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Bitcoin as a National Currency: A Case Study for the Czech Republic

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Abstract
In an era of changing financial landscapes, the position of cryptocurrencies like Bitcoin as possible national currencies is worth investigating. This study investigates Bitcoin's adherence to currency criteria and its consequences for GDP development in a certain country. The mining industry plays a significant role in the GDP of many countries. The extraction of raw materials such as metals, minerals, and fossil fuels is essential for producing a wide range of goods and services. This generates jobs and tax revenues and supports economic growth. Understanding these processes is critical, given the ongoing debate about Bitcoin's place in modern economies. This research looks into Bitcoin's usefulness as a currency and its possible influence on a certain country's GDP. The results show that Bitcoin fits the requirements for money, acting as a means of exchange and a store of value, with features including mobility, divisibility, commensurability, and fungibility. When examining its influence on GDP, empirical data indicate that, while currency appreciation may provide the illusion of stronger GDP growth when denominated in foreign currency, it damages growth domestically. According to a neural network study, Bitcoin's large impact on GDP renders it unsuitable for use as a national currency in the Czech Republic. Despite matching currency criteria, Bitcoin's adoption confronts problems such as volatility, a lack of central authority, and its worldwide nature, which limit its usefulness in promoting national economic growth. This analysis emphasizes country selection and length restrictions, finding that Bitcoin's existing position as an investment instrument restricts its viability as a national currency.

Keywords
Bitcoin, National Currency, Gross Domestic Product, Mining Industry, Neural Networks

Introduction

Bitcoin is a cryptocurrency based on blockchain. All historical Bitcoin transactions are stored in the Bitcoin blockchain, but the owners of Bitcoins are generally unknown (Qin et al., 2022). Other cryptocurrencies include Ripple, Ethereum, Dogecoin, NEO, and Litecoin. Bitcoin is becoming a popular financial asset and a means of transactions. However, little is known about an essential aspect of the Bitcoin market: its liquidity (Ma et al., 2022).

With the proliferation of smartphones and high-speed mobile internet, an increasing number of users have started accessing their Bitcoin wallets on their smartphones. Users can download and install various applications for Bitcoin wallets (for instance, Coinbase, Luno, Bitcoin Wallet) on their smartphones and access their Bitcoin wallets anytime and anywhere (Hu et al., 2021).

In some cases, Bitcoin can serve as an investment instrument. Evaluating the fundamental value of Bitcoin is challenging because there is no underlying company or cash flow (Ma & Luan, 2022). Given that the price of Bitcoin is highly volatile, forecasting volatility is crucial for various applications, such as risk management or hedging (Bergsli et al., 2022). Bitcoin volatility reacts most strongly to news about Bitcoin regulation, positive investor sentiment regarding Bitcoin regulation extracted through Google search, and, notably, cyberattacks on cryptocurrency exchanges (Lyócsa et al., 2020). However, the process of trading Bitcoin volatility weakens the short-term spillover effect of volatility from the Bitcoin market to the banking sector in the United States, and the volatility of returns in the banking sector (i.e., operational results' volatility) weakens the short-term spillover effect of volatility from the banking sector to the Bitcoin market, mainly due to the inability to adapt in the short term (Senarathne & Jianguo, 2020).

In the future, cryptocurrency could replace a state currency. Bitcoin may meet the needs of future electronic commerce, but it suffers from several types of risks – including social, ethical, and economic risks – that could pose a threat to online users and need to be addressed (Sultan & Tice, 2022). In this context, currency volatility is also crucial. For developing economies, foreign loans are a double-edged sword: they can cushion adverse economic shocks and smooth their domestic consumption, but they can also amplify consumption volatility depending on the currency in which the debt is denominated and the cyclicality of the debtor's exchange rate (Fujii, 2023; Tkacova and Gavurova, 2023; Sinicakova et al. 2017). Negative realized semivariance associated with appreciation plays an important role in explaining quantile-dependent dynamics of volatility for safe currencies (Cho & Rho, 2022; Bilan et al. 2017). The Bitcoin payment system involves two types of agents: users who trade in the currency and pay fees and miners responsible for authorizing transactions and securing the system in exchange for these fees (Lavi et al., 2022). No bank manages this international currency, and it can be used to purchase goods from anywhere in the world. It can also be traded like stocks or coins (Ayboğa & Ganii, 2022).

For it to function as a currency, it must be stable or supported by the government (Sinicakova & Gavurova, 2017; Baur & Dimpfl, 2021). Predictability arises from the fact that Bitcoin prices are prospective: Bitcoins effectively incorporate exchange rate expectations and their driving forces because exchange rates are the foundation of Bitcoin (Feng & Zhang, 2023).

The study aims to evaluate, using a specific developed country as a case study, whether Bitcoin could become its national currency.

In connection with this objective, the following research questions are formulated:

If Bitcoin is to be considered the currency of a state, it must fulfill the parameters of a currency.

