Evolving Dynamics in the Global Financial System: Assessing the Impact of Cryptocurrency on the U.S. Dollar's Dominance

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ABSTRACT

In this study, we dive into the exciting world of cryptocurrencies like Bitcoin and Ethereum and their impact on the U.S. Dollar, which has long been the kingpin in global finance. With the digital age in full swing, these new digital currencies are shaking things up, challenging the traditional role of established currencies like the Dollar. Our adventure into this topic uses a rich set of data from 2019 to 2023, including cryptocurrency prices, the U.S. Dollar Index, and important U.S. economic figures. We've rolled up our sleeves and applied a mix of techniques – from looking at basic trends and connections in the data to more complex analyses like time series (which helps us see how things change over time), regression models (which help us understand relationships between variables), and even studying how big crypto events impact the Dollar.

We started with two main ideas: First, we thought that as cryptocurrencies become more valuable and traded more, they might start to overshadow the Dollar. Second, we guessed that the influence of cryptocurrencies on the Dollar might change depending on what's happening in the world economy, like during high inflation or economic downturns.

Our exploration is more than just number-crunching. It's about understanding how the digital revolution is changing the rules of finance and what that means for the future of money. This research is a stepping stone for decision-makers, investors, and anyone fascinated by the rapidly changing financial landscape, helping them to navigate these new waters.

INTRODUCTION

In a world where digital innovation is reshaping our lives, the financial landscape is not left untouched. The advent of cryptocurrencies, such as Bitcoin and Ethereum, has sparked a revolution in the way we think about money. No longer confined to the traditional bounds of banks and physical currency, the financial world is witnessing a seismic shift towards digital assets. This shift begs the question: How does this new digital financial frontier impact the longstanding dominance of traditional currencies, particularly the U.S. Dollar, which has been the cornerstone of global finance?

The U.S. Dollar has long been the heavyweight champion in the global financial arena. Its influence extends beyond borders, dictating the pace of international trade, investments, and reserve holdings. However, with the surge in popularity and value of cryptocurrencies, there's a growing narrative that these digital currencies might be more than just a speculative asset or a tech enthusiast's plaything; they could be potential challengers to the Dollar's reign.

Our study embarks on an exploratory journey to understand this evolving dynamic. We delve into the complex relationship between the rise of Bitcoin and Ethereum – the frontrunners in the crypto world – and the status of the U.S. Dollar. By harnessing data from 2019 to 2021, we examine not just the direct interactions between these digital and fiat currencies, but also how broader economic indicators intertwine in this narrative.

The heart of our research revolves around two key hypotheses. Firstly, we hypothesize that as the cryptocurrency market grows in value and trading volume, it might start to chip away at the Dollar's dominance. Secondly, we propose that the way cryptocurrencies affect the Dollar isn't static; it likely varies in different global economic climates, possibly intensifying during times of economic stress like high inflation or recessions.

This paper aims to offer a fresh perspective on the intersection of digital and traditional finance. It's not just about crunching numbers and drawing graphs; it's about piecing together a story of change, challenge, and the future of money. As we navigate through statistical analyses and economic theories, our goal is to provide insights that are valuable not just for economists and policymakers, but for anyone interested in the ever-evolving world of finance.

LITERATURE REVIEW

Recent research has shed light on the evolving landscape of digital currencies and their potential impacts on global finance. Scholars have emphasized the mutually reinforcing relationship between a country's economic fundamentals and the strength of its fiat currency (Garratt et al., 2023). The rise of cryptocurrencies, as presented in Bitcoin's whitepaper (Nakamoto, 2008), poses challenges to stronger fiat currencies but can offer opportunities for weaker currencies by reducing competition and dollarization. Central Bank Digital Currencies (CBDCs) have emerged as strategic tools for countries to navigate this shifting landscape. Studies highlight their potential to disrupt the dominance of the US dollar in international trade (McDermott & Öztürk, 2023) and their role in addressing global economic vulnerabilities, especially for Emerging Market and Developing Economies (EMDEs). These CBDCs could influence the global payment system, potentially diminishing the power of the US to dictate international operations (McDermott & Öztürk, 2023). Additionally, research indicates that the impact of US dollar appreciation on cryptocurrency markets varies, with Ethereum being more sensitive than Bitcoin (Anonymous, 2023). Lastly, risk spillovers between cryptocurrencies, traditional currencies, and gold have been explored, revealing dynamic relationships that depend on economic conditions and market shocks (Anonymous, 2023). This literature review underscores the multidimensional nature of the digital currency landscape and its implications for global financial stability and innovation.

