A Time Series Evaluation of Bitcoin Prices

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Introduction and Motivation

Cryptocurrencies, in particular Bitcoin have become a popular topic in economic, social and also academic discourse. Academia generally agrees that the main use is as an investment vehicle (Lammer, Hanspal, and Hackethal 2019; Voskobojnikov et al. 2020). This finding is of little use to policymakers since predictions are hard to make from investment alone. For this reason, other macroeconomic factors are often evaluated when looking for explanatory factors of Bitcoin price. In this paper we use updated data to test if the macroeconomic fundamentals of inflation and uncertainty effect the price of Bitcoin. We find no evidence that Bitcoin prices are effected by past inflation or volatility, the only predictor of future Bitcoin prices are past Bitcoin prices.

Literature Review

The literature on uncertainty neither conclusively suggests an effect nor direction. Wüstenfeld and Geldner (2022), Mokni *et al.* (2021) find no conclusive rule for if and how Bitcoin hedges against uncertainty and that such a mechanism is only present for subsets: either only in certain countries or for types of uncertainty. Colon *et al.* (2021) mirror these findings for the 25 largest cryptocurrencies by market capitalization. The literature on inflation is more diverse. Parino *et al.* (2018) and Ricci (2020) suggest a negative correlation of inflation and Bitcoin prices, and crucially Blau *et al.* (2021) find that Bitcoin price changes cause inflation but not the other way around. Finally, Matkovskyy and Jalan (2021) find that for certain, but not in most cases, the Bitcoin - Inflation hedge is not seen in their evaluated data. There are however a number of studies that do find an effect such as Choi and Shin (2022) as well as Sarker and Wang (2022) (only UK and Japan studied).

Despite the academic uncertainty, popular opinion and thus by implication investor sentiment repeatedly identifies Bitcoin as the "digital gold" (implying stability) due to two fundamental properties: credible commitment to a slow and stable growth in supply and lack of any central influence. This stands in stark contrast to post - Gold Standard FIAT currencies. Given that inflation rates in 2023 have not recovered to pre-Covid-19 levels ("Inflation, Consumer Prices (Annual %)" 2024), it is worth investigating the "old" research questions given the updated data available now (into August 2023). We therefore make no new theories, just apply the same hypothesis to the new data.

- *Research Question 1*: Is there a relationship between Bitcoin Prices and Inflation?
- *Research Question 2:* Is there a relationship between Bitcoin Prices and Economic Uncertainty?

Both of these questions are evaluated while controlling for the other's effect (if any). The standard significance level of 5% is used. For the sake of time, hypothesis will be presented directly in the methods.

Data Sources

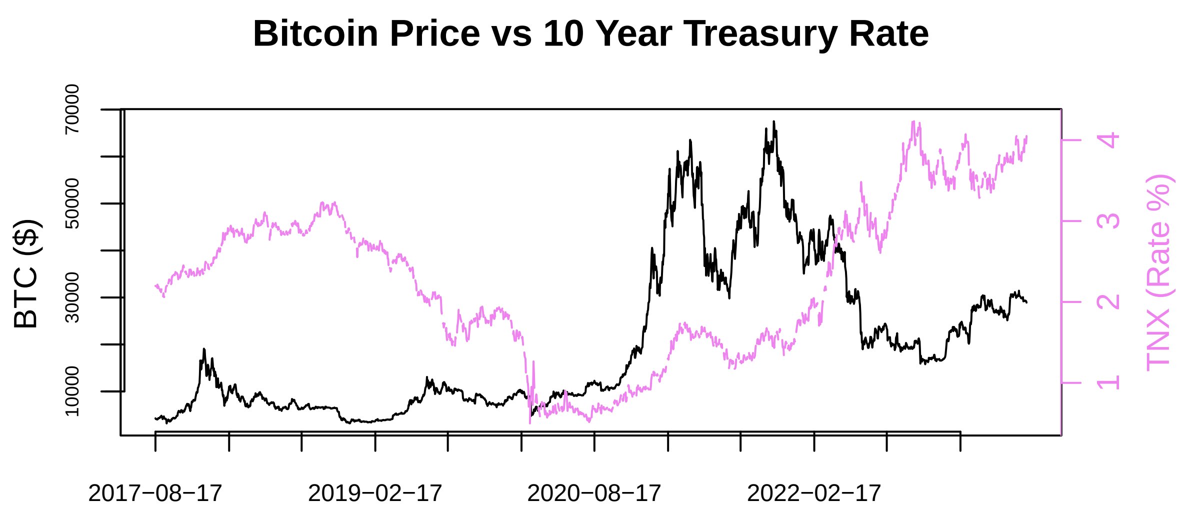
Bitcoin Closing Prices ($) : This information comes from a kaggle dataset which has the data from 2017 to 2023. We take the last price for each day, as the "closing" price. The original dataset is available every minute for the UTC+0 time zone. Loaded from Kaggle (Kottarathil 2020).