RQ1: Does Bitcoin meet all the parameters of a currency?

If Bitcoin meets all the parameters, it could become the national currency of a state. It is essential to compare for which countries Bitcoin would be suitable as a national currency.

RQ2: What impact would Bitcoin have on the GDP development of the selected country?

Literature Review

Realized Volatility (RV) is defined as the sum of the squared logarithmic returns on a high-frequency sampling grid, aggregated over a specific time interval, typically a trading day in finance. Using time series of RV, Miura et al. (2019) predict future values based on past patterns employing various machine learning methods, including Artificial Neural Networks (ANN) such as Multilayer Perceptron (MLP), Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), Support Vector Machine (SVM), and Ridge Regression, which are compared with heterogeneous autoregressive models. Guo et al. (2021) conduct matrix-vector multiplication operations and weight update operations, proposing a perceptron neural network model and implementing a simulation platform based on MLP neural networks. The results indicate accurate predictions, demonstrating the feasibility of the model in forecasting demand for industrial logistics in the Shanxi province.

This study proposes an efficient Multilayer Radial Basis Function Neural Network (RBF-MLP-II) for regression problems by combining Multilayer Perceptron (MLP) and Radial Basis Function Neural Networks (RBF-NNs). Verified with four regression problems, the proposed RBF-MLP-II demonstrates the best approximation accuracy and the fastest training convergence compared to conventional MLP, RBF-NN, and RBF-MLP-I (Jiang et al., 2022).

Rajabi et al. (2022) implement a primary deep neural network based on the observed price trend of bitcoins in past days and its fluctuations to predict the optimal window size. Pratas et al. (2023) aim to evaluate the forecasting properties of classical methodologies (ARCH and GARCH models) compared to deep learning methodologies (MLP, RNN, and LSTM architectures) for predicting Bitcoin volatility. The results show that deep learning methodologies have advantages in forecast quality, although significant computational costs are required. In the work of García-Medina & Aguayo-Moreno (2023), the volatility of leading cryptocurrencies is predicted through generalized autoregressive conditional heteroskedasticity (GARCH) models, multilayer perceptron (MLP), long short-term memory (LSTM), and hybrid LSTM-GARCH models, where GARCH family parameters are part of LSTM models. They found that various variants of deep neural network models outperform those from the GARCH family in terms of heteroscedastic errors and absolute and squared errors (HSE).

The proposed FBP-MLP method surpassed the conventional BP-MLP algorithm in terms of convergence speed and test accuracy (Sadiq & Yahya, 2021). Rathee et al. (2023) proposed an enhanced approach based on an ensemble of neural networks (NN) using Convolutional Neural Network (CNN) and Bidirectional Long Short-Term Memory (BiLSTM), i.e., CNN-BiLSTM, for long-term cryptocurrency price prediction, utilizing both live data through API and historical data. The proposed ensemble model, CNN-BiLSTM, was observed to have the lowest RMSE score of 0.164 for live Bitcoin API data and 0.166 for historical Dogecoin data.

Through construction, a one-to-one correspondence is created between MLP and piecewise polynomials. As the approximation ability of piecewise polynomials is well-known, our study sheds new light on the universal approximation ability of the MLP (Lin et al., 2021). Crowther et al. (2021) provide an overview of how second language researchers use cluster analysis, an advanced statistical method that is still uncommon but increasingly used to identify groups or patterns in a data set and explore group differences. For future use and to inform methodological procedures in second language research, they briefly inform about a sample cluster analysis study utilizing open data.

A new optimization criterion is introduced to define this analysis method, and the extension of cluster analysis to multiple sets of variables is discussed. The general analysis strategy is illustrated using two case studies (Llobell & Qannari, 2020). As a fundamental step in cluster analysis, the accuracy of clustering can be influenced by the results of distance measurements. Experiments with multiple datasets compared to other clustering algorithms illustrate the accuracy and efficiency of the proposed clustering algorithm (Cheng et al., 2021).

Castura et al. (2022) apply b-cluster analysis to the same toy dataset and demonstrate that identified paradoxes do not occur. They found that solutions for b-cluster analysis have better sensory differentiation within clusters, better sensory discrimination, and fewer redundant clusters than CLUSCATA solutions.

Focusing on the role of cluster analysis in data mining, an algorithm for cluster analysis and its applications in data mining are proposed. Research by Zou (2020) demonstrates that this algorithm exhibits strong universality and can be applied to most locations for data analysis, providing a theoretical foundation for the early detection and analysis of large amounts of data. The findings highlight a lack of quantitative analysis and evaluation in current practice for cluster analysis of IR and NIR spectroscopy data. Considering this, Crase et al. (2021) propose an analytical model or workflow with techniques specifically suitable for cluster analysis of IR and NIR spectroscopy data, along with a pragmatic application strategy.

The suggestion is to perform clustering using various similarity metrics for the same data and explore different types of relationships among them. The approach by Kondruk & Malyar is validated by analyzing demographic processes in several European countries.