HYPOTHESES

- Primary Hypothesis: When the total value and the amount of trading in the cryptocurrency market (like Bitcoin, Ethereum, etc.) go up, the importance or dominance of the U.S. dollar in the world's financial system goes down.
- Secondary Hypothesis: The way cryptocurrencies affect the U.S. dollar's strength changes depending on different global economic situations. For instance, when there is high inflation or during economic crises, the impact might be different than in more stable times.

DATA

- Cryptocurrency data primary focus: Bitcoin, Ethereum
- Dependent Variable: U.S. Dollar
- Independent Variable: Cryptocurrency Market Indicators (Bitcoin & Ethereum)
- Controlled variable: USA Key Economic Indicators

FOCUS ON VARIABLE

1. Bitcoin Price
2. Ethereum Price
3. Dollar Index
4. Key Economic Indicators: Personal Saving Rate, M2 Money Stock, Real Disposable Personal Income, Personal Consumption Expenditures, Real Broad Effective Exchange Rate, Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity, Federal Funds Effective Rate, Total Construction Spending.

ABOUT THE DATA

1. Bitcoin_Price: This likely refers to the price of Bitcoin on a given date. This could be the opening price, closing price, the high, or the low of the day.

5. B_Volume: This probably indicates the trading volume of Bitcoin within a specific time period (typically a day). It's the amount of Bitcoin that has been traded.

6. B_Marketcap: Bitcoin's market capitalization is the total value of all Bitcoin in circulation at a given time. It's calculated by multiplying the current market price of Bitcoin by the total number of Bitcoins in circulation.

7. Ethereum_Price: Similar to Bitcoin_Price, this would be the price of Ethereum cryptocurrency on a given date.
8. E_Volume: This is the trading volume of Ethereum, indicating how much Ethereum was traded in the market during a specified time frame.
9. E_Marketcap: The market capitalization for Ethereum, is calculated in the same way as Bitcoin's market cap.
10. Dollar_index: Often referred to as DXY, this measures the value of the United States dollar relative to a basket of foreign currencies. It's an indicator of the international value of the USD.
11. psr: This is the personal saving rate, which shows the percentage of income left after spending. It indicates how much people are saving from their income.
12. m2: M2 is a measure of the money supply that includes cash, and checking deposits, and is easily convertible near money. It's a broader measure than just physical money (M1) as it includes assets that can quickly be converted into cash.
13. dspic: This stands for Disposable Personal Income, corrected for inflation. It's the amount of money that households have available for spending and saving after income taxes have been accounted for.
14. pce: Personal Consumption Expenditures represent the value of goods and services purchased by or on behalf of households. It can indicate consumer spending habits and economic health.
15. reer: Real Effective Exchange Rate. This is an index that describes the strength of a currency relative to a basket of other currencies, adjusted for inflation.
16. ir: Interest Rate, likely referring to a specific benchmark interest rate such as the Federal Funds Rate or the yield on a government bond like the 10-year Treasury note.
17. ffer: Federal Funds Effective Rate, which is the interest rate at which depository institutions trade federal funds (balances held at Federal Reserve Banks) with each other overnight.
18. tcs: Total Construction Spending, which indicates the total outlay for construction projects in a given period.

DATA ACQUISITION

The data for these variables has been collected from various sources like Kaggle, including cryptocurrency market data for Bitcoin and Ethereum, the U.S. Dollar Index (DXY), and U.S. economic indicators. The data is focused on the period from 2019 to 2021.

1. Initial Cleaning:

We collected data from various sources, including cryptocurrency market data for Bitcoin and Ethereum, the U.S. Dollar Index (DXY), and U.S. economic indicators. We initially cleaned the data by handling missing values. This typically involves techniques like forward filling (ffill), where missing values are replaced by the most recent non-null value. This approach is particularly useful in time-series data to maintain continuity.