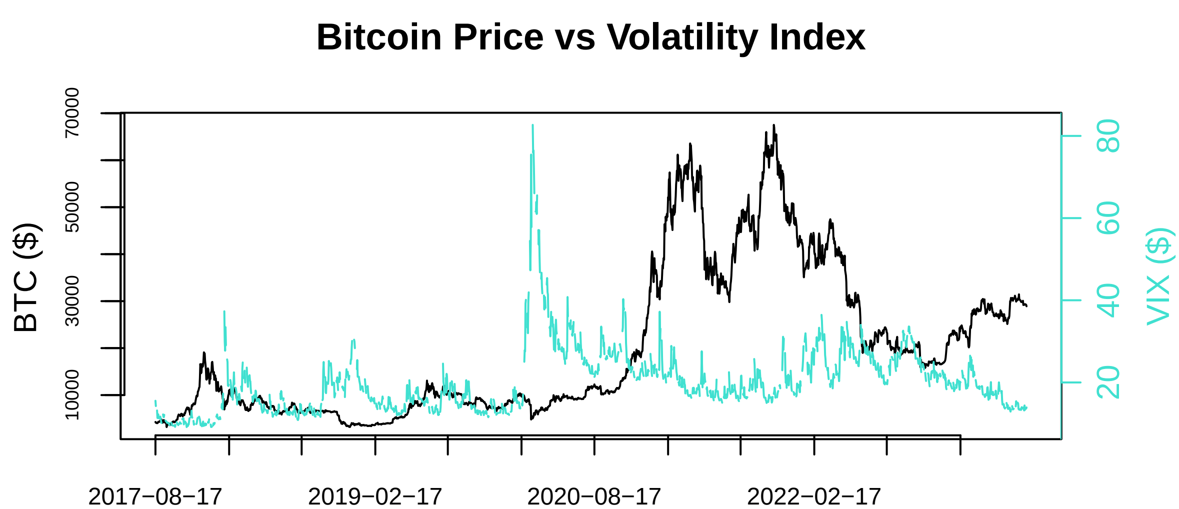
CBOE Interest Rate 10 Year (TNX): The 10 year treasury rate is a measure/proxy of inflation, with higher rate implying a higher inflation (expectation). Investors demand higher returns when they suspect inflation will increase. Loaded from Yahoo Finance ("CBOE Interest Rate 10 Year t No (TNX)," n.d.).

CBOE Volatility Index (VIX, $): This is a measure of volatility in the American Stock Market S&P500, and here it is used as a proxy for uncertainty. Loaded from Yahoo Finance ("CBOE Volatility Index (VIX)," n.d.).

Exploratory Data Analysis

Let us first plot the time series and analyse them.





By looking at the graphs we can observe some gaps in the VIX and TNX series, indicating missing values. Those values we dealt with by imputing the last available data point in each series. This is superior to imputing a summary statistics since in almost all cases a previous point has more relationship to the current point than the summary of all points.

Let's analyse the different time series one after each other:

Bitcoin Price

The Bitcoin price exhibited a considerable degree of volatility between August 2017 and August 2023. While the overall trend was upward, the course experienced several periods of pronounced upward movement, which are commonly referred to as "bull runs." A clear seasonal pattern could not be identified. The price began at approximately $4,000 in 2017 and closed at approximately $30,000 in August 2023. The price of Bitcoin increased on two occasions, reaching a high of over $60,000 in early and late 2021.