Nichols et al. (2022) initially examined clustering algorithms on simulated datasets containing 26 diseases with varying prevalence in predefined clusters. The derived clusters were compared to known clusters using the adjusted Rand Index (aRI). Quiroga-Garcia et al. (2022) analyzed the relationship between price and trade volume clustering in cryptocurrencies Ether, Ripple, and Litecoin.

The research results showed that the majority of clusters were composed of Generation Z individuals interested in cryptocurrency investment and groups with low to moderate incomes, most of whom were interested in BTC and ETH, well-known cryptocurrency groups. The analysis was then divided into three groups using K-Means Clustering analysis: "No Interest in Cryptocurrencies," "Moderate Interest," and "Risk-takers" who are interested in investing in cryptocurrencies (Sittivangkul et al., 2022).

Lorenzo & Arroyo (2022) aim to describe, summarize, and segment the main trends of the entire cryptocurrency market in 2018 using data analysis tools. Song et al. (2019) aim to analyze the structure of the cryptocurrency market based on correlation agglomerative hierarchical clustering and minimum spanning tree. Cluster analysis revealed two clusters, where the cluster with high cryptocurrency literacy (high literacy in Bitcoin, Ethereum, and Litecoin) has a distinct demographic profile and higher financial literacy than the cluster with low cryptocurrency literacy (low literacy in Bitcoin, Ethereum, and Litecoin). Financial literacy explains the literacy of Bitcoin and Ethereum but not the literacy of Litecoin (Khan, 2023).

For the asset allocation phase (Maghsoodi, 2023), cluster analysis was extended by enhancing the Cluster Analysis of the Multiple Criteria Decision Analysis (CLUS-MCDA) algorithm by adding additional features to this comprehensive decision-making technique, including density-based spatial clustering.

Through cluster analysis, patterns of behavior of three distinct user groups were revealed, differing in the intensity of their involvement in cryptocurrencies across mental, proactive, and financial aspects. The findings provide researchers and regulatory authorities with a better understanding of the cryptocurrency phenomenon and the psychological involvement of users (Steinmetz, 2023). Almeida & Gonçalves (2023) employ a systematic review process supported by bibliographic coupling in VOSviewer to review 482 articles published in the ABS 2021 journal list, considering various knowledge domains.

Guo et al. (2021) results indicate that the forecast is accurate. Based on these findings, I will choose the neural network method for RQ1. Steinmetz's (2023) findings provide researchers and regulatory authorities with a better understanding of the cryptocurrency phenomenon and the psychological involvement of users. Thanks to these results, I will opt for cluster analysis for RQ2.

Materials and methods

For evaluating how Bitcoin has impacted the GDP of the Czech Republic, specific calculations for the dataset are needed. The sources for this will be the Yahoo Finance website and kurzy.cz. Time series data is used for calculations in this case. Since the dataset is not in the correct format, it needs to be transformed into a time series using Wolfram Mathematica software. The Data is available from October 31, 2022, to October 30, 2023.

First, the date of the time series of the converted exchange rate of USD to Czech koruna from October 31, 2022, to October 30, 2023, exactly one year, will be taken. Also, the exchange rate (in Czech koruna) for the same period will be taken, and both variables will be combined in a time series format. Before creating time series data, it should be ensured that the Czech koruna is normalized. For this purpose, each value of the Czech koruna exchange rate will be divided by the maximum value of the dataset. Equation (1) is stated below:

Let $R_1, R_2, R_3, \ldots, R_\mathrm{n}$ be the exchange rate of USD to Czech koruna, and the normalized rate is calculated as:

$$R_{norm} = \frac{R_i}{R_{max}} \tag{1}$$

where

R_{norm} is normalized exchange rate of Czech koruna,
R_i is each individual exchange rate,
R_{max} is the maximum value among all exchange rates.

After obtaining the normalized exchange rate data, the next step is plotting the time series data to better understand its trends. Additionally, we will proceed with the opening price of Bitcoin in USD from October 28, 2022, to October 28, 2023. Similar to the normalization process for the exchange rate, the Bitcoin price data will be converted into time series and normalized using the equation (2):

Let $P_1, P_2, P_3, \ldots, P_n$ be Bitcoin prices, and the normalized Bitcoin price is calculated as:

$$P_{norm} = \frac{P_i}{P_{max}} \tag{2}$$

where

P_{norm} is normalized Bitcoin price,
P_i is each individual Bitcoin price,
P_{max} is the maximum value among all Bitcoin prices.

The next step involves comparing the normalized exchange rate and the normalized Bitcoin price by plotting multiple line charts. To find the comparison between the normalized exchange rate and the Bitcoin price, we need to calculate the difference between them. The difference in the normalized exchange rate is given by the equation:

$$R_{norm} - P_{norm} = \left(\frac{R_i}{R_{max}}\right) - \left(\frac{P_i}{P_{max}}\right) \tag{3}$$

This equation (3) subtracts the normalized Bitcoin price from the normalized exchange rate for each corresponding data point, providing the difference between the normalized values.