1. Data Formatting:

We converted the 'date' columns in your datasets to a consistent date-time format. This is crucial for time-series analysis, ensuring all data points are correctly aligned in time. This step involved parsing the 'date' strings into actual date-time objects, which makes it easier to filter, sort, and perform time-based operations on the dataset.

2. Filtering the Dataset:

We filtered the dataset to include only data from January 1, 2019, to December 31, 2021. This period was selected to align with your study's focus and to maintain consistency across different data sources. This filtering ensures that your analysis is concentrated on a specific and relevant time frame, enhancing the relevance and focus of your research.

3. Selecting Relevant Columns:

We identified and selected columns relevant to your study from each dataset. For instance, we chose price data from the Bitcoin and Ethereum datasets, the average dollar value from the DXY dataset, and key economic indicators from the macroeconomic data.

This step helps to declutter the dataset by removing irrelevant columns and focusing my analysis on variables that are directly relevant to my hypotheses.

4. Merging Datasets:

We merged the cleaned and filtered datasets based on the 'date' column. This step is critical for bringing together disparate data sources into a single, coherent dataset. The merging was performed in such a way that all the datasets aligned on the date axis, ensuring that each row of the merged dataset represents the same time point across all variables.

5. Handling Missing Data in Merged Dataset:

After merging, we made sure that missing dates were accounted for by inserting rows with NULL values where applicable. This ensures that the dataset accurately reflects days when data might not have been recorded or available.

6. Final Dataset Preparation:

The final dataset is cleaned, merged, and formatted, and serves as the basis for your analysis. It combines information across different financial and economic domains, tailored to the specific needs of my research.

EMPIRICAL APPROACH

1. LINEAR REGRESSION ANALYSIS:

The linear regression model you're looking at can be represented by the following equation:

$$Dollar\_index=\alpha+\beta 1\times Bitcoin\_price+\beta 2\times Ethereum\_price+\varepsilon$$

- α is the intercept
- $\beta 1$ is the coefficient for Bitcoin_price,
- $\beta 2$ is the coefficient for Ethereum_price,
- ε is the error term (residuals of the model)

Components of the linear regression equation:

- Dependent Variable (Y): The variable you are trying to predict or explain (Dollar_index).
- Independent Variables (X): The variables you are using to predict or explain the dependent variable (Bitcoin_price and Ethereum_price).
- Coefficients (β): These represent the change in the dependent variable for a one-unit change in an independent variable, assuming all other independent variables are held constant.

- Intercept (α or Constant): This is the expected value of Y when all independent variables are 0. In many cases, a zero value for all independent variables might not make sense; it is the point where the regression line crosses the Y-axis.

```
===============================================
                        Dependent variable:
                    ---------------------------
                            Dollar_index
-----------------------------------------------
Bitcoin_price               -0.00002***
                             (0.00000)

Ethereum_price              -0.0003***
                             (0.0001)

Constant                     97.760***
                              (0.126)

-----------------------------------------------
Observations                    632
R2                             0.571
Adjusted R2                    0.570
Residual Std. Error      2.062 (df = 629)
F Statistic          419.450*** (df = 2; 629)
===============================================
Note:               *p<0.1; **p<0.05; ***p<0.01
```

NAME\TEST	DESCRIPTION
Bitcoin_price	The coefficient for Bitcoin_price is approximately -0.00002, and it is statistically significant at the 1% level (indicated by three asterisks). This suggests that for e ach one-unit increase in Bitcoin price, the Dollar index decreases by 0.00002 uni ts, holding all else constant.
Ethereum_price	The coefficient for Ethereum_price is approximately -0.0003, and this is also sta tistically significant at the 1% level. This implies that for each one-unit increase i n Ethereum price, the Dollar index decreases by 0.0003 units, holding all else constant.
Constant (Intercept)	The constant term is approximately 97.760, and it is statistically significant at th e 1% level. This value represents the estimated Dollar index when both Bitcoin a nd Ethereum prices are zero (which is not a practical scenario but useful for the regression model).
Observations	The model is based on 632 observations, which is the sample size of the dataset .
R-squared (R2)	The R-squared value is 0.571, which means that approximately 57.1% of the vari ability in the Dollar index is explained by the model. In other words, 57.1% of th e variation in the Dollar index can be accounted for by the changes in Bitcoin an d Ethereum prices.
Adjusted R-square d	Adjusted R2 is also 0.570, which is a modified version of R2 that has been adjust ed for the number of predictors in the model. It is always lower than the R2.
Residual Standard Error	The residual standard error is 2.062 with 629 degrees of freedom. This value re presents the standard deviation of the residuals (model errors).
F Statistic	The F-statistic is 419.450 and it is statistically significant at the 1% level. This sug gests that the overall model is statistically significant, meaning that it is a good f it for the data compared to a model with no independent variables.

