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Testing if Bitcoin Can Act as a Hedge Against High Inflation Levels

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Abstract

This study investigates whether Bitcoin can be used for hedging against high inflation levels. In this report, the countries Argentina, Turkey, Venezuela, and Zimbabwe are examined. The study covers a ten-year period, where month-on-month inflation data and monthly Bitcoin prices from the beginning of 2014 to the end of 2023 were used. The results are based on bivariate vector autoregressions, where Granger causality tests and impulse response functions provide an indication of Bitcoin's potential to hedge against inflation. The only case of Granger causality identified was between the Bitcoin price and the inflation for Turkey. The impulse response function suggested that the relationship was not significant enough for Bitcoin to be considered a hedging opportunity.

Keywords: Cryptocurrency, hedging, behavioural economics, inflation.

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1. Introduction

The introduction aims to provide the reader with the context needed to fully grasp the remainder of the study. This is done by first giving an overview of what Bitcoin is and how it works when compared to traditional currency. Additionally, the similarities between gold and Bitcoin are brought to the reader's attention. The topic of high inflation is then introduced, and it is explained that Bitcoin is popular in many countries with particularly high inflation. Finally, the purpose of the thesis is described, and the research question is presented.

1.1 Background

Bitcoin is a decentralized peer-to-peer digital currency first introduced in 2008 by the anonymous Satoshi Nakamoto.[1] Since its inception, it has experienced rapid global adoption and has played an influential role in the development and emergence of numerous cryptocurrencies in recent years.

In contrast to traditional currencies, Bitcoin is not directly regulated by financial and regulatory authorities. Central banks and other government agencies are unable to control the money supply and distribution of Bitcoin through monetary policy. Instead, Bitcoin employs a unique mechanism designed to limit supply through a maximum cap on available coins (21 million).[2] Moreover, Bitcoin mining, which is an important process in validating activity and transactions on the blockchain, becomes more costly and less profitable to maintain over time. Approximately every four years, the mining reward undergoes a reduction (a procedure known as Bitcoin halving). This process lowers the profitability of mining and reduces the rate at which newly minted Bitcoin enters circulation.[3] A finite supply and changing mining rewards combine to provide a controlled adjustment to the money supply. Different to conventional currencies, which are subject to monetary and fiscal policies set by central banks or governments, Bitcoin is less susceptible to sudden supply and structural changes.[4]

[1] Usman W. Chohan, A History of Bitcoin (February 5, 2022).
[2] Adam Hayes. (2024, March 13). What happens to Bitcoin after all 21 million are mined? Investopedia.
[3] Luke Conway (21 May 2021). Bitcoin Halving: What You Need to Know. Investopedia.
[4] Björn Segendorf (2014). What is bitcoin. Sveriges Riksbank Economic Review: 2-71.

Over the past decade, cryptocurrencies have seen a surge in popularity with the market capitalization of Bitcoin exceeding 1.3 trillion USD as of May 17th, 2024.[5] This has led to significant price movements during certain periods and has attracted investors seeking to speculate and capitalize on price shifts. Bitcoin has also come to be referred to as the digital version of gold by some. This is due to the decentralized characteristics of cryptocurrencies like Bitcoin positioning the asset class as an alternative means of safeguarding wealth against inflation. Bitcoin and gold share many features, notably; fungibility, limited supply, portability, divisibility, and liquidity.

Investing in Bitcoin, and other cryptocurrencies, as a hedge against inflation has become increasingly favored among individuals residing in countries with persistently high inflation levels.[6] Here, uncertainty in the monetary and fiscal environment, as well as deprecating domestic currencies has fueled interest in decentralized assets.[7] Cryptocurrencies are also viewed as an accessible alternative to stable foreign currencies (primarily USD) as they allow individuals to bypass strict domestic currency controls.[8]

It is currently estimated that out of Turkey's total population of 86.2 million, around 12 million adults in Turkey are active in cryptocurrency investing in the year 2024.[9] Turkey, along with other countries studied in this report - Argentina, Zimbabwe, and Venezuela, have over the past decades experienced highly volatile inflation levels. Many factors may be the cause of this, such as unsustainable debt levels, faulty economic policy decisions, budget deficits, and supply and demand shocks, to name a few.

The Federal Reserve in the U.S. has put the ideal inflation level at 2% on an annual basis.[10] This target is pursued by most economies around the world. However, the countries focused on in this report have experienced inflation over certain periods exceeding 70% year-on-year. These high inflation levels have eroded domestic wealth and purchasing power, encouraging citizens to evaluate other stores of value. A result of this has been an increased adoption of cryptocurrencies. Argentina and Turkey were both ranked among the top 20 countries for the

[5] Bitcoin Price Today, BTC to USD Live Price, Marketcap and Chart. CoinMarketCap
[6] Olivera Doll, I. (2024, March 19). Bitcoin Is Trumping Dollars for Many Inflation-Weary Argentines. Blomberg
[7] Diwakar, A. (2021, April 12). Why are cryptocurrencies booming in Turkey? Why Are Cryptocurrencies Booming in Turkey? TRT World
[8] Di Salvo, B. M. (2019, March 19). Why are Venezuelans seeking refuge in crypto-currencies? BBC.
[9] Statista. Cryptocurrencies – Turkey. Statista market forecast.
[10] Why does the Federal Reserve aim for inflation of 2 percent over the longer run?. Board of Governors of the Federal Reserve System.

2023 Global Crypto Adoption Index.[11] However, until now it is unclear whether cryptocurrencies are appropriate assets for hedging against high inflation.

Several key events and occurrences related to Bitcoin are listed below to provide context to the currency's rise in popularity.

- 2008: Bitcoin was announced by the anonymous user Satoshi Nakamoto. Initially, the project did not receive much recognition apart from a few early adapters.[12]
- 2010: A now renowned story – 10 000 bitcoins were used to purchase pizza by Laszlo Hanyecz. The transaction was at the time valued at around 41.00$. This is generally seen as one of the first transactions where Bitcoin was used to acquire traditional goods (its original intention).[13]
- 2011: The price of Bitcoin sees rapid movement during this year, going from 1.00$ to 13.00$ at the end of the year. Many new cryptocurrencies were also announced during this year, with two examples being Litecoin and Ripple.[14]
- 2013: Bitcoin price begins to increase quickly, going from around 13.00$ to crossing the 1000$ mark and ending the year at around 750.00$.[15]
- 2018: Venezuela issues its own cryptocurrency, the Petro token.
- COVID-19 Pandemic: The pandemic and subsequent economic concerns further fueled the interest and capital allocation to Bitcoin.
- 2021: El Salvador becomes one of the first nations to use government reserves to acquire Bitcoin. In 2021, El Salvador also introduced new legislation to make Bitcoin legal tender.
- 2024: The SEC approved the first exchange-traded fund backed by underlying holdings of Bitcoin. This has been seen as a major step for large institutions and government entities to approve and engage in cryptocurrency investments. [16]
- 2024: The price of Bitcoin surpassed 70,000.00 USD.

[11] The Global Crypto Adoption Index.
[12] Chohan, A History of Bitcoin
[13] Nick Bilton (22 Dec. 2013). Disruptions: Betting on a Coin with No Realm. Bits Blog.
[14] Historical Bitcoin Prices, CoinMarketCap,
[15] Historical Bitcoin Prices, CoinMarketCap,
[16] Statement on the Approval of Spot Bitcoin Exchange-Traded Products, (2024, January 10), SEC.gov

1.2 Purpose

The purpose of this thesis is to investigate the efficacy of Bitcoin as a hedging instrument against extreme inflation. The paper focuses on countries with exceptionally high inflation rates and will cover: Zimbabwe, Venezuela, Argentina, and Turkey. Most of the previous research concerning Bitcoin's relative price to inflation has primarily focused on inflation in the U.S. and Euro-Zone.[17] However, this study will specifically be focused on high inflation environments. Using vector-autoregressions, the study indicates whether Bitcoin is a viable hedge against high inflation rates. By focusing on high inflation environments, this study contributes to an area with limited research in economic academia. Additionally, this may also serve as useful insight for those residing in countries with high inflation. By knowing whether Bitcoin is a suitable option for protecting wealth against inflation, individuals can make more informed decisions on asset allocation. The main research question is therefore formulated as the following: Can Bitcoin effectively be used to hedge against extreme inflation in volatile economies?

[17] Roman Matkovskyy, and Akanksha Jalan, (2020), Bitcoin vs Inflation: Can Bitcoin Be a Macro Hedge?

2. Theoretical Framework

The research project has taken a theoretical approach based on traditional macroeconomic and financial theory. These cover concepts including inflation, efficient markets, safe-haven assets, behavior economics, and hedging. The selected concepts provide a foundation for informed analysis, discourse, and application of results to real-life scenarios.