10 Year Treasury Rate

It is challenging to ascertain the existence of a trend based on a cursory examination of the plot. However, it can be posited that the rate in August 2017 was approximately 2% and in August 2023 was approximately 4%. This indicates a near doubling of the rate. Upon examination of the interest rate between the commencement and conclusion of the period under consideration, it becomes evident that following an increase in 2018, the rate declined from approximately 3% to below 1% in 2019 and 2020. The impact of the Covid-19 pandemic on this decline was considerable. Following the pandemic, the rate recovered and reached a rate of over 4% in 2022.

When the rate is compared with the Bitcoin price, it becomes evident that no meaningful connection exists between the two time series when examined visually.

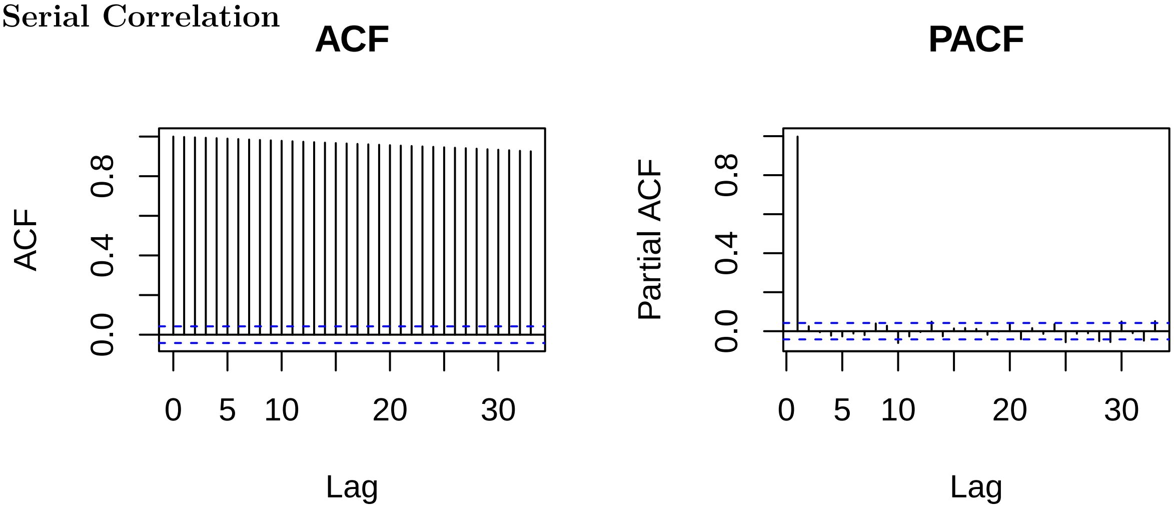
Volatility Index

The index is relatively steady, though it experiences a notable outlier during the initial stages of 2020, likely due to the uncertainty surrounding the global impact of the Covid-19 pandemic and the associated economic consequences. It is not possible to discern from a cursory examination whether the time series is stationary or not. Furthermore, it is not possible to identify a trend.

Upon visual examination of the index in relation to the Bitcoin price, it becomes evident that there is no discernible connection between the two time series.