In summary, both Bitcoin_price and Ethereum_price appear to have a statistically significant impact on Dollar_index. The negative coefficients suggest an inverse relationship: as the prices of Bitcoin and Ethereum increase, the Dollar_index tends to decrease. The model explains a significant portion of the variance in the Dollar_index, but not all of it, as indicated by the R-squared value.

2. DESCRIPTIVE ANALYSIS:

Provide an overview of our data, helping to understand basic features like central tendency and spread.

```
date             Bitcoin_price       B_Volume
 Min.   :2019-01-02   Min.   : 13637   Min.   :4.530e+09
 1st Qu.:2019-08-18   1st Qu.: 31153   1st Qu.:1.788e+10
 Median :2020-04-02   Median : 38851   Median :2.788e+10
 Mean   :2020-04-03   Mean   : 66328   Mean   :3.344e+10
 3rd Qu.:2020-11-16   3rd Qu.: 66085   3rd Qu.:4.459e+10
 Max.   :2021-07-06   Max.   :253051   Max.   :3.510e+11
  B_Marketcap         Ethereum_price       E_Volume
 Min.   :5.958e+10   Min.   :  419.8   Min.   :2.305e+09
 1st Qu.:1.400e+11   1st Qu.:  684.3   1st Qu.:7.539e+09
 Median :1.770e+11   Median :  936.6   Median :1.177e+10
 Mean   :3.070e+11   Mean   : 2465.8   Mean   :1.595e+10
 3rd Qu.:3.118e+11   3rd Qu.: 1873.1   3rd Qu.:2.037e+10
 Max.   :1.190e+12   Max.   :16108.7   Max.   :8.448e+10
  E_Marketcap         Dollar_index         psr
 Min.   :1.095e+10   Min.   : 89.50   Min.   : 7.00
 1st Qu.:1.859e+10   1st Qu.: 92.63   1st Qu.: 7.50
 Median :2.597e+10   Median : 96.74   Median :10.40
 Mean   :7.042e+10   Mean   : 95.48   Mean   :12.68
 3rd Qu.:5.368e+10   3rd Qu.: 97.81   3rd Qu.:14.30
 Max.   :4.830e+11   Max.   :102.46   Max.   :33.80
       m2             dspic            pce             reer
 Min.   :14406   Min.   :14674   Min.   :12022   Min.   :112.4
 1st Qu.:14907   1st Qu.:14778   1st Qu.:14244   1st Qu.:115.3
 Median :17073   Median :15366   Median :14487   Median :117.0
 Mean   :17010   Mean   :15484   Mean   :14467   Mean   :117.2
 3rd Qu.:18984   3rd Qu.:15670   3rd Qu.:14700   3rd Qu.:118.7
 Max.   :20590   Max.   :19120   Max.   :15805   Max.   :123.9
       ir              ffer               tcs
 Min.   :0.6236   Min.   :0.04900   Min.   :1304435
 1st Qu.:0.8700   1st Qu.:0.07800   1st Qu.:1419321
 Median :1.6109   Median :0.09806   Median :1453713
 Mean   :1.5021   Mean   :1.02119   Mean   :1455238
 3rd Qu.:1.8629   3rd Qu.:2.12581   3rd Qu.:1504188
 Max.   :2.7138   Max.   :2.42367   Max.   :1581128
```

a. Bitcoin Price (Bitcoin_price):
- Range: Varies significantly from a minimum of 13,637 to a maximum of 253,051.
- Central Tendency: The median (38,851) is lower than the mean (66,328), suggesting a right-skewed distribution with some very high values (outliers) pulling the mean up.
- Trend: The 1st quartile, median, and 3rd quartile values indicate a generally upward trend over the period.