2.1 Inflation Theory

Inflation occurs when there is a general increase in the price level in an economy. This means that the price of goods and services rises.[18] Various factors contribute to inflation including monetary policy, supply and demand shocks, changes in currency exchange rates, and more.[19] Inflationary pressure devalues real wealth and wages within the economy. Hence, alternative capital allocation methods are often used to "hedge" or minimize the exposure to inflation. Common hedging methods include investing in the stock market, holding stable foreign currencies (e.g. USD), real estate portfolios, precious metals, treasury bills, and more recently, cryptocurrency investments.[20]

In this study, the Consumer Price Index (CPI) is used as the measure of inflation for each country. The CPI is determined by calculating a weighted change in the price of many day-to-day products. This offers a broad base measurement of price changes for a basket of goods and services over time.[21] CPI is often used as the primary measurement when determining changes to salaries, rent, government assistance, policy changes, and other rate-adjustable economic factors.[22]

An extreme level of inflation is referred to as hyperinflation. In scenarios where hyperinflation prevails, the price of goods and services can rise by several hundred or thousands of percentages in short amounts of time (e.g. 50% monthly).[23] Experiencing

[18] Riksbank, S. (2022, September 27). What is inflation? Sveriges Riksbank.
[19] Ceyda Oner. (2024), Inflation: Prices on the Rise, International Monetary Fund, International Monetary Fund.
[20] Salisu A. Afees, Raheem D. Ibrahim, Ndako B. Umar, The inflation hedging properties of gold, stocks and real estate: A comparative analysis, Resources Policy, Volume 66, 2020, 101605, ISSN 0301-4207
[21] Prices - Inflation (CPI) - OECD Data. The OECD, 2023.
[22] Frequently asked questions - United States Department of Labor.
[23] Phillip Cagan. Hyperinflation. The World of Economics. The New Palgrave. Palgrave Macmillan, London,

prolonged periods of unusually high inflation can have detrimental effects on the economy of a nation. The purchasing power of its citizens often decreases significantly as the cost of living rises quicker than salaries. Additionally, faith in government institutions may deteriorate, along with high adjustment costs for firms adapting to rising prices. Moreover, due to higher uncertainty in future economic conditions, risk premiums increase, and the cost of financing and transacting surge.[24]

2.2 Efficient Market Hypothesis

The efficient market hypothesis (EMH) is a theoretical framework that stipulates that the price of traded securities reflects all available information. This implies that market participants should be unable to consistently perform better than the market (e.g. it should not be possible to achieve a positive alpha).[25]

Markets reflect one of three stages of the EMH. These stages are a foundational part of the EMH theory and are designed to describe the conditions under which markets may exhibit weak, partial, and strong efficiency. These stages include:

1: Weak

In this state, securities prices reflect available historical price data. Therefore, having access to data related to a security or company other than historical price data can provide an advantageous position for market participants.

2: Semi-strong

In addition to historical price data, in the semi-strong stage, company-related information that is publicly available is also a part of the securities prices. Thus, having access to insider information not publicly available may facilitate investment decisions that yield excess returns for certain market participants.

3: Strong

All market participants are aware of all available information related to a security or company. This means that no market participant has access to information that may give them

24 Rogers, John H., and Ping Wang (1993). "High inflation: causes and consequences." Economic Review 4.1993: 37-51.

25 Alexandra Gabriela Ţiţan, The Efficient Market Hypothesis: Review of Specialized Literature and Empirical Research, Procedia Economics and Finance, Volume 32, 2015, Pages 442-449, ISSN 2212-5671

an advantage.[26] In a market experiencing strong efficiency, it is not possible to consistently outperform the market.

2.3 Herding Behavior

Investors are assumed to make investment decisions based on private information and their analysis in efficient markets. In certain situations, a mentality of herd behavior can arise among investors where they cease to rely on their own findings and instead copy the actions of the crowd. Researchers have reasoned that this pattern may exist because investors become unsure of their conclusions and assume that the crowd collectively possesses more information. This has been found to be more prevalent in markets experiencing high levels of uncertainty.[27]

Research has pointed toward the cryptocurrency market having exhibited signs of herd behavior. Some of the reasons for this include the weak regulatory framework governing cryptocurrencies, as well as many cryptocurrency investors lacking adequate investment experience and may not be fully aware of the associated risks. Studies on the cryptocurrency markets have discovered that herd behavior could be one of the major reasons for the high volatility present in cryptocurrency assets.[28]

2.4 Overconfidence

Overconfidence is a common cognitive bias within the field of behavioral economics. It is frequently observed when looking at individual investors and their decision-making. When someone exhibits overconfidence bias, they tend to overestimate their ability and have overconfidence in their predictions of uncertain events. An example of an overconfident investor is one who falsely believes to have a full understanding of financial markets. In doing so, they often overlook statistics and the opinions of experts when making their decisions. Therefore, overconfidence will often lead to the investor taking on unfavorable and

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[26] Malkiel G. Burton, (1989). Efficient Market Hypothesis, Finance. The New Palgrave. Palgrave Macmillan, London.

[27] Michelle Baddeley. (2010). Herding, social influence and economic decision-making: socio-psychological and neuroscientific analyses. Philosophical transactions of the Royal Society of London. Series B, Biological sciences, 365(1538), 281–290.

[28] Elie Bouri et.al. Herding behaviour in cryptocurrencies, Finance Research Letters, Volume 29, 2019, Pages 216-221

overly risky investments, as well as trading excessively.[29] Overconfidence, along with other biases in behavioral economics, may help explain why cryptocurrency markets do not entail full efficiency. This is further elaborated on in the proceeding discussion section.

2.5 Loss Aversion

The concept known as loss aversion is often used to understand why investors make certain decisions. The theory is built upon the notion that losses result in larger emotional responses than gains do. Individuals will try to avoid making losses even though it may lead to them passing up on investments that have a higher expected utility. When in a losing position, loss aversion can lead to investors holding onto unfavorable positions because they have an innate unwillingness to realize their losses. When investors find themselves in especially large losing positions, loss aversion can influence them to take on riskier investments to try to recuperate their losses.[30]

2.6 Hedging and Safe Haven Assets

When investors are exposed to downside risk, they may desire to protect themselves if the risk is significant enough. This can be done by buying assets that will appreciate if the undesired outcome materializes, a process known as hedging. By using hedging strategies, one can mitigate the negative effects of unfavorable outcomes. Derivative instruments are commonly used for this purpose, but other asset classes can be effective depending on the type of risk being hedged. When hedging against the effect of inflation, it is common to invest in treasury bonds, real estate or precious metals such as gold or silver.[31]

Safe haven assets are different from other asset classes in that they do not move in the same direction as financial markets during periods of economic turmoil and crisis. Investors can minimize their exposure to large negative overarching events by holding such assets. Gold and U.S. treasury bonds have both been viewed as safe haven assets.[32]

[29] Overconfidence Bias, (2023), Charles Schwab Asset Management.
[30] Loss aversion - The Decision Lab.
[31] Hedging, Corporate Finance Institute
[32] Dirk G. Baur, Thomas K.J. McDermott, Why is gold a safe haven?, Journal of Behavioural and Experimental Finance, Volume 10, 2016, Pages 63-71

3. Literature review

Bitcoin, and cryptocurrencies in general, are a relatively new asset class that has primarily seen widespread interest in the past 10-15 years. It is an area of finance that is comparably unexplored in academic research and literature. Up until this point, most of the papers written on the hedging properties of Bitcoin have been concerned with hedging against the stock market and comparing the currency to gold. A limited number of studies are available that specifically focus on Bitcoin's capability to protect against inflation. Even less research exists that focuses on high inflation levels. As a result, the previous studies highlighted in the following section will feature selected articles covering broader research into Bitcoin's hedging capacity and do not specifically concern high inflation environments. However, many of the overarching topics, theories, and approaches are still applicable and relevant to this thesis research topic.

Jalan & Matovskyy 2020 "Bitcoin vs inflation: Can Bitcoin be a macro hedge? Evidence from a quantile-on-quantile model."

This study investigates whether Bitcoin is an asset capable of hedging against inflation in different regions. It focuses on how the hedging capabilities are affected by changes in the level of inflation, as well as on different market states. Both realized inflation and unexpected inflation are used in the study. The expected inflation was estimated for each period using an ARMA (Autoregression Moving Average) model, with the unexpected inflation being the difference between expected inflation and actual inflation. By comparing monthly CPI levels for the US, Euro zone, Japan, and the UK, with monthly Bitcoin prices denominated in the respective currencies, Jalan and Matovskyy can draw separate conclusions for the different economic areas depending on varying economic scenarios. These comparisons are made using quantile to quantile regressions. With this model, the authors can see if the results differ when the Bitcoin market is bullish or bearish combined with low and high levels of inflation. Their results point toward Bitcoin performing worse when the US inflation increases whilst performing well against high inflation in the UK and Japan. The authors conclude that when in a bullish state, Bitcoin exhibits safe haven qualities and can be used to hedge against the actual inflation in the UK and Japan.[33]

[33] Roman Matkovskyy, and Akanksha JalanCan Bitcoin Be a Macro Hedge?

Klein et al. 2018 "Bitcoin is not the New Gold– A comparison of volatility, correlation, and portfolio performance"

The authors employ a GARCH model (generalized autoregressive conditional heteroskedasticity model) to examine the volatility and returns of Bitcoin in relation to the price of gold and silver. Comparisons were also made with various indexes, such as the S&P 500. In doing this, they sought to find out if the assets can be classed as safe havens. Time series data was used with daily closing prices. According to the study, gold showed only hedging potential in recent years whilst Bitcoin fails to show any forms of hedging or safe haven properties. Although there are some similarities between Bitcoin and the other metal commodities, there is a large difference in how they react to a downturn in equity markets. Gold tends to increase in price when the equity market declines, whilst the opposite effect is found for Bitcoin. The authors caveat their findings by mentioning that it can be difficult to conclude how Bitcoin behaves in different market states. This is due to it being a relatively new asset and the number of data points therefore being limited.[34]

Blau et al. 2021 "Inflation and Bitcoin: A descriptive time-series analysis"

The findings discussed in the paper indicate that Bitcoin can hedge against inflation. This statement is based on time series data that suggests the existence of a causal relationship between the price of Bitcoin and the expected inflation rate. Such a relationship was found by conducting vector autoregression analysis (VAR) with different lag lengths. Daily Bitcoin prices and the five-year forward expected U.S. inflation rate were used to conduct the regressions. The authors discovered that an exterior event that causes a percentage change in the price of Bitcoin will lead the expected inflation rate to increase significantly shortly after the price shock. When running the same tests with data from pre- and post-pandemic, the results are found to be similar. This suggests that the causal relationship holds up generally and not solely under the unique circumstances of the COVID-19 pandemic.[35]

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[34] Tony Klein, Hien Pham Thu, Thomas Walther, Bitcoin is not the New Gold – A comparison of volatility, correlation, and portfolio performance, International Review of Financial Analysis, Volume 59, Pages 105-116,
[35] Benjamin M. Blau, Todd G. Griffith, Ryan J. Whitby, Inflation and Bitcoin: A descriptive time-series analysis, Economics Letters, Volume 203, 2021

<u>Sakurai & Kurosaki 2023</u> "Have cryptocurrencies become an inflation hedge after the reopening of the U.S. economy?"