To examine the impact of Bitcoin on the GDP of a specific country, we need time series data for GDP. For this purpose, GDP time series data is collected for the period from December 31, 2019, to September 30, 2023. Then, specifically, a time series of GDP changes is plotted every quarter. A multi-line line chart is used, where each line likely represents a different category or aspect of the change. To calculate the normalized GDP using the mathematical equation (4):

Let $G_1, G_2, G_3, \ldots, G_n$ be the GDP values of the Czech Republic, and the normalized GDP is calculated as:

$$G_{norm} = \frac{G_i}{max\ (|G_i|)} \tag{4}$$

where

G_{norm}	is the normalized GDP,
G_i	is each individual GDP,
$\lvert G_i \rvert$	is the absolute value of all individual GDP,
$max\ (\lvert G_i \rvert)$	is the maximum absolute value of individual GDP.

From the normalized time series data, the normalized GDP changes every quarter are plotted between -1 and 1. The next step involves determining the difference between the averages of two sets of normalized rates: the Bitcoin rate and the Czech koruna rate. For this purpose, it is divided into four quarters. The average differences for the first quarter are calculated as follows:

$$Q_{M1} = \left(\frac{\sum_{i=1}^{65} P_{norm}}{n_1}\right) - \left(\frac{\sum_{i=-1}^{-43} R_{norm}}{n_2}\right) \tag{5}$$

where

Q_{M1}	is the average difference for the first quarter,
n_1	is the number of normalized days, here: 65.
n_2	is the number of normalized days; here, the last number of data is for 43 days.

The average differences for the second quarter are calculated as follows:

$$Q_{M2} = \left(\frac{\sum_{i=66}^{155} P_{norm}}{n_1}\right) - \left(\frac{\sum_{i=-44}^{-108} R_{norm}}{n_2}\right) \tag{6}$$

where

Q_{M2}	is the average difference for the second quarter,
n_1	is the number of normalized days, here: 155-65=90.
n_2	is the number of normalized days; here, the last number of days of data is 108-43=65.

The average differences for the third quarter are calculated as follows:

$$Q_{M3} = \left(\frac{\sum_{i=156}^{246} P_{norm}}{n_1}\right) - \left(\frac{\sum_{i=-109}^{-169} R_{norm}}{n_2}\right) \tag{7}$$

where

Q_{M3}	is the average difference for the third quarter,
n_1	is the number of normalized days, as follows: 246-155=91.
n_2	is the number of normalized days; here, the last number of days of data is 169-108=61.

The average differences for the fourth quarter are calculated as follows:

$$Q_{M4} = \left(\frac{\sum_{i=247}^{338} P_{norm}}{n_1}\right) - \left(\frac{\sum_{i=-170}^{-231} R_{norm}}{n_2}\right) \tag{8}$$

where

Q_{M4} is the average difference for the fourth quarter,

n_1 is the number of normalized days, here: 338-246=92.

n_2 is the number of normalized days; here, the last number of days of data is 31-169=62.

The next step is to find adjusted or corrected normalized GDP values. The first quarterly GDP for the period from December 31, 2022, to September 30, 2023, encompasses four quarters of data. To obtain adjusted or corrected normalized GDP values, we need to calculate the differences between specific elements of GDP values (four quarters) and the computed averages of specific subsets of Bitcoin and Czech koruna exchange rates. The mathematical equation for corrected, normalized GDP values is provided below:

$$GDP_{corr.norm} = G_{norm} - Q_{mi} \tag{9}$$

where

$GDP_{corr.norm}$ is corrected normalized GDP values

G_{norm} is normalized GDP values

Q_{mi} Quarterly mean differences ($i = 1,2,3,4$)

We can see the difference by comparing the short-term GDP (4 quarters of normalized GDP) with the corrected normalized GDP.

Results

Let's move into the first research question, which is that Bitcoin meets the parameters of a currency. Money is one of the assets. Unlike other assets, money is distinguished by its liquidity. A liquid asset can be used directly as a medium of exchange, or at least it can be easily (quickly and without significant costs) converted into a medium of exchange. Liquidity is a valued property of an asset.

Traditionally, three basic functions of money are defined. Money serves as a medium of exchange, an accounting unit, and a means of storing value. Some economists consider it necessary to define a greater number of money functions. As a fourth function, they state the role of money as a means of payment arising from the use of money as a medium of exchange, where money serves to settle a debt. As the fifth function of money, they define its role as a means of controlling the level of economic activity (Polouček, 2009). The general acceptability of an asset in exchange relationships expresses the practical usability for the majority of traders and the existence of certain properties that this asset must exhibit. Crucial among these are its homogeneity and standardized quality, the ability to retain its properties over time, easy transferability, and usability even for paying relatively small amounts (Polouček, 2009) (Polouček, 2009).