Univariate Analysis - BTC

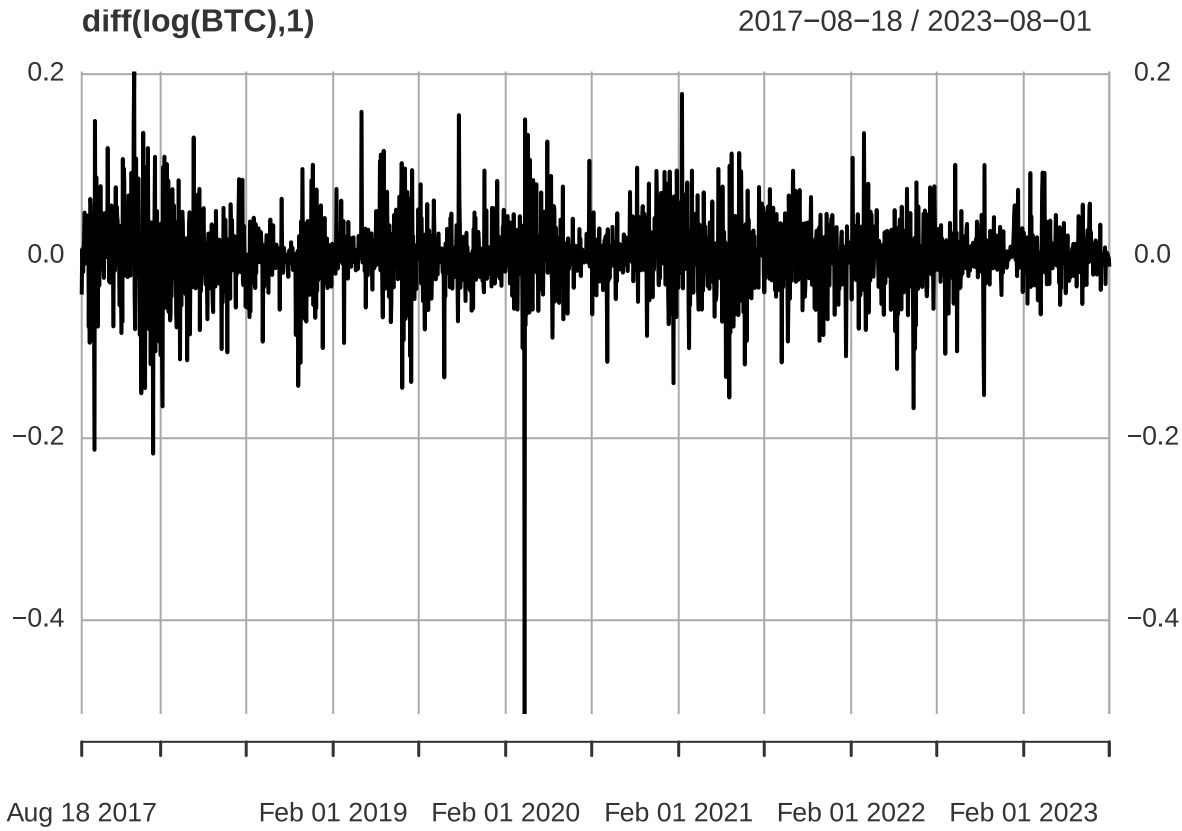
Serial Correlation



The PACF of BTC is 0.998 at lag one and, there is never any more a significant lag. This suggests a model with an Auto regressive Component of 1. The ACF function suggests that the model is not stationary as there is a clear, slow decline of ACF as the lags are increasing. To be sure about stationary, we perform the augmented Dickey-Fuller test (ADF) (see Appendix ADF Test TS BTC for code output), which accepts the H_0 = no stationary. Therefore transformations must be made to the data before Time Series Analysis can be done.

Achieving Stationarity

A first initial transformation of the data was performed. The first difference of the log is taken (where first observation is lost). This results in the plot below.



Performing the ADF test (see Appendix ADF Test stat BTC for code and output) on the data after the diff-log has been performed implies rejecting the Null Hypothesis (no stationarity). We can now assume stationarity. Identical test-transformations-tests are performed for VIX and TIX (see Appendix ADF Test stat TNX and VIX). This allows the use of the next TS models.

Modelling

Autoregressive Integrated Moving Average (ARIMA)

It would first be interesting to see what predictive power the past prices alone have without any additional information. For this, an ARIMA model is used.

For summary output see Appendix ARIMA Summary. The model output shows the model with the best (lowest) AIC. It is an ARIMA(2,0,0) model, with coefficients AR1 = -0.0480679, AR2 = 0.0466715. The model did not identify a Moving Average component or further differencing, which would have had to be included in the formula. This model is one way of attempting to predict BTC prices into the future. As a uni variate approach, it considers only the same series.