In this research paper, the authors employ a co-kurtosis approach to investigate the effectiveness of using cryptocurrency as a hedge against inflation after the U.S. economy opened following the COVID-19 pandemic. This approach is combined with the use of different variations of the GARCH model. The model makes use of daily data for the cryptocurrencies Bitcoin, Litecoin, and Ethereum, as well as five-year expected break-even inflation data. The results from the research indicate that cryptocurrencies have become a better hedging tool after the COVID19-pandemic. However, the research also shows that the limited supply mechanism of cryptocurrencies, such as Bitcoin, does not contribute to its effectiveness. This conclusion could be drawn since Ethereum, a cryptocurrency that does not have limited supply, proved to be a better hedge against inflation.[36]

<u>Choi & Shin 2020</u> "Bitcoin An inflation hedge but not a safe haven"

By using vector autoregressions in Bitcoin price data, the authors were able to see how the value of Bitcoin behaves when faced with various exogenous shocks. By studying the effects of the shocks, conclusions could be drawn on the asset's capacity to hedge against different factors, including inflation. The VAR model was used with weekly time series data. The findings include that positive shocks to the U.S. stock market leads to a significant increase in the price of Bitcoin. Additionally, the price of Bitcoin was found to be largely unaffected by shocks to the nominal interest rate. However, it did tend to increase in price after positive shocks to the U.S. inflation. This suggests that Bitcoin can hedge against inflation. Comparisons were made between gold and Bitcoin, and the authors confirm that they behave very differently. One difference put forth was that the price of gold was heavily affected by changes in the nominal interest rate.[37]

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[36] Yuji Sakurai, Tetsuo Kurosaki, Have cryptocurrencies become an inflation hedge after the reopening of the U.S. economy?, Research in International Business and Finance, Volume 65, 2023

[37] Sangyup Choi, Junhyeok Shin, Bitcoin: An inflation hedge but not a safe haven, Finance Research Letters, Volume 46, Part B, 2022

4. Method

The goal of the method section is to carefully explain the way the study has been conducted as well as motivate the choices made when deciding on a model. The methodology is based on bivariate autoregressions which make use of time-series data with lag. By using this model one can find interdependencies between variables over time. The variables in question are one variable which represents the Bitcoin price, and another represents the inflation of a country of interest. All the tests used to ensure that the model was correctly specified are described. The same thing goes for the Granger causality test and impulse response function. These final tests will determine if there are hedging opportunities present or not.

4.1 Model Specification

To test if Bitcoin can act as a hedge against inflation, bivariate vector autoregressions (VAR) were performed. The VAR models were tested to ensure compliance with key system assumptions; variable stationarity and no autocorrelation in the error-terms. This was done by conducting Phillips-Perron and Dickey-Fuller tests, as well as residual diagnostics and Lagrange multiplier tests. This was followed by Granger causality tests to determine the predictability of historical values on future values. If Granger causality existed, then impulse reaction functions were deployed to identify the degree to which variables predict one another. This was done by introducing a shock to the system and measuring the impact of change.

When deciding on which method to use for this study, VAR and GARCH regressions were both evaluated as they both appear in previous research. In terms of performance and suitability, both regression models appeared appropriate to investigate the paper's objective. Ultimately, VAR was chosen due to its better alignment with the scope and timeframe of this study.

Vector autoregression models use time-series data with lag to find interdependence among variables over time. In this model, the variables used were month-on-month inflation rates for the selected countries, and the difference in month-on-month Bitcoin price, both on a 10-year basis. If Granger causality exists between these variables for a country, it may signal that

Bitcoin is an effective hedge against inflation. The impulse response function was then used to indicate whether the hedging opportunity was economically significant or not.

The equation for bivariate VAR in its general form is as follows:

$$Yt = k_1 \sum_{i=1}^{P} (\phi_{11}, iYt - i + \phi_{12}, iXt - i) + \varepsilon_1 t$$

$$Xt = k_2 + \sum_{i=1}^{P} (\phi_{21}, iYt - i + \phi_{22}, iXt - i) + \varepsilon_2 t$$

Yt: Is the current value of inflation (for Argentina it is the current value for the first difference inflation).
Xt: Is the current value of the first difference Bitcoin price.
k1, k2: Constants.
ϕ11, ϕ12, ϕ21, ϕ22: Are coefficients of the lagged values.
ε1, ε2: Represent the serially uncorrelated error terms.
P: Is the lag length for the specific VAR model.

4.2 Phillips Perron and Dickey-Fuller Test

VAR models mandate that all variables must be stationary. This assumption ensures that the regression system yields a higher degree of predictability and reduces possible spurious regressions. Non-stationary variables may lead to inaccurate model predictions due to the variables not changing around a constant mean and variance.

The variables of month-on-month inflation and monthly Bitcoin prices were subjected to the Dickey-Fuller and Phillips-Perron tests. These check for stationarity by finding out if there exists a unit root within the autoregressive model. If a unit root is present, it would indicate non-stationarity.[38] To transform non-stationary variables into stationary, first-difference variables were created. When using the Dickey-Fuller and Phillips-Perron tests on the new variables, they should exhibit stationarity at the 5% significance level.

[38] Science Direct, Dickey Fuller Test.

4.3 Determining the Optimal Lag Length

Selecting the correct lag length is a crucial step in conducting an accurate VAR model. This since using too few lags may result in an increased estimation bias. However, including too many lag periods may contribute to a higher forecasting error.[39] Therefore, an optimal lag length must be determined before proceeding. This was done by using several tests designed to identify the optimal lag length. These tests included Hannan and Quinn‘s information criterion (HQIC), Akaike’s information criterion (AIC), Schwarz’s Bayesian information criterion (BIC), and the final prediction error (FPE). Each of the three first tests used different weights when punishing adding more lag to the model. This makes it possible for the different models to come to distinct conclusions. FPE works differently by picking the amount of lag that leads to the smallest prediction error. When doing these tests, a limit for the maximum amount of lag possible was set at 12 periods. This was deemed appropriate as inflation may experience a delay in reaction when faced with different shocks. Using more than twelve periods of lag seemed excessive since this would limit the sample size greatly.

4.4 VAR Model Stability

After the optimal number of lag lengths were chosen, the bivariate VAR model was run with the variable month-on-month inflation for the specific countries and the difference in month-on-month Bitcoin prices. Following this step, the VAR model was checked for stability. Checking for stability is done to ensure that the VAR model satisfies the stability condition.

If the stability condition is satisfied, the variables of the VAR model are stationary – a key condition for VAR models. Stationarity means that components of the regression (e.g. mean and variance) remain constant and do not change over time.[40] This is important in ensuring that the model output is accurate.

One way of testing for the stability condition is by checking the eigenvalue stability condition. If the stability condition is satisfied, it indicates that “all the eigenvalues lie inside the unit circle.”. This means that the absolute value of the eigenvalues falls under one. If the

[39] Christoph Hanck et.al., Introduction to Econometrics with R, 2024, 14.6
[40] Nist Sematech, Stationarity.

condition was not satisfied, it would indicate that the statistical model was wrongly specified. This misspecification could be corrected by using more lag periods in the model.

4.5 Analyzing Error Terms

A new variable was generated containing the residuals (error terms) of each variable in the regression model. This was found by computing the difference between actual and predicted values of the dependent variables.[41] This was done so that residual diagnostics could be conducted to investigate if the no-autocorrelation assumption of the VAR model holds or not. The residuals provide an indication of possible correlation that may exist between proportions of the dependent variables that is not captured entirely by the regression system itself. If residuals exhibit correlation, it may mean that some factors not taken into consideration may influence the variables (e.g. omitted variables).[42] This can reduce the reliability of the output and limit further inference. By summarizing the residual variable, it is possible to determine the mean and its closeness to zero. This provides an initial perception of the variable's alignment with the no-autocorrelation assumption.

To ensure that the error term represents random error and cannot be used to predict the independent variables, Lagrange multiplier tests were employed. The test was done with the same amount of lag as in the previous tests. The null hypothesis for the test is, H0: “no autocorrelation at lag order”. If the test shows a p-value that is greater than 0.05, it suggests that there are no signs of autocorrelation at the chosen lag length.

4.6 Granger-Causality Test

To determine if the variables inflation and Bitcoin price can be used to predict one another, Granger-causality tests were performed. If the tests show that the observed level of inflation can predict Bitcoin price or vice versa, it will indicate that Bitcoin could be used to hedge against inflation. The first null hypothesis for the test is H0: Lagged values of differenced Bitcoin price does not cause inflation. The second null hypothesis for the test is H0: Lagged values of inflation does not cause differenced Bitcoin price. In the case that both tests reveal

[41] Numeracy, Maths and Statistics - Academic Skills kit.
[42] 10.2 - Autocorrelation and time series Methods. STAT 462.

p-values of less than 0.05 both null hypotheses are rejected, which indicates that both variables Granger-cause each other.

4.7 Impulse Response Function

Where Granger causality exists, an impulse response function is used to determine the impact on an endogenous variable when presented with an external impulse.[43] The impulse response function is created by introducing a one-time shock the size of one standard deviation on the impulse variable (the variable that affects another variable) and simulating how this shock will affect the response variable (the variable that is affected by the impulse variable). The impulse response function graph then illustrates the magnitude of the effect as well as how long the response variable is affected by the shock to the impulse variable.[44]

[43] The Intuition Behind Impulse Response Functions and Forecast Error Variance Decomposition, (2021), Aptech.
[44] Rehal, V., & Rehal, V. (2023, August 9). Impulse Response Functions after VAR and VECM. SPUR ECONOMICS - Learn and Excel.

5. Data

Month-on-month data for CPI rates in the countries Argentina, Zimbabwe, Turkey, and Venezuela was collected for the period of January 2014 to December 2023. This data was downloaded from the website of each country's central bank or statistical institute. Monthly Bitcoin price data was also collected for the same period using the online data aggregator Investing.com. The 10-year period was chosen as it was deemed long enough to reduce the influence of short-term trends. Additionally, starting from the mid-2010s, Bitcoin began to experience more widespread appeal as it was not well known during its early years. Monthly data was used as it was the highest frequency available for CPI data. Preferably, higher frequency data, such as daily or weekly, would be used. This would provide a larger sample size for more in-depth statistical analysis.