Nevertheless, even though the forms of money have changed, their essence remains the same – money is a medium of exchange. Barter (exchange of goods for goods) requires a mutual agreement of needs (Holman, 2004). Transaction balances are cash balances that people want to hold to secure regular transactions, such as regular purchases of goods and services for household operations, regular purchases of raw materials and materials for business operations, rent payments, insurance payments, etc. If people's incomes and expenditures were temporally aligned so that each income could be immediately converted into an expenditure, people would not need any transaction balances. The temporal mismatch between incomes and expenditures requires maintaining transaction balances (Holman, 2004).

The equilibrium of the money market means that people, in aggregate, hold just as much cash balances as they want to hold. In other words, the money supply equals the sum of demanded money balances (Holman, 2004). The demand for money is the effort to hold cash balances instead of other assets. The demand for money reflects a person's decision about the structure of their wealth (Holman, 2004).

Given that the influence of digital technology in our daily lives is continually growing, Pardi & Paolucci (2021) explore methods to assess the stability, sustainability, and design of token economic systems, which include tokens and conventional currencies. Applying the law of supply and demand to recalculate product prices requires prior knowledge of certain attributes of tokens – token divisibility and token-money exchange rates.

For a central bank digital currency to be used as a national legal tender, it must be universal and accessible regardless of time and place, similar to physical cash. Therefore, offline payment features become attractive, extending the availability of central bank digital currency. However, due to the characteristics of the electronic financial system, central bank digital currency is vulnerable to potential harmful behavior in offline situations, such as power outages and system downtimes (Chu et al., 2022). Nevertheless, not only the central bank but also commercial banks create money. This is because commercial banks are fractional reserve banks, meaning they keep only a portion of deposits in reserves and lend the rest (Holman, 2004). More precisely, the mobility, divisibility, commensurability, and fungibility of money help make small-money political donations potentially democratic by making them potentially accessible, unintrusive, and collective. Money is the coin of the economic realm but can also be the currency of democratic politics (Rubenstein, 2022).

Let's look into the impact of bitcoin on the GDP development of the selected country. In Figure 1, a red curve depicts the exchange rate development between the Czech Koruna and the US Dollar between 2022 and 2023. In November 2022, the exchange rate stood at 24 USD. By December of the same year, it had declined to 23 USD/CZK. At the beginning of 2023, the rate remained at 23 USD/CZK. In the subsequent months, there was a decrease to 22 USD/CZK. The exchange rate was approximately the same in March as the previous month. In April of the same year, the rate fluctuated around 21 USD/CZK. The exchange rate remained relatively constant with minor fluctuations. From July onwards, the rate began to rise again. In September, the exchange rate peaked at 22.5 USD/CZK. In October, the rate reached 23 USD/CZK.

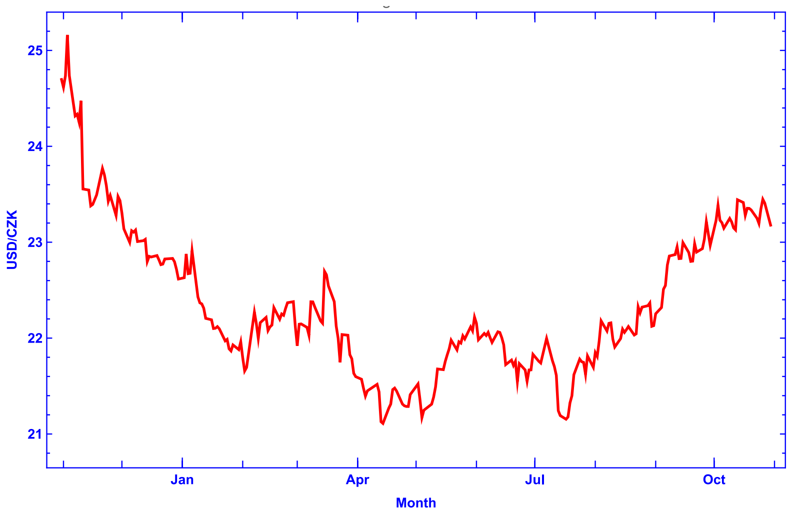

Figure 1: The exchange rate development of the Czech Koruna
Source: Author

In Figure 2, the blue curve illustrates the trajectory of the Bitcoin exchange rate from 2022 to 2023. In November 2022, the price of Bitcoin was 20,000 USD. By December of the same year, it decreased to 15,000 USD. At the beginning of 2023, the price of Bitcoin hovered around 15,000 USD. In the subsequent months, the value increased. In March, the price of Bitcoin was around 25,000 USD. In April, the price reached 30,000 USD. Throughout the year, there were not too significant fluctuations. In July, there was a decline, and the price of Bitcoin was 25,000 USD, remaining constant until October. In November, the exchange rate dropped to 15,000 USD.

