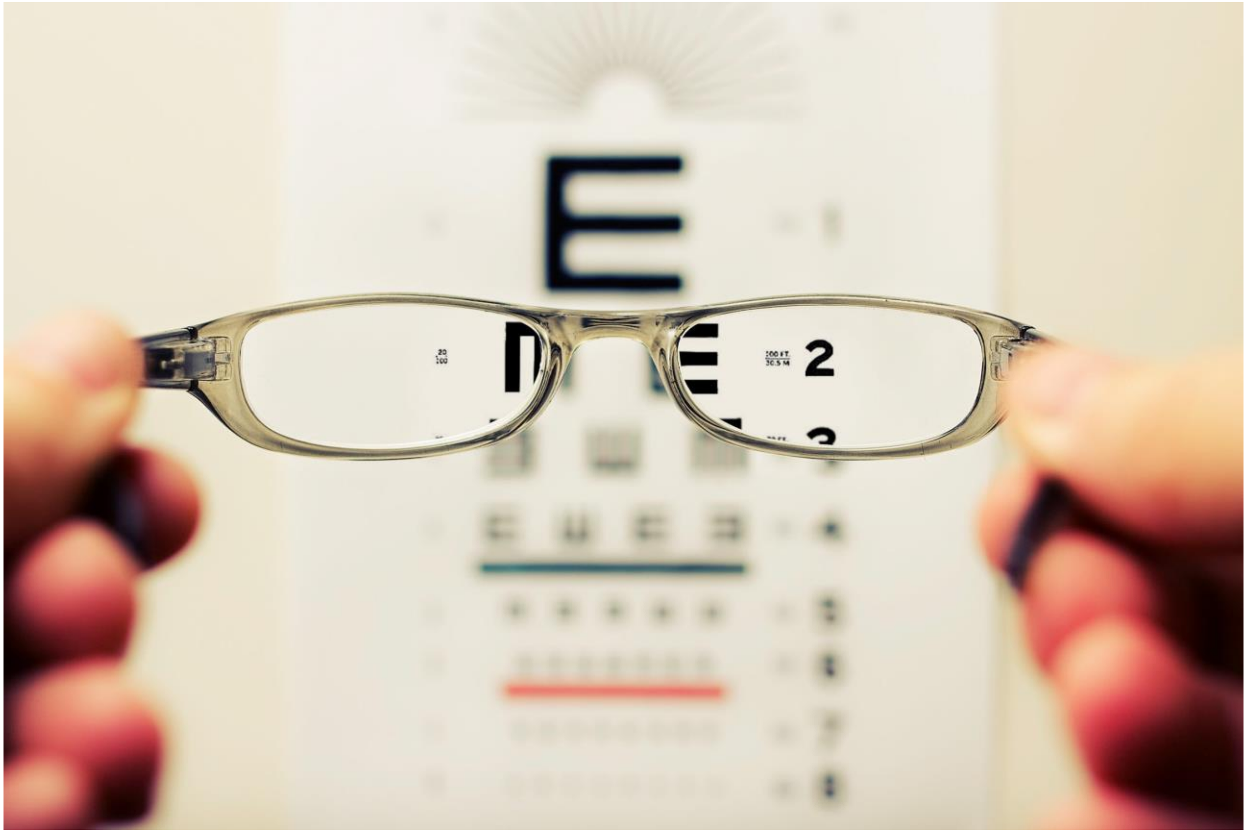


VALIENDERO DIGITAL ASSETS

A quantitative crypto investment fund, founded out of Carnegie Mellon, providing investors clarity via machine learning and data-driven investment strategies.

2019 END OF YEAR BITCOIN REPORT

CHRISTOPHER BROOKINS
FOUNDER AND CIO
CHRIS@VALIENDERO.IO

Valiendero
Digital Assets

For educational purposes only. This is not investment advice nor a recommendation or solicitation of any kind.

TABLE OF CONTENTS

Contents

Originally released October 10, 2019.

Executive Summary

EXECUTIVE SUMMARY

The goal of the research report is to provide the reader with a structured, data-first approach to discerning whether bitcoin volatility will increase in the fourth quarter (Q4), and if so, the probabilistic direction. In order to create the aforementioned, we must breakdown several key elements into multiple sections whereby each build upon one another.