No data cleansing was undertaken as the data set did not contain duplicates or other inconsistencies. Additionally, when looking at the data, some extreme values are present that deviate significantly from other values. However, these are factual data-points collected from official sources, and thus they cannot be considered outlier values and be removed.

Figures 1-4 show the inflation rate for the countries studied and its evolution during the period of interest. According to Figure 1, the inflation rate for Turkey was consistently below 2% per month up until late 2021, except for a sudden spike between July and October of 2018. The inflation rate later became more severe with the highest recorded level within the timespan being 13.58% for December 2021. From that point onwards, inflation has continued to be high and volatile.

In Venezuela, inflation reached its peak of 196.6% in January 2019, as seen in Figure 2. Since then, it has mellowed out with inflation hovering around 5% in the final months of 2023. 5% inflation is still a considerable amount, but significantly lower than previously.

The reported inflation in Zimbabwe was close to zero for a sustained period until prices increased abruptly in 2018 and 2019. Since then, inflation has remained high, see Figure 3.

The inflation in Argentina experienced a slow and steady increase until prices rose rapidly during the second half of 2023, as seen in Figure 4. In the final month of 2023, the inflation recorded was at 25.5%.

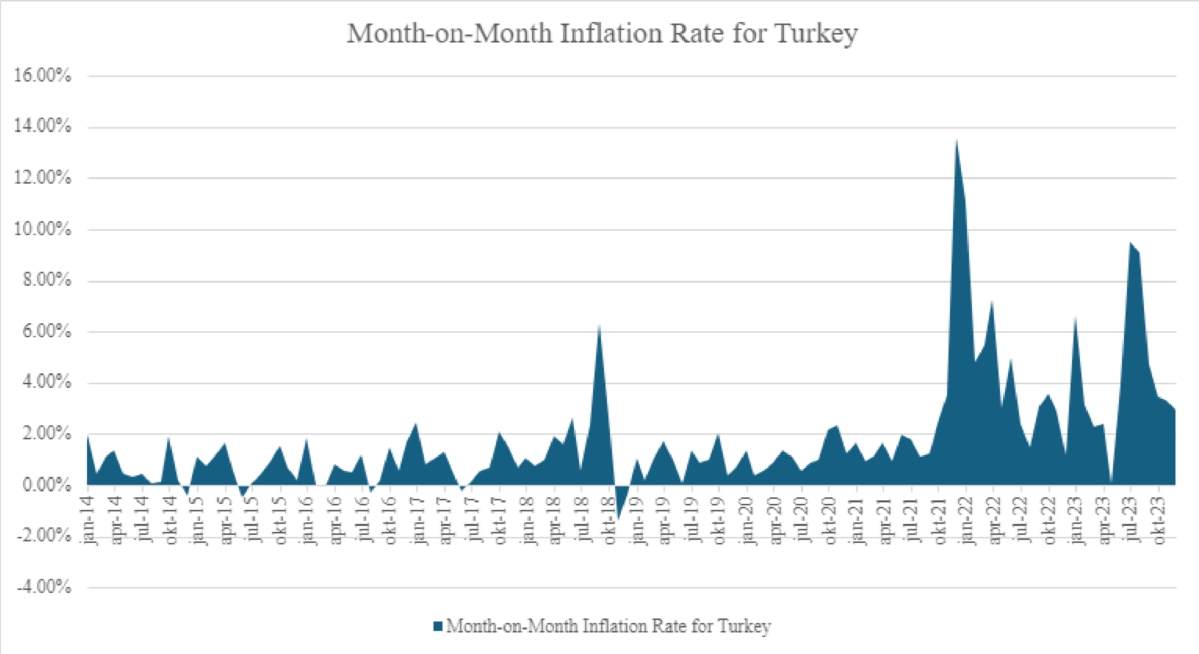

Figure 1: Shows the month-on-month inflation rate for Turkey from the beginning of 2014 to the end of 2023.

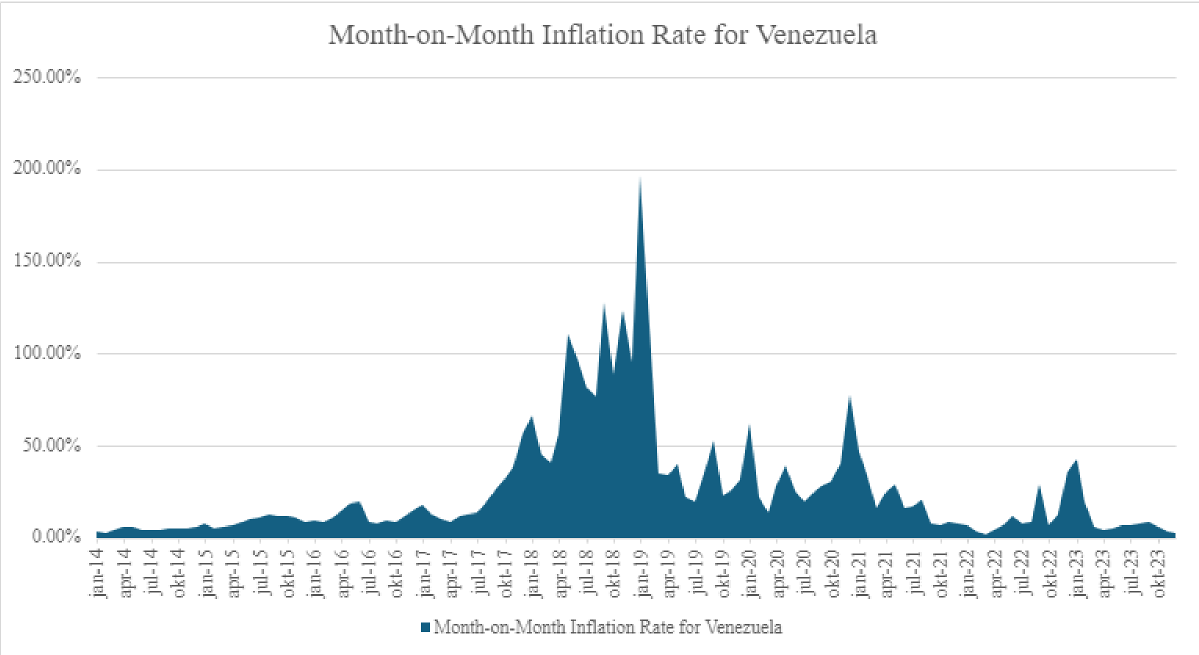

Figure 2: Shows the month-on-month inflation rate for Venezuela from the beginning of 2014 to the end of 2023.

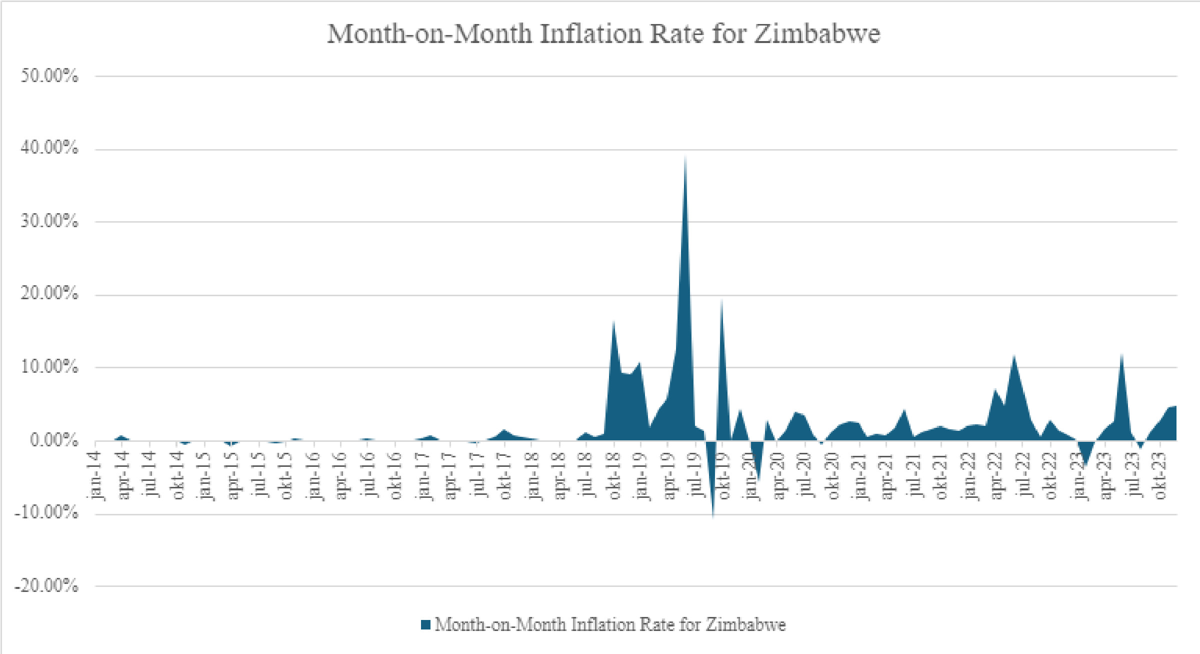

Figure 3: Shows the month-on-month inflation rate for Zimbabwe from the beginning of 2014 to the end of 2023.