Figure 2: The Bitcoin exchange rate development
Source: Author

Figure 3 represents a comparison of normalized exchange rates between Bitcoin and CZK. The normalized rate is obtained by dividing each value by the maximum absolute value. The blue curve represents Bitcoin, and the red curve represents CZK. The observation period spans one year. In November 2022, the value of Bitcoin was 0.6, while CZK was 1. In the last month of that year, Bitcoin's value was 0.5, and CZK's value was 0.9. In January, Bitcoin's value remained at 0.5, while CZK reached a value of 1. In March, Bitcoin's value fluctuated around 0.7, and CZK was at 0.9. In April, Bitcoin's value increased to 0.7, while CZK slightly decreased to 0.9. In July, both curves intersected. In October, Bitcoin's value was around 0.8, and CZK's value was 0.9. In November, Bitcoin's rate reached 1, while CZK remained at 0.9.

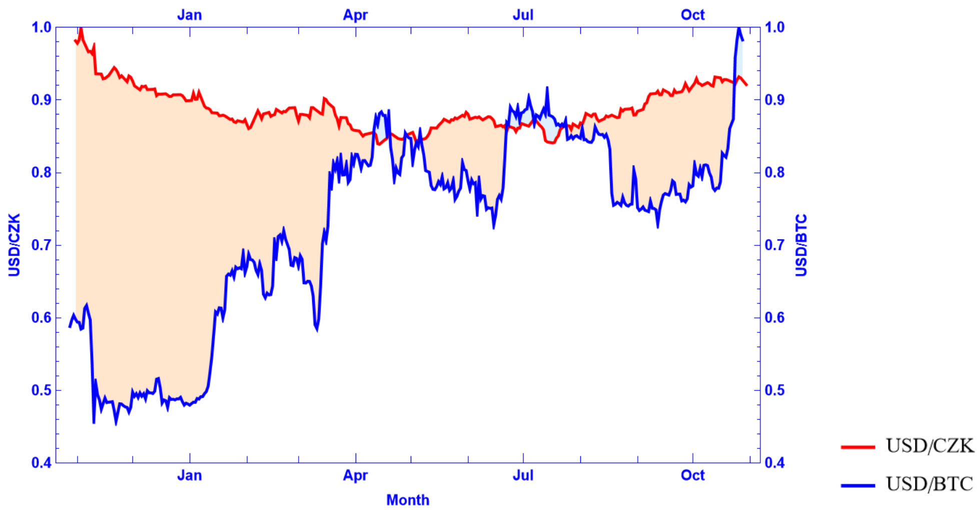

Figure 3: The comparison of normalized exchange rates between Bitcoin and CZK
Source: Author

In Figure 4, a black dashed curve represents the difference in fluctuations between CZK and Bitcoin exchange rates. The observation period spans 1 year. In November 2022, the difference fluctuated around 0.4. In the last month of the same year, the value approached 0.5. At the beginning of 2023, the value hovered around 0.4. Subsequently, there was a decline, and in February, the difference was 0.2. In April, the amplitude of the fluctuation was negative. In May, the difference was 0. In June, there was a slight increase to 0.1. In July, the amplitude of the fluctuation was -0.1. Throughout the year, there was a subsequent rise. In October, the difference almost reached 0.2. In November, the value of the difference decreased again to -0.1.

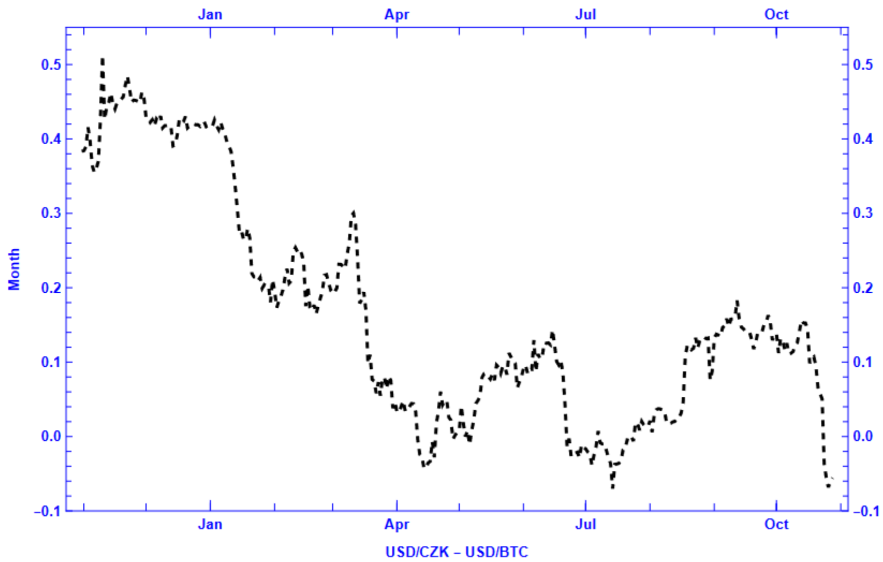

Figure 4: The difference in fluctuations between CZK and Bitcoin Exchange rates
Source: Author

In Figure 5, the GDP development of the Czech Republic is depicted for the period 2020-2023. In 2020, the GDP initially stood at 0 and subsequently decreased to -10. Within the same year, it again rose to a value of 8. In 2021, the GDP fluctuated around 0. The same pattern persisted in 2022. In the years 2022 and 2023, no significant deviations were recorded. However, in March 2023, the GDP decreased to -0.5.