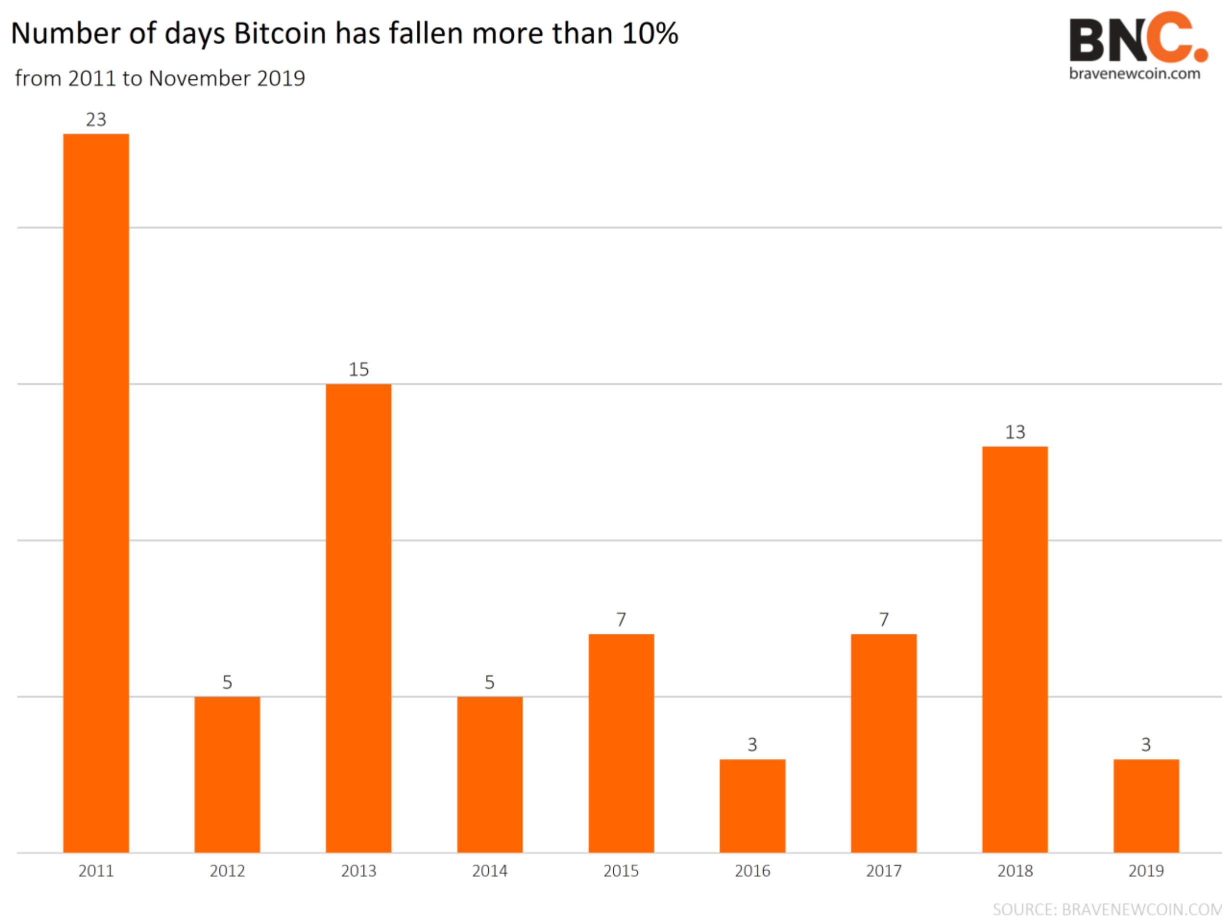
First, a discussion of the September 2019 "flash crash" and its likely drivers. Second, an explanation of the repeatable patterns in bitcoin's price and volatility data, subject to seasonal characteristics. Third, an application of a robust quantitative methodology that captures the likely price direction of bitcoin in Q4 via change point detection. Fourth, a price prediction using the prior cyclical and quantitative analysis, coupled with one additional fundamental feature. Finally, an evaluation of the key risks to our analysis and potential mitigants, before summarizing the report.

TL; DR – the data appears to suggest that bitcoin will have a Q4 breakout, and the direction is likely to be to the upside.