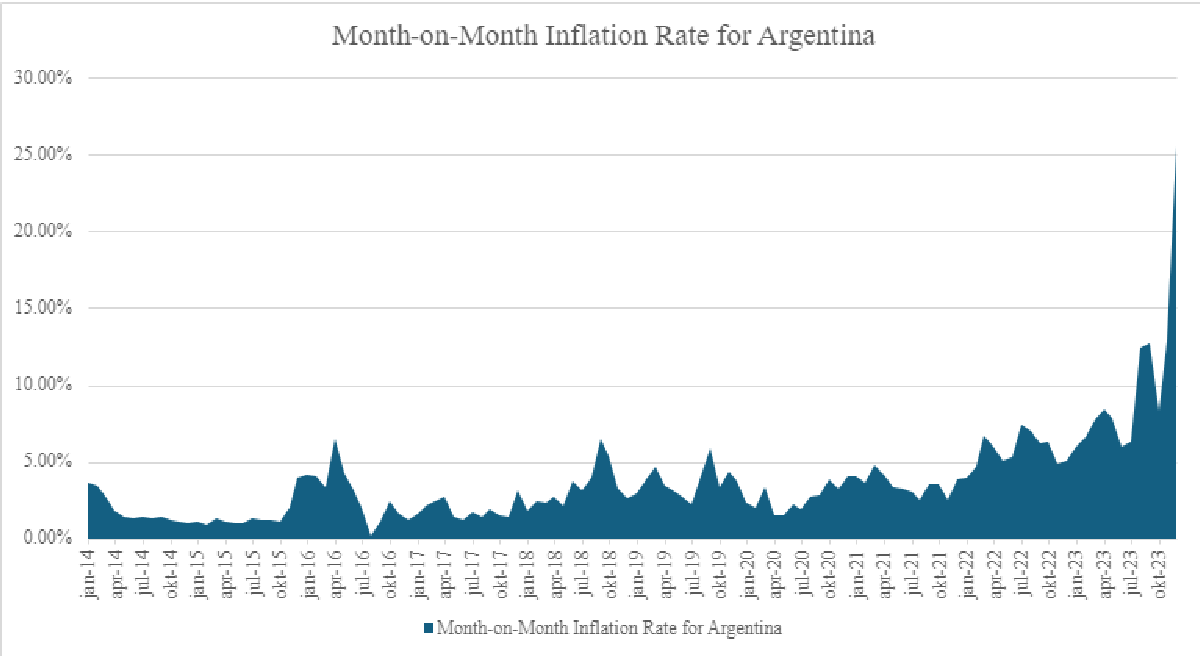

Figure 4: Shows the month-on-month inflation rate for Argentina from the beginning of 2014 to the end of 2023.

As illustrated in Figure 5, Bitcoin has undergone an extraordinary rise in price during the period of study. In 2014, one Bitcoin was valued at 938.00 USD. By the end of 2023, the market price was approximately 42,000.00 USD. In between these years, the asset has experienced very high volatility. Sharp price increases have at times been promptly followed by drastic price drops. An example of this is the price falling from 57,720.00 USD in April of 2021 to 37,298.00 USD a month later, a price fall of more than 20,000.00 USD per Bitcoin.

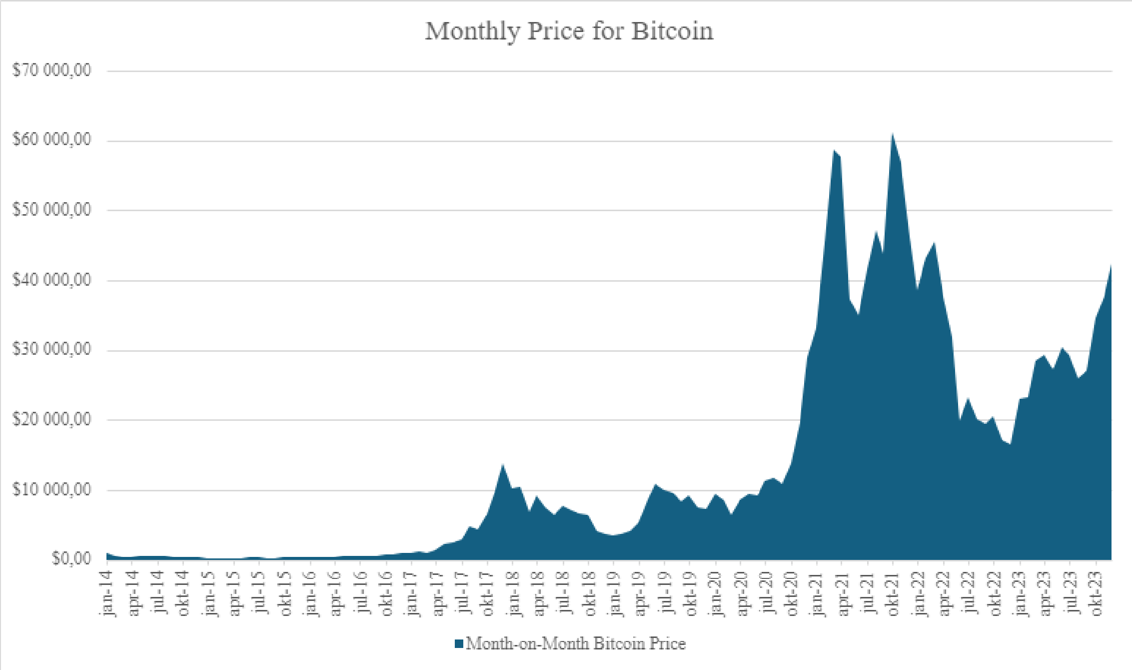

Figure 5: Shows the monthly Bitcoin price in terms of USD from the beginning of 2014 to the end of 2023.

6. Empirical Results

This section of the thesis presents the main findings of the study. This is done by referring to relevant graphs and tables. Before that, the results of the various tests that were used when specifying the model are revealed. Only the most important tables are featured in the text. The remaining tables are found in the Appendix.

6.1 Results of initial tests

Dickey-Fuller and Phillips-Perron tests were performed on all the variables to ensure that stationarity was exhibited. The output showed that all variables passed both tests at the 5% significance level, except for BTCPRICE and CPIARGENTINA. These variables were transformed into first-difference variables called dBTCPRICE and dCPIARGENTINA. The new variables were proven to be stationary when using the same tests as before (see Tables 3-6 in the appendix).

The tests used to decide the optimal lag length provided varying results for the inflation rate in the different countries. This indicates that the amount of lag periods used varied between VAR models. The amount of lag represents how many past values of the time-series are included when making the predictions. Table 1 shows the results of the tests where the * symbol marks the suggested lag length.

One period of lag was deemed optimal for Venezuela as FPE, AIC, HQIC, and SBIC all suggested this amount, see Table 1.

When performing the tests for Zimbabwe's inflation, FPE and AIC recommended one period of lag, while HQIC and SBIC recommended not using any lag at all. One lag was used because the VAR model needs at least one period of lag to produce impulse response functions, see Table 1.

For Argentina the optimal lag length was two periods as FPE, AIC, HQIC, and SBIC all recommended this, see Table 1.

As seen from Table 1, when analyzing the data for Turkey, FPE and AIC recommend using 10 lags while HQIC and SBIC suggested the use of only one period of lag. In this case, 10 periods of lag were deemed optimal due to the VAR model generally performing better with the use of more lag.

Table 1: Tests for optimal lag selection

LAG ORDER SPECIFICATION CRITERIA - ZIMBABWE

Sample: ***2015m2 thru 2023m12*** *Number of Obs = 107*

Lag	df	p	FPE	AIC	HQIC	SBIC
0			5.7e+08	25.8304	25.8506*	25.8803*
1	4	0.025	5.5e+08*	25.8012*	25.862	25.9511
2	4	0.198	5.6e+08	25.8197	25.921	26.0695
3	4	0.684	5.9e+08	25.8732	26.015	26.2229
4	4	0.149	6.0e+08	25.8847	26.067	26.3344
5	4	0.039	5.9e+08	25.8652	26.088	26.4148
6	4	0.798	6.2e+08	25.9244	26.1877	26.5739
7	4	0.114	6.3e+08	25.9297	26.2335	26.6791
8	4	0.340	6.5e+08	25.9622	26.3065	26.8115
9	4	0.436	6.8e+08	26.0016	26.3864	26.9509
10	4	0.598	7.1e+08	26.0506	26.4759	27.0997
11	4	0.480	7.5e+08	26.0928	26.5586	27.2418
12	4	0.443	7.8e+08	26.1326	26.639	27.3816

***Optimal Lag**

LAG ORDER SPECIFICATION CRITERIA - VENEZUELA

Sample: ***2015m2 thru 2023m12*** *Number of Obs = 107*

Lag	df	p	FPE	AIC	HQIC	SBIC
0			2.1e+10	29.4336	29.4539	29.4836
1	4	0.00	7.9e+09*	28.4666*	28.5274*	28.6165*
2	4	0.142	8.0e+09	28.477	28.5783	28.7268
3	4	0.661	8.4e+09	28.5293	28.6711	28.879
4	4	0.058	8.3e+09	28.5186	28.7008	28.9682
5	4	0.011	8.0e+09	28.4719	28.6947	29.0214
6	4	0.819	8.5e+09	28.5322	28.7955	29.1817
7	4	0.141	8.6e+09	28.5425	28.8463	29.2919
8	4	0.711	9.1e+09	28.5973	28.9416	29.4466
9	4	0.018	8.8e+09	28.5608	28.9456	29.51
10	4	0.725	9.3e+09	28.6163	29.0416	29.6654
11	4	0.369	9.6e+09	28.651	29.1168	29.8001
12	4	0.686	1.0e+10	28.7045	29.2108	29.9535

***Optimal Lag**

LAG ORDER SPECIFICATION CRITERIA - ARGENTINA

Sample: ***2015m2 thru 2023m12*** *Number of Obs = 107*

Lag	df	p	FPE	AIC	HQIC	SBIC
0			6.4e+07	23.6573	23.6775	23.7072
1	4	0.226	6.6e+07	23.6791	23.7398	23.829
2	4	0.000	5.1e+07*	23.4216*	23.5228*	23.6714*
3	4	0.416	5.3e+07	23.4596	23.6014	23.8093
4	4	0.336	5.5e+07	23.4918	23.6741	23.9414
5	4	0.192	5.6e+07	23.5096	23.7324	24.0592
6	4	0.625	5.9e+07	23.56	23.8233	24.2094
7	4	0.276	6.0e+07	23.587	23.8908	24.3364
8	4	0.961	6.5e+07	23.6559	24.0002	24.5052
9	4	0.901	6.9e+07	23.7208	24.1056	24.67
10	4	0.331	7.2e+07	23.7526	24.1779	24.8017
11	4	0.133	7.3e+07	23.7613	24.2271	24.9104
12	4	0.623	7.7e+07	23.8116	24.3179	25.0606

LAG ORDER SPECIFICATION CRITERIA - TURKEY

Sample: ***2015m2 thru 2023m12*** *Number of Obs = 107*

Lag	df	p	FPE	AIC	HQIC	SBIC
0			1.0e+08	24.1339	24.1541	24.1838
1	4	0.00	6.3e+07	23.6329	23.6937*	23.7828*
2	4	0.056	6.2e+07	23.6215	23.7228	23.8713
3	4	0.064	6.2e+07	23.6133	23.755	23.963
4	4	0.260	6.3e+07	23.6387	23.821	24.0884
5	4	0.013	6.1e+07	23.5951	23.8179	24.1446
6	4	0.300	6.3e+07	23.6243	23.8875	24.2737
7	4	0.000	5.4e+07	23.4772	23.781	24.2266
8	4	0.118	5.4e+07	23.4831	23.8274	24.3324
9	4	0.006	5.1e+07	23.4216	23.8064	24.3708
10	4	0.009	4.9e+07*	23.3691*	23.7944	24.4183
11	4	0.260	5.0e+07	23.3945	23.8604	24.5436
12	4	0.052	5.0e+07	23.3817	23.888	24.6307

*Table 1: Results from FPE, AIC, HQIC, and SBIC tests are shown for the four countries with the maximum lag length set at 12 periods. The symbol * marks the optimal lag suggested by the different metrics.*

According to Table 7 found in the appendix, all VAR models were stationary as they all passed the eigenvalue stability condition.