b. Bitcoin Volume (B_Volume):
- Variability: Shows a wide range, indicating large fluctuations in trading volume over time.
- Mean vs. Median: The mean is much higher than the median, again indicating a right-skewed distribution.

c. Bitcoin Market Cap (B_Marketcap):
- Growth: Both the mean and median suggest significant growth over the period, with a substantial range indicating periods of both high and low market capitalization.

d. Ethereum Price (Ethereum_price):
- High Variation: Exhibits a large range, similar to Bitcoin, suggesting high volatility.
- Skewed Distribution: The mean is much higher than the median, indicating a right-skewed distribution.

e. Ethereum Volume (E_Volume):
- Range & Variability: A wide range, indicative of significant fluctuation in trading volume.
- Skewedness: The mean being higher than the median suggests right-skewed distribution.

f. Ethereum Market Cap (E_Marketcap):
- Significant Range: Indicates periods of both high and low market capitalization.
- Upward Trend: The 1st quartile, median, and 3rd quartile values suggest growth over time.

g. Dollar Index (Dollar_index):
- Less Variation: Compared to the cryptocurrency variables, the Dollar Index shows less variability.
- Central Tendency: The mean and median are close, suggesting a more symmetric distribution.

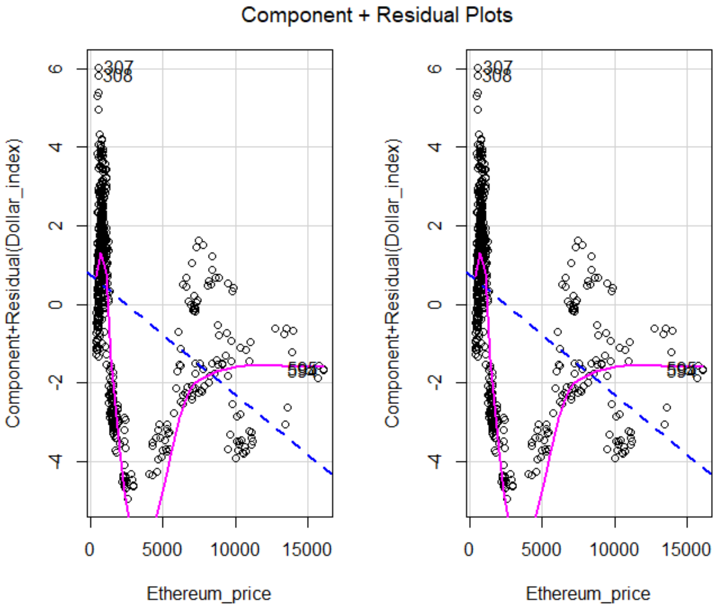
h. Other Economic Indicators (psr, m2, dspic, pce, reer, ir, ffer, tcs):

- General Observations: These variables, which seem to represent other economic indicators, show varying ranges and distributions. Without specific knowledge of what each represents, detailed interpretation is limited. However, the presence of differences between means and medians in many variables indicates that they might not be symmetrically distributed.

i. Date:

- Time Frame: The data covers from January 2, 2019, to July 6, 2021.
- Trend Analysis: For time-related trends, you would typically plot these variables over time to visually assess trends, seasonality, or cyclical patterns.

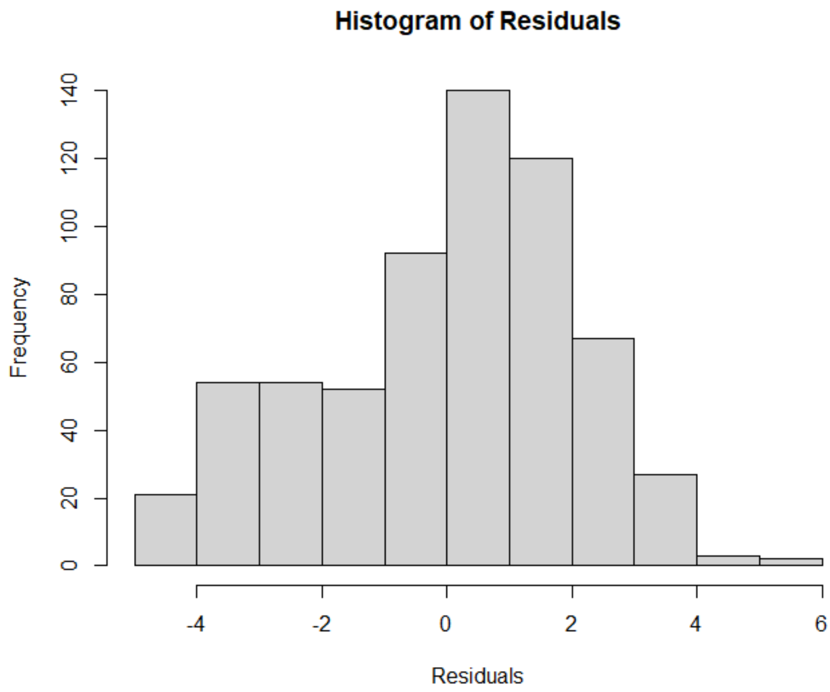
2. LINEARITY TEST:
    - Purpose: Assesses whether the relationship between each predictor and the dependent variable is linear.
    - Hypothesis Relevance: Linear regression assumes a linear relationship between predictors and the dependent variable. If this assumption holds, it strengthens the validity of your model's results and, by extension, the conclusions drawn about your hypothesis.