Mathematically, the fitted value is (mean centered): $\hat{y} = (-0.0481 * Y_{t-1}) + (0.0214 * Y_{t-2})$

All AR components are statistically significant at the 5% level (see Appendix Coefficent Test Arima for code and output). This means that the chance that the pattern seen in the data are not due to chance is at least 95%. A true relationship can thus be reasonably argued.

Vector Autoregressive Model (VAR)

As discussed in the introduction, there are reasons to suspect that TNX, VIX may be related to Bitcoin. For this reason, a model which can include not just the BTC system's past, but also other systems must be evaluated. The VAR model presents a possibility for doing just that. The VAR model in R is automatically selected based on the best (lowest) AIC.

Interpretation VAR

The VAR model tests (for summary output see Appendix VAR Summary BTC) the null hypothesis that the components of the VAR (coefficient for internal system at lag, external system(s) at lag and constant) are 0.

None of the p-values are statistically significant at the 5% level, except for the "internal system". As such, there is insufficient evidence to claim that there is any influence from past VIX or TNX variables, on the current BTC price, which is why these terms are modelled as 0 in the formula.

The estimates model is, for BTC as a response: $BTC = 0 + (0.99 * BTC_{-1}) + (0 * TNX_{-1}) + (0 * VIX_{-1})$

One interesting thing is that the VAR identifies the lagged BTC component as a statistically significant model component in TNX's prediction, implies the causality runs the other way than we thought.

Granger Causality:

Both Granger causality tests for both TNX and VIX are also statistically insignificant at the 5% level. Due to this, we accept the null hypothesis that there are no past information for TNX and VIX which could predict the variable BTC. In practice this means including either predictor in the model does not improve the prediction. The granger test also tests the coefficients of the external system against 0 (like VAR), however using a different approach for statistical significance, therefore it is commonly used as a sanity check. Please see: Appendix Granger Causality, for full results.

Limitations

- Bitcoin is a global "currency", yet the measures we consider are only US specific. While this is not totally a false approach since the US is arguably the most powerful and influential economy, future research could consider an approach of using more global proxies for the economic predictors.
- General forecasting limitations apply: predictions should be made in the short term and when underlying factors change the model's fit is no longer appropriate.
- TNX is a measure of expectations, not actual inflation values. Future research could leverage big data to perform regular web scraping of a "bucket" of prices from online vendors to get a higher frequency of actual inflation data. This could work by scraping websites in different sectors (groceries, housing, transport etc) to create a "bucket" that does not need to be manually calculated .

Conclusion

We have applied standard time series methodology on established academic questions around Bitcoin causality, considering new data up to August 2023, which encompasses a period where inflation rates have begun to recover, but have not gone back to their pre-Covid-19 levels. Using ARIMA and VAR models, the main findings is that BTC prices can be predicted as a function of the previous two values and the previous two error terms. Unfortunately, like many papers before, proxies for inflation and uncertainty are not identified as predictive factors of Bitcoin prices. Thus both the first and second null hypothesis are not rejected.

Further research could expand on the VAR model findings that Bitcoin is a statistically significant predictor of TNX. However no interpretation can be made here since the model does not control for other factors theorized to cause inflation.

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Appendix I: AI Disclosure

Vayloyan Alec: AI was used in most aspects of this project, mainly however for coding issues and model inputs. Although also used for interpretation, I tried to use the slides from the course first and only use AI as a secondary check of my own interpretation.

Schmid Raphael: In this project, I employed AI in a variety of ways. Primarily, I utilized it to enhance graphical outputs, improve the code, and to rewrite my text in a more academic style.

Appendix II: Code Snippets with Outputs

ADF Test TS BTC

```r
adf.test(TS$BTC)
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  TS$BTC
```

```
## Dickey-Fuller = -1.7852, Lag order = 12, p-value = 0.6693
## alternative hypothesis: stationary
```

ADF Test stat BTC

```r
adf.test(BTC_stat)
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  BTC_stat
## Dickey-Fuller = -12.177, Lag order = 12, p-value = 0.01
## alternative hypothesis: stationary
```