The mean value for the error terms, as well as the results from the Lagrange multiplier tests, indicate that none of the regressions exhibit autocorrelation problems. This is determined in part due to the mean values of the error terms all being close to zero. The Lagrange multiplier tests further confirm this, as they all show no indication of autocorrelation at the specified lag levels *since the p-value > 0.05, (see Tables 8 and 9 in the appendix).*

6.2 Granger Causality and Impulse Response Functions

For the regressions containing the inflation for Venezuela, Argentina, and Zimbabwe, there was no granger causality between the inflation rate and Bitcoin price in any direction. This is seen by looking at Table 2 for the column *"Prob>chi2"*. The value must be less than 0.05 to show Granger causality at the 5% significance level. Since there is no Granger causality for Argentina, Zimbabwe, or Venezuela, the output conveys that it is not possible to use inflation to predict the price of Bitcoin, and vice versa.

When conducting the Granger causality test for the Turkish inflation and Bitcoin price, the results show that the price of Bitcoin Granger causes Turkish inflation, see column *"Prob>chi2"* for Table 2. Since the value is less than 0.05 when dBTC_PRICE is the excluded variable, it indicates that there is a hedging opportunity present here. This is because the price of Bitcoin can be used to predict changes in the inflation rate. However, since the value is larger than 0.05 when CPI_TUR is the excluded variable, it shows that Turkish inflation does not Granger-cause the Bitcoin price. This means that Turkish inflation cannot be used to predict the price of Bitcoin.

Table 2: Granger causality tests for all VAR models

Granger causality Wald tests - Argentina

Equation	*Excluded*	*chi2*	*df*	*Prob > chi2*
dCPIARGENTINA	dBTCPRICE	3.5835	2	0.167
dCPIARGENTINA	ALL	3.5835	2	0.167
dBTCPRICE	dCPIARGENTINA	0.61752	2	0.734
dBTCPRICE	ALL	0.61752	2	0.734

Granger causality Wald tests - Turkey

Equation	*Excluded*	*chi2*	*df*	*Prob > chi2*
dBTC_PRICE	CPI_TUR	15.887	10	0/103
dBTC_PRICE	ALL	15.887	10	0.103
CPI_TUR	dBTC_PRICE	74.599	10	0.000
CPI_TUR	ALL	74.599	10	0.000

Granger causality Wald tests - Zimbabwe

Equation	*Excluded*	*chi2*	*df*	*Prob > chi2*
dBTCPRICE	CPIZIMBABWE	0.26369	1	0.608
dBTCPRICE	ALL	0.26369	1	0.608
CPIZIMBABWE	dBTCPRICE	0.59267	1	0.441
CPIZIMBABWE	ALL	0.59267	1	0.441

Granger causality Wald tests - Venezuela

Equation	*Excluded*	*chi2*	*df*	*Prob > chi2*
CPIVENEZUELA	dBTCPRICE	0.00022	1	0.988
CPIVENEZUELA	ALL	0.00022	1	0.988
dBTCPRICE	CPIVENEZUELA	0.20162	1	0.653
dBTCPRICE	ALL	0.20162	1	0.653

Table 2: Shows the results from Granger causality tests for all regressions. The test checks if the "excluded" variable Granger causes the "equation" variable. When looking at the p-values it is evident that the only case of Granger causality is for the variable dBTCPRICE on CPITURKEY, since the p-value is smaller than 0.05.

Figure 6 shows the impulse response function for how Turkish inflation is affected during the next 36 months following the introduction of a one-standard-deviation shock to the price of

Bitcoin. The graph shows that the shock will lead to inflation increasing in the next five months before dropping again. After approximately 12 months, the inflation will start to stabilize. The graph also indicates that the effect of the shock is minimal. According to the y axis, the shock will at most produce an increase in inflation of roughly 0.0002%. The implication of this is that the effect is not large enough for it to be economically significant in this context. Therefore, these results indicate that one cannot determine that Bitcoin can be used as an effective hedge against inflation.

Figure 6: Impulse response function for Turkish inflation with a shock to the Bitcoin price

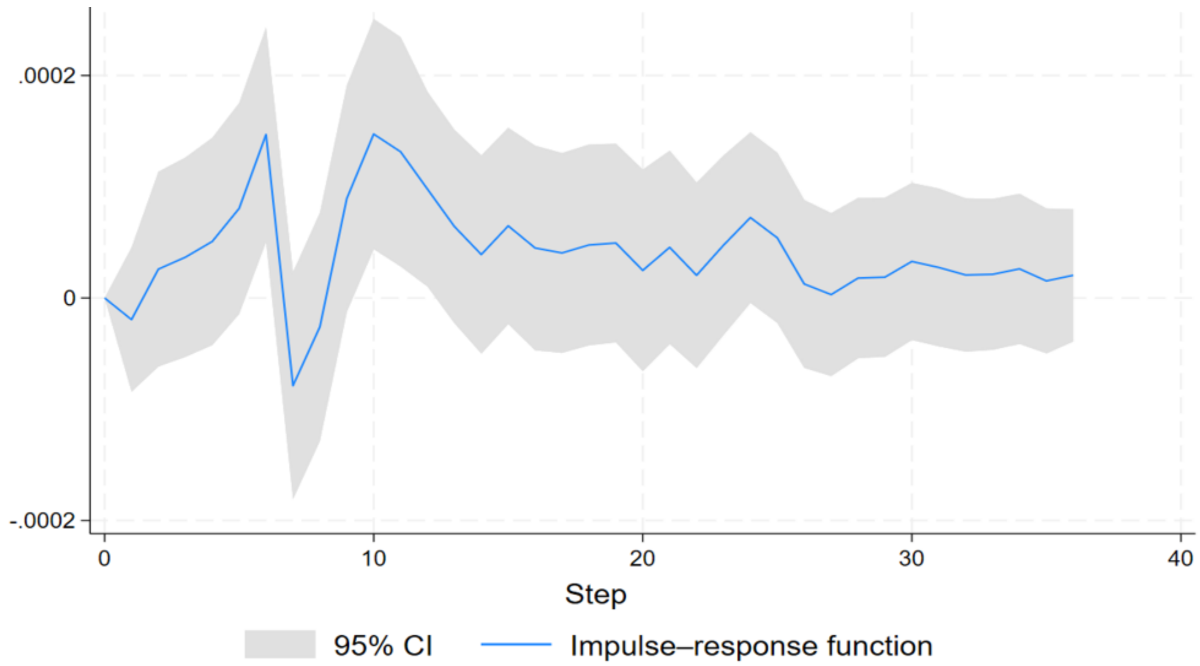

Figure 6: Shows how the Turkish inflation will react to a one standard deviation shock to the Bitcoin price. The Y-axis shows how large the impact is on the Turkish inflation rate in percentages. The X-axis signifies the time with it showing the effect up until 36 months after the initial shock. The grey area represents the 95% confidence interval, meaning that the effect will be within the grey area with a 95% chance at any different point on the X-axis.

7. Discussion

In the first part of the discussion, the results previously presented are expounded upon. This is done partly by comparing said results with previous studies that employed a similar model. On top of this, the theoretical framework is employed to further explain why the results came out the way they did. The second part of the discussion is used to explain the various limitations of the study. The discussion brings up how the limitations may have impacted the results. Various ways to improve upon the study are also highlighted in the text.

7.1 Results

As depicted in the results section, no Granger causality was identified for Argentina, Zimbabwe, and Venezuela. This implies that Bitcoin is not an effective hedge against inflation in these countries. The only variable that exhibited Granger causality was the first difference in Bitcoin price. This variable was able to only influence the inflation rate for Turkey. However, as seen from the impulse response function the effect was minimal. Therefore, it was concluded that it lacked economic relevance and that Bitcoin could not be considered an effective hedge.

The result is not surprising as the sentiment in previous research has been mixed regarding Bitcoin's efficiency in hedging against inflation. Prior studies tend to come to varying conclusions based on the model that was used. For example, Klein et al. (2018), found no signs of hedging potential when using the GARCH model. However, most studies using the VAR framework found at least some signs of hedging properties, with two examples of such studies being Choi & Shin (2020) and Blau et al. (2021).

A possible reason why the result in this paper differs from other similar studies using the VAR framework may be because the economies included in this study are much smaller in size when compared to the U.S., which was studied by Choi & Shin (2020) and Blau et al. (2021). This is of importance because a change to the U.S. inflation will have a broader overall impact on the global economic landscape when compared to a similar change to the inflation of a smaller economy, like those studied in this report. Thus, it is reasonable to believe that the U.S. inflation also can affect the Bitcoin price to a greater extent, which would suggest increased hedging possibilities compared to smaller economies. When taking this into account, it seems likely that similar results would have been found had the study looked at different nations with high inflation. This since they all tend to be smaller economies.