September 2019 Flash Crash

ABNORMALLY HIGH VOLATILITY

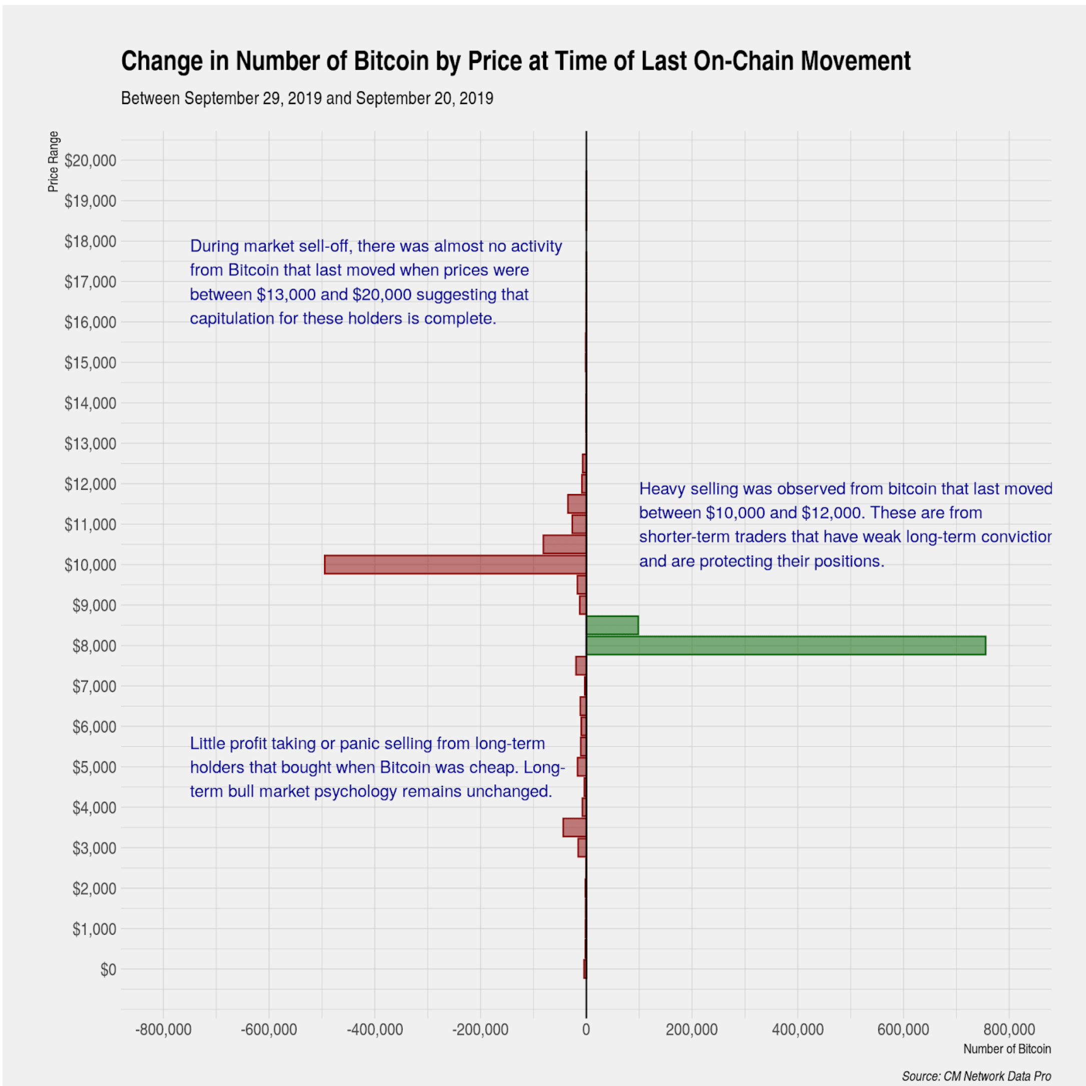
Seven days prior to entering the fourth quarter (Q4), bitcoin's price experienced a dramatic weekly decline of ~20%, where ~13% of which occurred in a single day; leaving bitcoin sitting near $8,200, at the time of writing. As we will show in the BTC Seasonality section, momentary spikes in volatility are not uncommon going into Q4, but the magnitude of the spike was unexpected. The below chart from Brave New Coin's and our own analysis, e.g. 7σ daily event since 2019, 10σ event since the past 60 days, and 3σ event since 2010, illustrate the abnormally high volatility.