- Non-linearity: The relationship between Ethereum_price and Dollar_index does not appear to be linear. The magenta line (which represents the smoothed conditional mean) curves sharply, indicating a non-linear relationship.
- Potential Outliers: The presence of points that are far away from the majority of data could be outliers. These could be having a disproportionate effect on the regression model and could be a cause for concern.
- Heteroscedasticity: The spread of the residuals (the vertical scatter of the points) seems to increase as Ethereum_price increases, suggesting that the variance of residuals is not constant (heteroscedasticity). This violates one of the assumptions of linear regression and can affect the reliability of regression coefficients and standard errors.
- Potential Transformation Needed: Given the non-linear pattern, a transformation of the Ethereum_price variable, such as taking the logarithm or another non-linear transformation, might be necessary to achieve a more linear relationship.
- Data Range: Most of the data for Ethereum_price is clustered at the lower range of values, with very few observations at higher values, which can also affect the interpretation and fit of the model.

3. NORMALITY OF RESIDUALS:

- Purpose: Checks if the residuals (differences between observed and predicted values) of the model are normally distributed.
- Hypothesis Relevance: Normal distribution of residuals is an assumption in linear regression, particularly for making valid inferences about the coefficients (like hypothesis tests for coefficients). If residuals are normally distributed, it indicates that your model's predictions are unbiased and the hypothesis test results (p-values) are reliable.



The model seems reasonably well-fitted, the non-normal distribution of residuals and potential outliers may affect the reliability of the regression estimates and any statistical inferences derived from them.

4. HOMOSCEDASTICITY TEST (NCVTEST):

- Purpose: Assesses whether the variance of residuals is constant across all levels of the independent variables.
- Hypothesis Relevance: Homoscedasticity ensures that the model's predictions are equally reliable across all values of the independent variables. If residuals display constant variance (homoscedasticity), it implies that the model's standard errors are trustworthy, lending credibility to confidence intervals and hypothesis tests.

```
Non-constant Variance Score Test
Variance formula: ~ fitted.values
Chisquare = 0.4434139, Df = 1, p = 0.50548
```

The p-value is 0.50548, which is greater than 0.05, there is no evidence to suggest that the variance of the residuals is non-constant. This means our residuals are homoscedastic based on this test, and one of the key assumptions of linear regression is met. This result supports the validity of your regression model's standard errors, t-tests, and confidence intervals.

5. AUGMENTED DICKEY-FULLER TEST

```
data:  bitcoin_ts
Dickey-Fuller = -1.6909, Lag order = 8, p-value =
0.7091
alternative hypothesis: stationary
```