Another factor that may explain why hedging capabilities were not identified is the high rate of volatility. The inflation data used in the report, as well as the price for Bitcoin, are highly volatile with large shifts in rates over time. This makes it challenging to hedge as the return necessary to protect against inflation must consistently exceed very high levels when compared to that of the U.S. As stated in the preceding section, most of the research conducted on this topic focuses on inflation rates in the U.S. and Euro-Zone. Here, the inflation is far less volatile and generally remains stable at lower rates. This makes achieving exceeding returns easier and could be an explanation as to why the studies that are looking at these regions have found evidence of effective hedging opportunities.

There exist reasons to believe that Bitcoin, and cryptocurrency markets at large, are operating inefficiently and that the EMH is not satisfied. These inefficiencies can be explained partly due to so-called irrational investors who trade these assets while influenced by different cognitive biases or emotionally based decisions. As previously mentioned, a reason for the high volatility in cryptocurrency assets could be due to herding behavior.[45] Another form of bias that has been affecting investors in cryptocurrency markets is overconfidence.[46] As with herding behavior, one likely reason for this is that there are many inexperienced investors trading in cryptocurrency markets who are more likely to make irrational and emotionally driven decisions. When doing so they often expose themselves to unnecessarily large risks. The fact that these types of biases are present can lead one to believe that Bitcoin price changes are not always entirely justified. This could be a contributing factor in why significant Granger relationships between the movements in Bitcoin price and the inflation rates were not found.

As mentioned in the introduction, both Argentina and Turkey rank high in cryptocurrency adoption. This may be due to an array of reasons, such as a lack of faith in monetary and fiscal policymaking, depreciating domestic currencies, cryptocurrencies being an accessible alternative to foreign currency, and lower transaction costs for international transfers.[47] In

[45] Elie Bouri et.al.
[46] Chhatwani, M., & Parija, A. K. (2023). Who invests in cryptocurrency? The role of overconfidence among American investors. Journal of Behavioral and Experimental Economics, 107, 102107.
[47] The Global Crypto Adoption Index. Chainalysis.

addition to this, the concept of loss aversion could also offer reason as to why cryptocurrency investments are widely popular in the studied countries. There is a widespread awareness that wealth diminishes over time due to high inflation (yearly inflation was 64.8% in Turkey for 2023). [48] Individuals therefore find themselves in a losing financial position. The awareness of losing wealth to inflation tends to lead to an increase in risk-taking as individuals seek to recoup and recover losses. Instead of making investments that give the highest expected utility, they are incentivized to invest in high-risk assets such as cryptocurrencies. This is because extraordinary returns are necessary to fully offset the impact of inflation. Since Bitcoin has experienced sharp price increases over the past few years, risky investments have seemingly paid off. A herd mentality could form because of this, where investors and speculators are buying cryptocurrencies based on others' success. This may occur despite many not being fully aware of the inherent risks associated with cryptocurrency investments (e.g. fraud, lack of regulatory protection, rug-pulls, and many more).

7.2 Limitations

As introduced in the data section of the thesis, the low frequency of data used (month-on-month) merits some concern. The low data frequency may not adequately capture trends and dynamics in the short term. Every week, Bitcoin can experience significant price shifts, and using monthly data may therefore not accurately portray the actual movement of the price in between data measurements. Additionally, using higher frequency data may improve estimates of model parameters, and possibly reduce standard errors. An array of analyzed research and academic papers covering similar concepts tend to utilize more frequent intervals in their data.[49] This could possibly contribute to why the results in this thesis reach a different conclusion to that of some literature.

Inflation can be measured in a multitude of ways, and it is unlikely that all the countries in this study have used the exact same process when measuring their inflation. CPI data is dependent on the choice of input, and by assigning different weights to input factors, the result can vary between countries.[50] This may create some discrepancies when conducting comparative analysis. Furthermore, CPI data generally consists of thousands of data points across numerous sectors and categories, making manual verification of data difficult. There is

[48] Mercan, M. (2024, January 3). Turkish inflation rises in December. ING Think.
[49] Benjamin M. Blau, Todd G. Griffith, Ryan J. Whitby, Inflation and Bitcoin: A descriptive time-series analysis
[50] Inflation Not Fully Comparable Between Countries, (2020), Sveriges Riksbank

also the possibility that data is intentionally manipulated prior to being published. This may be due to an unwillingness to fully disclose the deteriorating condition of the economy. Despite these limitations, the data collected was deemed the best available as it was sourced primarily from official government and institutional databases.

An additional limitation is that other external variables that may influence the price of Bitcoin or the inflation rate were not considered. If more variables were included, the results could provide a broader understanding of the relationship between the price of Bitcoin and inflation. Moreover, including other forms of asset appreciation and investment vehicles, such as equities markets, could provide a relative comparison for the efficiency of Bitcoin in hedging against inflation. In the model used in this thesis, two variables are used, the inflation rate in the country and the price of Bitcoin. No specific consideration has been taken regarding the possibility of external variables or influences impacting the dynamic relationship between inflation and Bitcoin price. In a non-test environment, a myriad of factors may have a direct or indirect impact on the inflation rate or Bitcoin price, and it is nearly impossible to account for all. For instance, inflation rates may be affected by monetary policies or other economic conditions. Additionally, the model assumes no currency exchange rate exposure as the Bitcoin prices are listed in USD. This contrasts with other research that has denominated Bitcoin prices in the domestic currency for the countries researched, such as in Jalan & Matovskyy 2020. The decision to keep Bitcoin prices in USD as opposed to local currencies was due to periods of devaluation by central banks in attempts to strengthen the currency. This increased the complexity of accurately comparing domestic currencies and Bitcoin prices. However, it is acknowledged that converting the price may be a more viable option, as in reality, purchasing or selling Bitcoin through certain exchanges may require individuals to convert local currency to USD and then acquire Bitcoin (vice versa for selling). Therefore, currency fluctuations may cause changes in the actual value transacted and could contribute to different results.

Several previous studies have used expected future inflation rates to complement unexpected inflation rates in the regression models.[51] In this thesis, however, only unexpected inflation was used as expected future values and projections could not be found. A decision was made not to predict expected inflation using estimation techniques due to the complexity in standardizing calculation methods and solidifying the accuracy of the output. However,

[51] Yuji Sakurai, Tetsuo Kurosaki, Have cryptocurrencies become an inflation hedge after the reopening of the U.S. economy?

having access to such data in alignment with previous research would provide an interesting insight into the possible hedging potential of Bitcoin. Future expectations could be an influencing factor in how individuals position themselves in the moment.

8. Conclusion

Using bivariate vector autoregressions, the thesis concludes that Bitcoin is not an effective hedge against extreme inflation levels in the studied countries. Only a single variable, the inflation rates for Turkey, showed one-directional Granger causality (the price of Bitcoin affected inflation levels), able

it to a low degree. This causality was deemed not significant enough to justify any economic relevance. The findings align with some research while contrasting others. The differences may be due to several reasons as presented in the discussion section:

1. The low frequency of data intervals may have led to the regression model not properly capturing possible trends. This is especially prevalent in the price of Bitcoin which experiences large price shifts over short periods of time.

2. Much of the previous research on this topic has focused on the US and Euro-Zone economies. These economies, especially the U.S., are among the largest in the world and their monetary and fiscal position may have a greater impact on cryptocurrency markets. Moreover, the inflation levels are generally lower, which makes hedging easier as the required return will be lower.

3. Cryptocurrency markets may not be entirely efficient and be subjected to a range of biases, such as overconfidence and herding behavior. This leads to the price of cryptocurrencies, such as Bitcoin, not being fully justified. The Granger causality may therefore not accurately portray the true relationship.

This paper expands on currently available research covering the hedging efficacy of Bitcoin by laying focus on economies with high inflation levels. This is an area of finance that until this point has been relatively unexplored. This is despite the widespread use of cryptocurrencies as an investment alternative in economies facing volatile inflation levels. The paper also leaves room for future research to be conducted to expand upon the topic. Examples of such research could include comparing Bitcoin with alternative stores of value and asset appreciation vehicles, such as the stock market, real estate, or commodities, in countries experiencing high inflation levels. Moreover, future research could also compare results from alternative regression methods such as GARCH. Finally, research could be conducted that resolves the limitations put forth in this report. This could enhance the results and provide a more reliable inferential analysis.

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10. Appendix, Model Specification Tests

The following tables show Stata output from the various model specification tests explained in the methodology.

Table 3: Dickey-Fuller tests for the different inflation rates.

DICKEY-FULLER - TURKEY

Dickey-Fuller test for unit root *Number of obs = 119*
Variable: CPI_TUR *Number of lags = 0*

H0: Random walk without drift, d = 0

	Test Statistics	Critical Value 1%	Critical Value 5%	Critical Value 10%
Z(t)	-4.960	-3.504	-2.889	-2.579

MacKinnon approximate p-value for Z(t) = 0.0000

DICKEY-FULLER - VENEZUELA

Dickey-Fuller test for unit root *Number of obs = 119*
Variable: CPI_VENEZUELA *Number of lags = 0*

H0: Random walk without drift, d = 0

	Test Statistics	Critical Value 1%	Critical Value 5%	Critical Value 10%
Z(t)	-3.549	-3.504	-2.889	-2.579

MacKinnon approximate p-value for Z(t) = 0.0068

DICKEY-FULLER - ZIMBABWE

Dickey-Fuller test for unit root *Number of obs = 119*
Variable: CPIZIMBABWE *Number of lags = 0*

H0: Random walk without drift, d = 0

	Test Statistics	Critical Value 1%	Critical Value 5%	Critical Value 10%
Z(t)	-8.426	-3.504	-2.889	-2.579

MacKinnon approximate p-value for Z(t) = 0.0000

DICKEY-FULLER - ARGENTINA

Dickey-Fuller test for unit root *Number of obs = 119*
Variable: CPIARGENTINA *Number of lags = 0*

H0: Random walk without drift, d = 0

	Test Statistics	Critical Value 1%	Critical Value 5%	Critical Value 10%
Z(t)	1.522	-3.504	-2.889	-2.579

MacKinnon approximate p-value for Z(t) = 0.9976

Table 3: Shows the result of the Dickey-Fuller tests that check for stationarity. As seen from the p-value, all variables except for CPIARGENTINA are deemed to be stationary.