ADF Test stat TNX and VIX

```r
adf.test(stat$TNX)
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  stat$TNX
## Dickey-Fuller = -14.346, Lag order = 12, p-value = 0.01
## alternative hypothesis: stationary
```

```r
adf.test(stat$VIX)
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  stat$VIX
## Dickey-Fuller = -14.195, Lag order = 12, p-value = 0.01
## alternative hypothesis: stationary
```

Arima Summary

```r
summary(m.1)
```

```
## Series: stat$BTC
## ARIMA(2,0,0) with zero mean
##
## Coefficients:
##           ar1     ar2
##       -0.0481  0.0467
## s.e.   0.0214  0.0214
##
## sigma^2 = 0.001596:  log likelihood = 3918.64
## AIC=-7831.28   AICc=-7831.27   BIC=-7814.23
##
## Training set error measures:
##                        ME       RMSE        MAE      MPE     MAPE      MASE
## Training set 0.0008787982 0.03993051 0.02641903 20.28707 200.7249 0.6536294
##                      ACF1
## Training set -0.001056223
```

Coefficient Test Arima

```r
coeftest(m.1)
```

```
##
## z test of coefficients:
##
##       Estimate Std. Error z value Pr(>|z|)
## ar1 -0.048068   0.021420 -2.2440  0.02483 *
## ar2  0.046671   0.021414  2.1795  0.02930 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

VAR summary BTC

```r
summary(VAR)$varresult
```

```
## $BTC
##
## Call:
## lm(formula = y ~ -1 + ., data = datamat)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6990.4  -239.3   -19.0   222.9  7570.8
##
## Coefficients:
##            Estimate Std. Error t value Pr(>|t|)
## BTC.l1     0.997726   0.001298 768.754   <2e-16 ***
## TNX.l1   -36.715448  22.609578  -1.624    0.105
## VIX.l1     0.668136   2.642199   0.253    0.800
## const    125.561052  90.965354   1.380    0.168
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 962.2 on 2171 degrees of freedom
## Multiple R-squared:  0.9964, Adjusted R-squared:  0.9964
## F-statistic: 2.01e+05 on 3 and 2171 DF,  p-value: < 2.2e-16
##
##
## $TNX
##
## Call:
## lm(formula = y ~ -1 + ., data = datamat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.32251 -0.01559  0.00042  0.01718  0.26916
##
## Coefficients:
##            Estimate Std. Error t value Pr(>|t|)
## BTC.l1    1.482e-07  6.185e-08   2.396   0.0167 *
## TNX.l1    1.000e+00  1.077e-03 928.158   <2e-16 ***
## VIX.l1    2.269e-05  1.259e-04   0.180   0.8570
```

```
## const  -2.747e-03  4.335e-03  -0.634   0.5263
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.04586 on 2171 degrees of freedom
## Multiple R-squared:  0.9977, Adjusted R-squared:  0.9977
## F-statistic: 3.18e+05 on 3 and 2171 DF,  p-value: < 2.2e-16
##
##
## $VIX
##
## Call:
## lm(formula = y ~ -1 + ., data = datamat)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.2735  -0.5383  -0.0972   0.2564  25.7778
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## BTC.l1  1.262e-06  2.387e-06   0.529 0.597004
## TNX.l1 -5.386e-02  4.158e-02  -1.295 0.195359
## VIX.l1  9.743e-01  4.859e-03 200.505  < 2e-16 ***
## const   6.132e-01  1.673e-01   3.665 0.000253 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.77 on 2171 degrees of freedom
## Multiple R-squared:  0.9531, Adjusted R-squared:  0.953
## F-statistic: 1.47e+04 on 3 and 2171 DF,  p-value: < 2.2e-16
```

Granger Causality

TNX

```r
causality(VAR, cause = "TNX" )$Granger
```

```
##
##  Granger causality H0: TNX do not Granger-cause BTC VIX
##
## data:  VAR object VAR
## F-Test = 2.7578, df1 = 2, df2 = 6513, p-value = 0.0635
```

VIX

```r
causality(VAR, cause = "VIX" )$Granger
```

```
##
##  Granger causality H0: VIX do not Granger-cause BTC TNX
##
## data:  VAR object VAR
## F-Test = 0.04869, df1 = 2, df2 = 6513, p-value = 0.9525
```