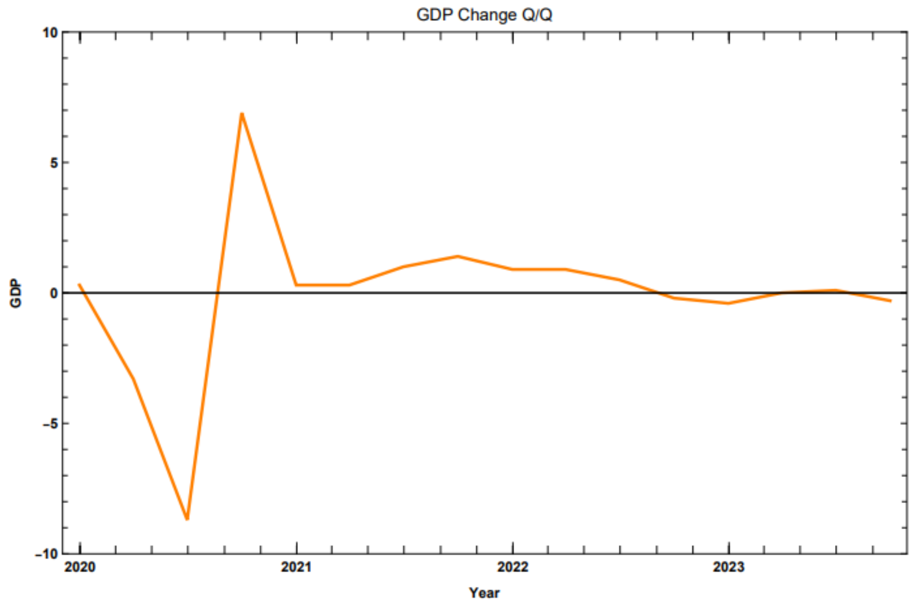

Figure 5: The development of the GDP of the Czech Republic
Source: Author

In Figure 6, a curve is plotted illustrating the development of the normalized GDP of the Czech Republic. The observation period spans the years 2020-2023. Normalized GDP is obtained by dividing each value by the maximum absolute value. In 2020, the normalized GDP reached negative values, specifically -1. However, over the year, the value increased to 0.5. In the following year, there was growth, with the maximum value recorded in 2021 being 0.8. In the years 2022 and 2023, the values fluctuated around 0, and the development was constant.

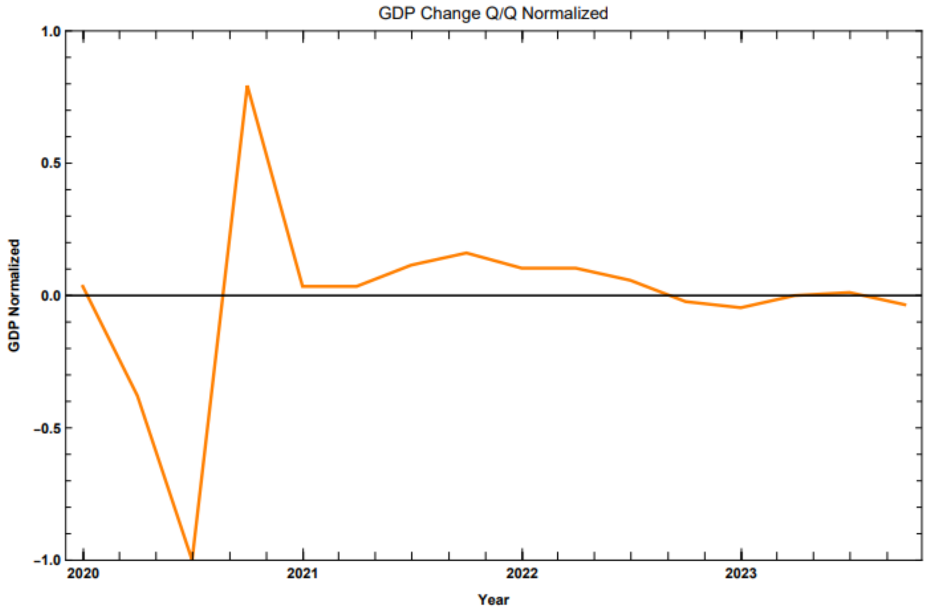

Figure 6: The development of the normalized GDP of the Czech Republic
Source: Author

Figure 7 depicts how the GDP evolves while maintaining CZK and how it would develop if the currency were changed to Bitcoin.