Table 4: Phillips-Perron tests for the different inflation rates

PHILLIPS-PERRON - TURKEY

Phillips-Perron test for unit root — *Number of obs = 119*
Variable: CPI_TUR — *Newey-West lags = 4*

H0: Random walk without drift, d = 0

	Test Statistics	Critical Value 1%	Critical Value 5%	Critical Value 10%
z(rho)	-39.765	-19.863	-13.738	-11.025
Z(t)	-4.960	-3.504	-2.889	-2.579

MacKinnon approximate p-value for Z(t) = 0.0000

PHILLIPS-PERRON - VENEZUELA

Phillips-Perron test for unit root — *Number of obs = 119*
Variable: CPI_TUR — *Newey-West lags = 4*

H0: Random walk without drift, d = 0

	Test Statistics	Critical Value 1%	Critical Value 5%	Critical Value 10%
z(rho)	-19.778	-19.863	-13.738	-11.025
Z(t)	-3.306	-3.504	-2.889	-2.579

MacKinnon approximate p-value for Z(t) = 0.0146

PHILLIPS-PERRON - ZIMBABWE

Phillips-Perron test for unit root — *Number of obs = 119*
Variable: CPIZIMBABWE — *Newey-West lags = 4*

H0: Random walk without drift, d = 0

	Test Statistics	Critical Value 1%	Critical Value 5%	Critical Value 10%
z(rho)	-94.729	-19.863	-13.738	-11.025
Z(t)	-8.521	-3.504	-2.889	-2.579

MacKinnon approximate p-value for Z(t) = 0.0000

PHILLIPS-PERRON- ARGENTINA

Phillips-Perron test for unit root — *Number of obs = 119*
Variable: CPIARGENTINA — *Newey-West lags = 4*

H0: Random walk without drift, d = 0

	Test Statistics	Critical Value 1%	Critical Value 5%	Critical Value 10%
z(rho)	20.969	-19.863	-13.738	-11.025
Z(t)	3.204	-3.504	-2.889	-2.579

MacKinnon approximate p-value for Z(t) = 1.0000

Table 4: Shows the result of the Phillips-Perron tests that check for stationarity. As seen from the p-value, all variables except for CPIARGENTINA are deemed to be stationary.

Table 5: Phillips-Perron and Dickey-Fuller tests for Bitcoin price

Phillips-Perron test for unit root — *Number of obs = 119*
Variable: BTCPRICE — *Newey-West lags = 4*

H0: Random walk without drift, d = 0

	Test Statistics	Critical Value 1%	Critical Value 5%	Critical Value 10%
z(rho)	-3.465	-19.863	-13.738	-11.025
Z(t)	-1.117	-3.504	-2.889	-2.579

MacKinnon approximate p-value for Z(t) = 0.7082

Dickey-Fuller test for unit root — *Number of obs = 119*
Variable: BTCPRICE — *Number of lags = 0*

H0: Random walk without drift, d = 0

	Test Statistics	Critical Value 1%	Critical Value 5%	Critical Value 10%
Z(t)	-0.982	-3.504	-2.889	-2.579

MacKinnon approximate p-value for Z(t) = 0.7597

Table 5: Shows the result of the Phillips-Perron and Dickey-Fuller tests that check for stationarity. As seen from the p-values, the variable for BTCPRICE was deemed to be non-stationary.

Table 6: Dickey-Fuller and Phillips-Perron tests for first-difference variables of Argentinian inflation rate and Bitcoin price.

DICKEY-FULLER (d) - ARGENTINA

DICKEY-FULLER (d) - ARGENTINA

Dickey-Fuller test for unit root — *Number of obs = 119*
Variable: dCPIARGENTINA — *Number of lags = 0*

H0: Random walk without drift, d = 0

	Test Statistics	Critical Value 1%	5%	10%
Z(t)	-6.935	-3.504	-2.889	-2.579

MacKinnon approximate p-value for Z(t) = 0.0000

PHILLIPS-PERRON (d)- ARGENTINA

Phillips-Perron test for unit root — *Number of obs = 118*
Variable: dCPIARGENTINA — *Newey-West lags = 4*

H0: Random walk without drift, d = 0

	Test Statistics	Critical Value 1%	5%	10%
z(rho)	-81.790	-19.860	-13.736	-11.024
Z(t)	-6.146	-3.504	-2.889	-2.579

MacKinnon approximate p-value for Z(t) = 0.0000

DICKEY-FULLER (d) - BITCOIN

Dickey-Fuller test for unit root — *Number of obs = 118*
Variable: dBTCPRICE — *Number of lags = 0*

H0: Random walk without drift, d = 0

	Test Statistics	Critical Value 1%	5%	10%
Z(t)	-8.744	-3.504	-2.889	-2.579

MacKinnon approximate p-value for Z(t) = 0.0000

PHILLIPS-PERRON (d) - BTCPRICE

Phillips-Perron test for unit root — *Number of obs = 118*
Variable: dBTCPRICE — *Newey-West lags = 4*

H0: Random walk without drift, d = 0

	Test Statistics	Critical Value 1%	5%	10%
z(rho)	-84.679	-19.860	-13.736	-11.024
Z(t)	-8.602	-3.504	-2.889	-2.579

MacKinnon approximate p-value for Z(t) = 0.0000

Table 6: Shows Dickey-Fuller and Phillips-Perron tests for the first-difference variables for the Argentinian inflation rate and the Bitcoin price. As shown by the p-values, both variables are deemed to be stationary.

Table 7: Eigenvalue stability condition tests for all VAR models

Eigenvalue Stability Condition - Argentina

Eigenvalue	*Modulus*
-0.00180029 + 0.8301981i	0.8302
-0.00180029 - 0.8301981i	0.8302
0.1289371 + 0.3962409i	0.416691
0.1289371 - 0.3962409i	0.416691

All the eigenvalues lie inside the unit circle.
VAR satisfied stability condition.

Eigenvalue Stability Condition - Zimbabwe

Eigenvalue	*Modulus*
0.2818865	0.281886
0.1615165	0.161516

All the eigenvalues lie inside the unit circle.
VAR satisfied stability condition.

Eigenvalue Stability Condition - Venezuela

Eigenvalue	*Modulus*
0.8044516	0.804452
0.2002461	0.200246

All the eigenvalues lie inside the unit circle.
VAR satisfied stability condition.

Eigenvalue Stability Condition - Turkey

Eigenvalue	*Modulus*
0.9463927	0.946393
0.7832835 + 0.506033i	0.932525
0.7832835 - 0.506033i	0.932525
0.5367061 + 0.7604888i	0.930804
0.5367061 - 0.7604888i	0.930804
0.2273288 + 0.8992889i	0.927577
0.2273288 - 0.8992889i	0.927577
-0.4149992 + 0.8273487i	0.925597
-0.4149992 - 0.8273487i	0.925597
-0.8979547 + 0.20844i	0.92183
-0.8979547 - 0.20844i	0.92183
-0.7320628 + 0.5244418i	0.90053
-0.7320628 - 0.5244418i	0.90053
-0.1119402 + 0.8878707i	0.894899
-0.1119402 - 0.8878707i	0.894899
0.7599201 + 0.1828265i	0.781603
0.7599201 - 0.1828265i	0.781603
-0.3026706 + 0.6615236i	0.727477
-0.3026706 - 0.6615236i	0.727477
0.4595164	0.459516

All the eigenvalues lie inside the unit circle.
VAR satisfied stability condition.

Table 7: Shows test results for Eigenvalue stability condition tests for all VAR models. All models are deemed to be stationary since all eigenvalues have an absolute value of less than one.

Table 8: Error term diagnostics for the different VAR models.

SUMMARIZE ERROR - TURKEY

Variable	Obs	Mean	Std. dev.	Min	Max
error	116	.0000131	4050.3	-17816.78	18944.6

SUMMARIZE ERROR - VENEZUELA

Variable	Obs	Mean	Std. dev.	Min	Max
error	118	8.42e-08	18.67554	-62.32251	114.7654

SUMMARIZE ERROR - ARGENTINA

Variable	Obs	Mean	Std. dev.	Min	Max
error	117	-1.36e-09	1.496118	-3.030569	8.962028

SUMMARIZE ERROR - ZIMBABWE

Variable	Obs	Mean	Std. dev.	Min	Max
error	118	8.42e-08	18.67554	-62.32251	114.7654

Table 8: Various measures of the error terms are on shown for each VAR model. The most significant in this case is the mean value. If the mean error is close to zero it indicates that there is no autocorrelation present.

Table 9: Lagrange multiplier tests for all VAR models

LAGRANGE MULTIPLIER - TURKEY

lag	chi2	df	Prob > chi2
1	4.3357	4	0.36248
2	6.3632	4	0.17362
3	2.0226	4	0.73160
4	7.4435	4	0.11423
5	2.1773	4	0.70319
6	7.3215	4	0.11984
7	13.2573	4	0.01008
8	1.4355	4	0.83801
9	8.4648	4	0.07596
10	**0.8552**	**4**	**0.93089**

H0: no autocorrelation at lag

LAGRANGE MULTIPLIER - ARGENTINA

lag	chi2	df	Prob > chi2
1	4.1480	4	0.38635
2	**4.7521**	**4**	**0.31369**

H0: no autocorrelation at lag

LAGRANGE MULTIPLIER - VENEZUELA

lag	chi2	df	Prob > chi2
1	**7.3632**	**4**	**0.11789**
2	4.1271	4	0.38908

H0: no autocorrelation at lag

LAGRANGE MULTIPLIER - ZIMBABWE

lag	chi2	df	Prob > chi2
1	**6.4406**	**4**	**0.16857**
2	7.0533	4	0.13310

H0: no autocorrelation at lag

Table 9: Shows the results from the different Lagrange multiplier tests for the different VAR models. None of the VAR models show signs of autocorrelation at their respective lag length since the p-values are all larger than 0.05 (the rows which are emboldened are the ones that show the results for the correct lag length).