SEPTEMBER 2019 FLASH CRASH

SELLOFF ORIGINS

Coinmetrics' analysis[1] of bitcoin onchain data, i.e. data derived from the public blockchain, suggests two primary culprits – 1) short-term traders that acquired bitcoin between $10,000 and $12,000 (see chart below) and 2) forced long derivatives liquidations.



coinmetrics.io

To explain, as price began to falter and short-term traders increasingly sold, price declined further. As all reflexive feedback loops, once the levy was broken, over-leveraged positions began to unwind

[1] https://coinmetrics.substack.com/p/coin-metrics-state-of-the-network-7a8

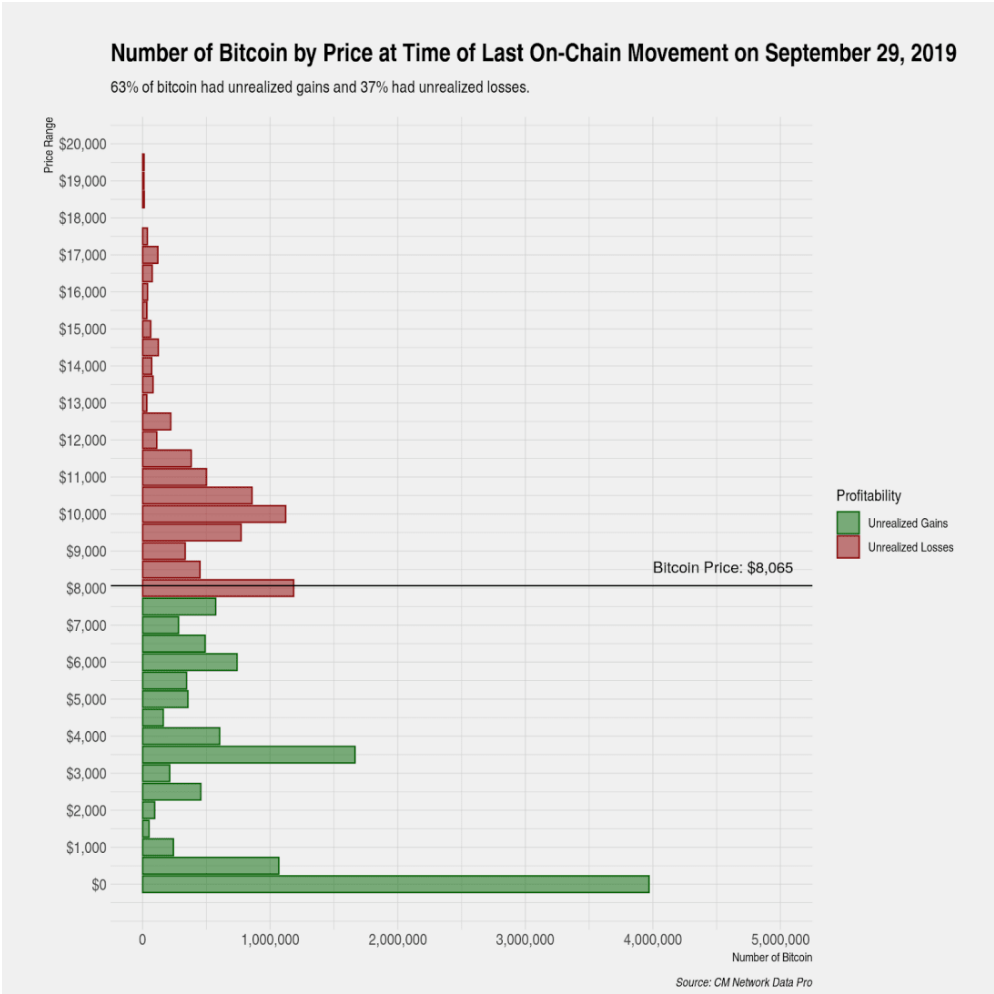
involuntarily, which further exacerbated the down move. For example, "according to an analysis by Skew, forced liquidations of long positions on BitMEX's XBTUSD contract alone totaled roughly $700 million over the past week[2]." As the market digests the down move and sentiment recalibrates, price is likely to stabilize with volatility beginning to recompress during Q4.

Additionally, one element that may provide a floor to further price declines is the majority of bitcoin holders are currently "in the money." Per Coinmetrics[3], currently, 63% of all bitcoin holders have unrealized gains compared to 37% with unrealized losses. Furthermore, the holders with a cost basis above $13,000 remained dormant during the selloff, which indicates the "weak money" has likely capitulated already and only long-term holders remain.

