY/USD	b	b	**-6459.048**	a	-6455.156	a
d_l_JPY/USD	-5828.954	-5827.362	**-5865.031**	-5858.285	-5859.034	-5852.438
d_l_CAD/USD	-5705.541	-5724.915	**-5773.718**	-5767.464	-5767.163	-5766.025
d_l_BRL/USD	b	-4458.165	**-4496.329**	-4490.367	-4489.770	-4485.982
d_l_CHF/USD	**-5794.890**	-5788.760	-5789.775	-5782.537	-5787.542	-5777.204
d_l_EUR/USD	b	-5875.617	**-5923.988**	-5917.693	a	a
d_l_GBP/USD	-5328.610	-5381.250	**-5398.501**	-5394.213	-5391.836	-5387.770

Notes*:* The letters *a* and *b* identify errors. In the case of the letter *a*, the matrix is not positively defined, and, in the case of the letter *b*, the norm of gradient exceeded the maximum of 5. X/USD represents the exchange return of the currencies in comparison to USD. "d" identifies the first difference of the series. "l" is the logarithm of the variable.

Source: authors, using CoinDesk (2021, accessed November 6th, 2021) and data from Federal Reserve Bank of Saint Louis (2021, accessed November 6th, 2021)

Table no. 5 – Parameter estimates of daily cryptocurrency returns for selected optimal (G)ARCH models

	BTC	DOGE	ETH	BCH	XRP	XLM	LTC
a_0	0.00325***	0.007***	0.0045***	0.0021	-0.0003	-0.0004	0.0024
ω	0.0003***	0.0017***	0.00049**	0.0003***	0.0005***	0.0005***	0.0002***
α_1	0.0257*	0.913***	0.0464	0.113***	0.559***	0.353***	0.0906***
α_2	0.224***	0.086***	0.1979**	-	-	-	-
β_1	0.0029	-	3.55e-12	0.822***	0.191***	0.577***	0.8493***
β_2	0.596***	-	0.594**	-	0.222***	-	-
LR ratio test for (G)ARCH terms							
	91.103***	695.83***	135.94***	120.118***	327.079***	205.636***	92.241***
Unconditional Variance							
	2.13e-03	2.96e+09	3.07e-03	4.66e-03	1.89e-02	7.50e-03	3.40e-03

Source: authors, using CoinDesk (2021, accessed November 6th, 2021)

Table no. 6 – Parameter estimates of daily exchange rate returns for selected optimal (G)ARCH models

	CNY	JPY	CAD	BRL	CHF	EUR	GBP
a_0	-0.00011	0.0001	0.0000959	0.00037	-0.00011	0.000054	-0.000063
ω	0.0000006	0.000001***	0.0000005**	0.0000019*	0.000011***	0.0000006**	0.000004***
α_1	0.0501***	0.1078***	0.0752***	0.0794***	0.2824***	0.0678***	0.1639***
α_2	-	-	-	-	-	-	-
β_1	0.834***	0.775***	0.891***	0.903***	-	0.8856***	0.707***
β_2	-	-	-	-	-	-	-
LR ratio test for (G)ARCH terms							
	18.806***	132.516***	104.716***	97.094***	38.384***	76.115***	114.872***
Unconditional Variance							
	5.87e-06	1.42e-05	1.66e-05	1.13e-04	1.60e-05	1.30e-05	2.86e-05

Source: authors, using Federal Reserve Bank of Saint Louis (2021, accessed November 6th, 2021)

The unconditional variance points out the volatility of each series or its variance in the long term. The results show that the return of cryptocurrencies it is more volatile when compared to the exchange rate return. In particular, Dogecoin (DOGE) is the cryptocurrency that presents the highest value, while Bitcoin (BTC) has the lowest. Focusing on the exchange rate, Yuan (CNY) presents the lowest volatility and the Brazilian Real (BRL) the highest. Even though the Brazilian Real has the highest volatility, the volatility of cryptocurrencies is substantially higher, confirming the idea that they cannot replace the currencies.

The results are in line with some papers on the same topic (Yermack, 2013; Balcilar *et al.*, 2017; Yi *et al.*, 2018; Bouri *et al.*, 2019; Katsiampa, 2019b; Katsiampa *et al.*, 2019; Kumar & Anandarao, 2019; BIS, 2021) that used similar methodologies.

Regarding the volatility of the cryptocurrencies, we can state that, although we are in the presence of an admirable world of cryptocurrencies, the volatility of their returns is very high. That being said, the cryptocurrencies will have a hard time replacing the currencies, if they ever do.

5. CONCLUSION

This paper aimed to study the volatility of seven main cryptocurrencies (Bitcoin, Dogecoin, Ethereum, BitcoinCash, Ripple, Stellar and Litecoin) that are traded in exchange offices and compare it to the volatility of seven currencies (Yuan, Yen, Canadian Dollar, Brazilian Real, Swiss Franc, Euro, and Pound Sterling) that belong to different and distinct monetary areas.

This study tried to find and analyze similarities and differences between the world of crypto-currencies and currencies. We started by analyzing the behavior of the cryptocurrencies and the exchange rates. After, we investigated the stationary characteristics of their returns. Finally, we used GARCH models to examine the levels of volatility of both returns and compared it.

The results suggest that the mean of returns of all currencies is significantly lower than the mean of returns of cryptocurrencies. Also, the volatility of the returns of cryptocurrencies is considerably higher when compared to the currencies. Among the seven cryptocurrencies that were studied, DOGE (Dogecoin) presented the highest, followed by Ripple (XRP). Surprisingly, Bitcoin is the cryptocurrency with the lowest volatility. Still, when compared with the volatility of any exchange rates, the volatility of the most famous cryptocurrency is considerably higher.

In this context, we conclude that cryptocurrencies are far from checking all the boxes to be considered a currency, especially the unit of account and the store of value functions. By a stretch of good will, cryptocurrencies can be seen as an imperfect substitute for currencies. Even so, we do not discard the possibility of them being accepted as currencies in the future. But, right now, the currencies are by far safer and more stable, while the cryptocurrencies are, for the most part, seen and sought after as speculative assets.

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Notes

[1] The recent war in Ukraine has drawn even more attention to the use of cryptocurrencies in this context. One of the most famous historical cases is the Silk Road, a dark-web market that allowed transactions of drugs (DeVries, 2016). Another one is Mt. Gox, a Bitcoin exchange based in Tokyo that was hacked and exposed the records of 18 million transactions (Gandal *et al.*, 2018).

[2] https://coinmarketcap.com/.

[3] https://bbc.com/news/technology-58678907.

[4]https://www.forbes.com/sites/annestevenson-yang/2022/01/12/crypto-vs-chinas-digital-currency-never-the-twain-shall-meet/?sh=b2f709c7555c.

[5] https://www.ecb.europa.eu/paym/digital_euro/html/index.en.html .

[6] For more details see Duarte (2022).

[7] ADF and KPSS tests statistics were also computed for the prices and the exchange rates. The results show that the series are non-stationary for all the cases. Results can be provided upon request.