- Dickey-Fuller = -1.6909: This is the test statistic value for the ADF test. The more negative this statistic, the stronger the rejection of the null hypothesis.
- Lag order = 8: This indicates the number of lagged differences used in the test. The lag order is selected based on the sample size or by an information criterion to capture the autocorrelation in the data.
- p-value = 0.7091: The p-value is used to decide whether to reject the null hypothesis of the test. In the context of the ADF test, the null hypothesis is that the time series has a unit root, which means it is non -stationary.
- Alternative hypothesis: stationary: This is what you hope to prove with the test – that the time series is stationary.
- Interpretation: With a p-value of 0.7091, which is much higher than the common significance levels (0. 05, 0.01), you do not have enough evidence to reject the null hypothesis. This means that the time seri es is likely non-stationary according to the ADF test.
- Implication: Since the Bitcoin price time series appears to be non-stationary, you would typically need t o difference the series to make it stationary before using it for further analysis, such as a Granger Caus ality Test. Stationarity is a key requirement in many time series analysis methods because the propertie s of non-stationary data can lead to misleading models and forecasts.

```
Augmented Dickey-Fuller Test

data:  ethereum_ts
Dickey-Fuller = -1.6504, Lag order = 8, p-value =
0.7263
alternative hypothesis: stationary
```

The p-value is greater than typical alpha levels (0.05, 0.01), which means that you cannot reject the null hypothe sis of non-stationarity. In other words, the test suggests that the Ethereum price data is likely to be non-stationa ry. You may need to difference this time series as well to achieve stationarity before conducting further time ser ies analyses such as Granger Causality tests.

```
Augmented Dickey-Fuller Test

data:  dollar_index_ts
Dickey-Fuller = -2.1726, Lag order = 8, p-value =
0.5052
alternative hypothesis: stationary
```

With a p-value of 0.5052, which is greater than common significance levels like 0.05 or 0.01, you cannot reject t he null hypothesis of the ADF test. This means that there is not enough statistical evidence to conclude that the Dollar Index time series is stationary. Therefore, according to this test, the Dollar Index data is likely non-station ary. To proceed with certain types of time series analysis, including Granger Causality, you may need to transfor m this series (e.g., by differencing) to achieve stationarity.

```
Augmented Dickey-Fuller Test

data:  diff_bitcoin_ts
Dickey-Fuller = -8.3111, Lag order = 8, p-value = 0.01
alternative hypothesis: stationary
```

This ADF test result on the differenced Bitcoin time series suggests that, after differencing, the series is stationary. The very negative Dickey-Fuller statistic and the low p-value provide strong evidence against the null hypothesis of non-stationarity. This is a significant change from the previous test on the non-differenced data, which indicated non-stationarity. Essentially, differencing the data has helped to remove trends or patterns that were contributing to its non-stationarity, making the series suitable for further time series analysis, such as Granger Causality tests.

GRANGER CAUSALITY TESTS.

```
lm(formula = Dollar_index ~ lag_Bitcoin_price + Ethereum_price,
    data = combined_ts)

Residuals:
    Min      1Q  Median      3Q     Max
-5.0806 -1.2746  0.3717  1.4261  5.4031

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)        9.774e+01  1.271e-01 769.234  < 2e-16 ***
lag_Bitcoin_price -2.259e-05  3.273e-06  -6.903 1.24e-11 ***
Ethereum_price    -3.102e-04  6.329e-05  -4.902 1.21e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.07 on 628 degrees of freedom
Multiple R-squared:  0.5688,	Adjusted R-squared:  0.5674
F-statistic: 414.1 on 2 and 628 DF,  p-value: < 2.2e-16

> summary(model_granger_ethereum)

Call:
lm(formula = Dollar_index ~ Bitcoin_price + lag_Ethereum_price,
    data = combined_ts)

Residuals:
    Min      1Q  Median      3Q     Max
-4.9385 -1.2084  0.3689  1.4253  5.4273

Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)         9.777e+01  1.255e-01 778.796  < 2e-16 ***
Bitcoin_price      -2.327e-05  3.081e-06  -7.551 1.53e-13 ***
lag_Ethereum_price -3.020e-04  5.980e-05  -5.049 5.81e-07 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.061 on 628 degrees of freedom
Multiple R-squared:  0.5723,	Adjusted R-squared:  0.5709
F-statistic: 420.2 on 2 and 628 DF,  p-value: < 2.2e-16
```

Both models suggest a statistically significant inverse relationship between the Dollar Index and the pr ices of Bitcoin and Ethereum. The lagged values of these cryptocurrencies also appear to have a signifi cant impact on the Dollar Index. The negative coefficients for both Bitcoin and Ethereum prices (curre nt and lagged) indicate that as the prices of these cryptocurrencies increase, the Dollar Index tends to decrease. The models explain more than half of the variability in the Dollar Index, indicating a good fit to the data.