[2] https://coinmetrics.substack.com/p/coin-metrics-state-of-the-network-7a8

[3] https://coinmetrics.substack.com/p/coin-metrics-state-of-the-network-7a8

SEPTEMBER 2019 FLASH CRASH



coinmetrics.io

Now, with the most recent events explained, we move onto breaking down the seasonality of bitcoin price and volatility.

Seasonal Investment Cycles

INTRODUCTION

Given the cryptocurrency market's nascency, several persistent trends still exist from its early days. These trends have manifested themselves into heuristics for investors and speculators. One of the more pervasive heuristics is the fourth quarter (Q4) price rally. Investors expecting price rallies in Q4 have typically been rewarded; baring 2018 when those heuristics punished them severely.

The flaw in their logic was that investors mistook repeatable volatility for price growth. Volatility can work for or against long positions depending on the market regime, i.e. bear or bull market. In reality, investors were actually betting on volatility growth in Q4 2018 rather than price. This was correct logically, but wrong directionally, which in hindsight is obvious given the overwhelming bear market conditions.

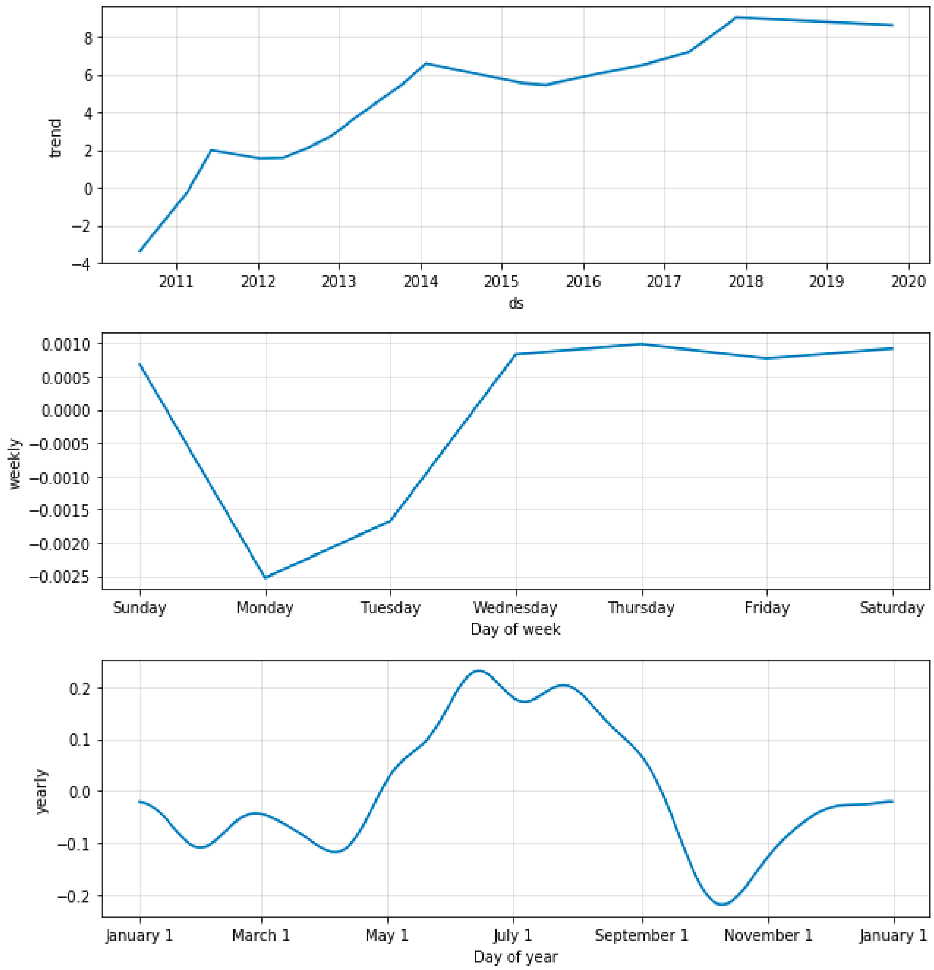
BITCOIN (BTC) SEASONALITY

The origin of the Q4 dynamic is unknown, but given the reflexive nature of the cryptocurrency market, it has become the norm because everyone expects it to happen. As stated above, the simple heuristic of buying into Q4 volatility aligning with the market regime has been profitable to-date. However, that methodology lacks robustness and flexibility to account for sudden regime changes. For example, despite BTC's return of ~120% in 2019, the recent "flash crash" has turned many technical indicators and sentiment bearish, producing uncertainty for investors going into Q4.