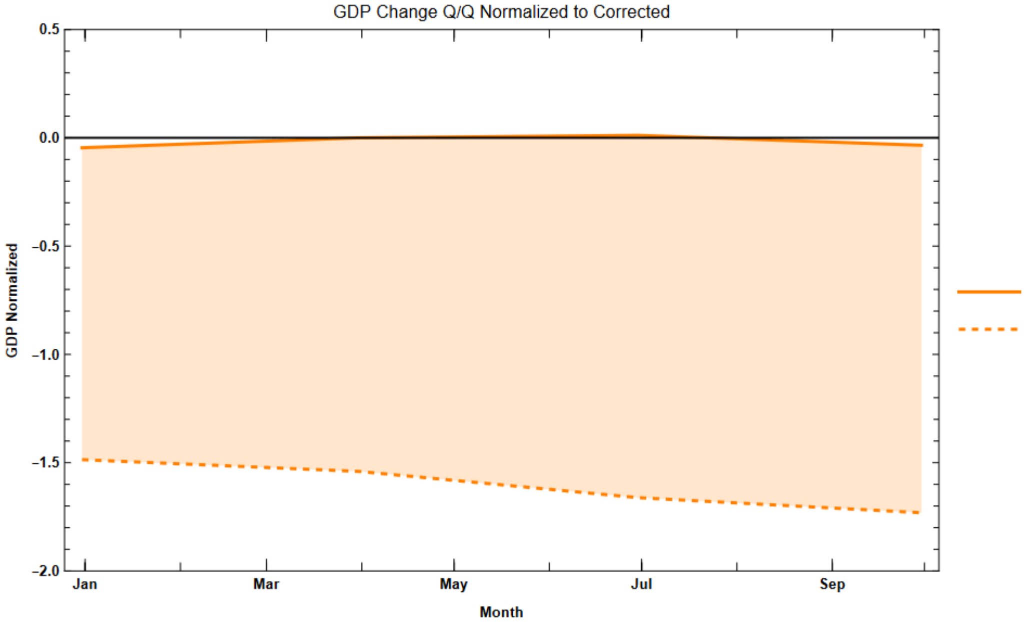

Figure 7: The development of normalized GDP of the Czech Republic and normalized GDP considering differences in Exchange rates between CZK and Bitcoin
Source: Author

Discussion

RQ1: Does Bitcoin meet the parameters of a currency?

The results indicate that Bitcoin fulfills the criteria of currency. One of the most common functions is that money is a medium of exchange. Additionally, it also serves as a means of storing value. Currency properties include mobility, divisibility, commensurability, and fungibility.

RQ2: What impact would Bitcoin have on the GDP development of the selected country?

Firstly, the determinants of the GDP share of each nation are variables representing the share of each nation in the world, such as shares in the world population, investments, human capital, exports, investments in research and development, and financial capital flows. Secondly, currency undervaluation supports per capita GDP growth through increasing exports but tends to decrease the country's share in the world GDP because undervaluation depreciates its GDP at market exchange rate, while its indirect effect through changes in the export share is uncertain due to the zero-sum nature of competitive undervaluation among nations. Thirdly, trade is crucial in determining the share of the world GDP as long as it is measured by the share in world exports representing economic rivalry among nations (Park et al., 2019).

Using the WIOD database, Zhao et al. (2020) applied a formula to calculate changes in value-added at the sector level under certain currency valuations. Empirical findings revealed that currency appreciation creates an illusion of higher GDP growth when denominated in foreign currency. However, if denominated in domestic currency, currency appreciation harms its GDP growth.

Maximum and cumulative multipliers are calculated to measure the impacts of fiscal shocks. In the baseline specification, which is the same for each country, the calculated multiplier for maximum expenditures (adjusted to be interpreted in the national currency) ranges from 0.2 in the Czech Republic to over 1 in Poland. The cumulative response of GDP to an expenditure shock is greater than 1 (Szymańska, 2019).

Conclusion

The paper addressed the issues surrounding Bitcoin and its potential impact on the gross domestic product if it became a national currency. The study's objective was to investigate whether Bitcoin fulfills the characteristics of a currency. These properties include divisibility, durability, universality, limited supply, and portability. The results indicate that Bitcoin indeed satisfies these criteria.

The second research question, tackled using neural networks, explored the potential impact of Bitcoin on the GDP. From the graphs, it is evident that Bitcoin could not become the national currency of the Czech Republic due to its significant influence on GDP.

The study aimed to assess whether Bitcoin could become the national currency of a specific developed country, and this goal was achieved. Limitations of the study include the choice of a specific country and a relatively short period.

Despite Bitcoin meeting currency characteristics, its adoption as a national currency is not feasible, primarily due to its volatility. Currently, Bitcoin serves primarily as an investment tool, and its role is not geared toward aiding the development of a national economy. Another challenge is its independence from the state's politics, as no central bank oversees or corrects its fluctuations. Additionally, given that Bitcoin is a global currency, a small country may lack the resources to support its management financially.

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