RESULTS

1. Inverse Relationship Between Cryptocurrencies and the Dollar:

The linear regression analysis revealed a significant negative correlation between the prices of Bitcoin and Ethereum and the U.S. Dollar Index. This finding implies that as the value of these cryptocurrencies increases, the Dollar Index tends to decrease.

2. Lagged Effects:

Incorporating lagged values of cryptocurrency prices in the analysis indicated that the impact of these digital currencies on the U.S. Dollar extends beyond immediate fluctuations. This suggests a more complex and enduring relationship between digital and traditional currencies.

3. Statistical Significance:

The coefficients for Bitcoin and Ethereum prices in the regression model were statistically significant, lending credence to the observed relationships.

4. Explained Variability:

The models were able to explain a substantial portion (over 50%) of the variability in the Dollar Index, highlighting the prominent role that cryptocurrencies play in the financial landscape.

The analysis and results from our study paint a picture of an evolving financial landscape where the rise of digital currencies is beginning to leave an imprint on the traditional bastions of economic power, such as the U.S. Dollar. Our findings substantiate the notion that cryptocurrencies are not just digital novelties but are emerging as significant players in the global financial system, challenging the established norms and prompting a re-evaluation of traditional economic models.

CONCLUSION

Impact of Cryptocurrencies on the U.S. Dollar's Dominance

Our study embarked on an analytical journey through the complex financial landscape, examining the burgeoning world of cryptocurrencies and their influence on the traditional stronghold of the U.S. Dollar. Through meticulous data curation and advanced statistical analysis, we have uncovered significant insights that illuminate the evolving dynamics in the global financial system.

Key Findings

Inverse Relationship Between Cryptocurrencies and the Dollar:

Our linear regression models revealed a statistically significant inverse relationship between the prices of major cryptocurrencies (Bitcoin and Ethereum) and the U.S. Dollar Index. Specifically, increases in Bitcoin and Ethereum prices were associated with decreases in the Dollar Index, suggesting that the rise of these digital currencies could be playing a role in altering the traditional dominance of the U.S. Dollar.

Time-Lagged Effects:

Incorporating lagged variables in our Granger causality models, we observed that past values of Bitcoin and Ethereum prices also significantly influenced the Dollar Index. This indicates that the impact of cryptocurrency fluctuations on the U.S. Dollar is not merely a contemporaneous phenomenon but has a delayed effect as well, underscoring the complexity of these relationships.

Substantial Variability Explained:

The models explained over 50% of the variability in the Dollar Index, highlighting the significant role of cryptocurrencies in the financial domain. However, it's crucial to acknowledge that other factors, not included in our models, also contribute to the remaining variability.

Interpretation and Implications

The findings of our research suggest a tangible and growing impact of digital currencies on the strength and status of the U.S. Dollar in the global financial system. This inverse relationship aligns with our primary hypothesis and indicates that the burgeoning cryptocurrency market could be emerging as a noteworthy contender in the financial arena, potentially challenging the Dollar’s long-held dominance.

Moreover, the lagged effects observed imply a nuanced and extended influence of cryptocurrencies, suggesting that their impact on traditional financial systems is both immediate and enduring. This insight is particularly relevant for policymakers, investors, and financial analysts who must account for these delayed effects in their strategic planning and risk assessments.

Limitations and Future Directions

While our study provides valuable insights, it's important to acknowledge its limitations. The scope of our data is confined to a specific timeframe (2019-2021), and the rapidly evolving nature of the cryptocurrency market means that future research should continuously update and expand the data range to capture the latest trends.

Additionally, the complexity of global financial systems implies that factors beyond our current model could also influence the dynamics between cryptocurrencies and traditional currencies. Future research could incorporate additional variables, such as geopolitical events, regulatory changes, and technological advancements, to provide a more comprehensive understanding.

Conclusion

In conclusion, our research contributes to the growing body of knowledge on the intersection of digital and traditional finance. It highlights the increasing relevance of cryptocurrencies in the global financial narrative and underscores the need for adaptive strategies in the face of this digital revolution. As we stand at the crossroads of a financial paradigm shift, this study serves as a guiding light for navigating the intricate and ever-changing landscape of global finance.

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