To understand the Q4 volatility dynamic well, one must understand the market seasonality from both price and volatility perspectives. Using a semi-robust time series model, we analyze the natural logarithm of bitcoin price in order to breakdown its seasonal and trend components.

PRICE SEASONALITY

The first chart, "historical trend," shows the positive linear trend of bitcoin using the natural logarithm (log) of price, since inception. The second chart, "weekly," shows the log price movement from Monday to Sunday, which exhibits a fairly stable trend, besides Monday and Tuesday. The last chart, "yearly," articulates the yearly components of bitcoin's log price trend on a month by month basis. The most fascinating element is that the model can isolate the specific months with positive price effects, e.g. April to early July and October to December (Q4).

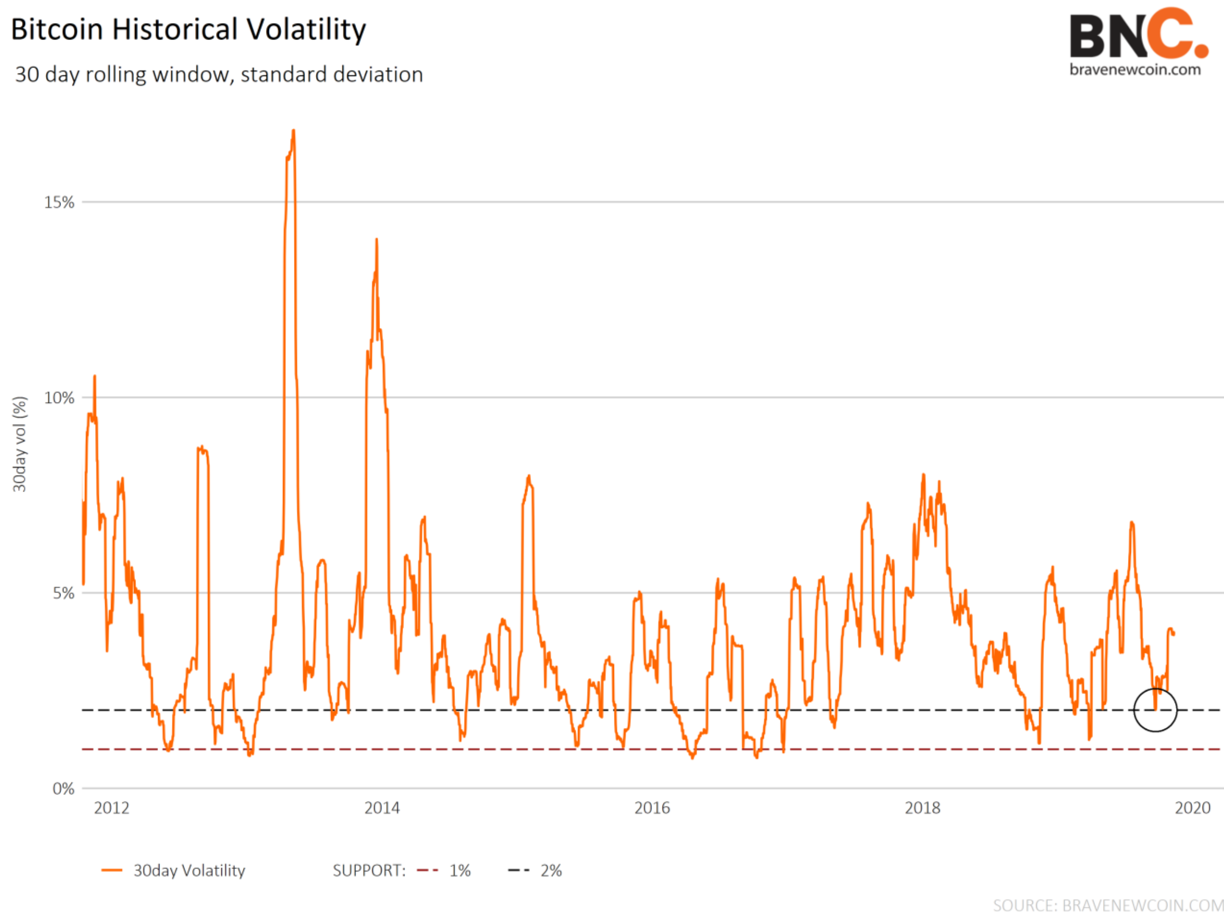


coinmetrics.io

VOLATILITY SEASONALITY

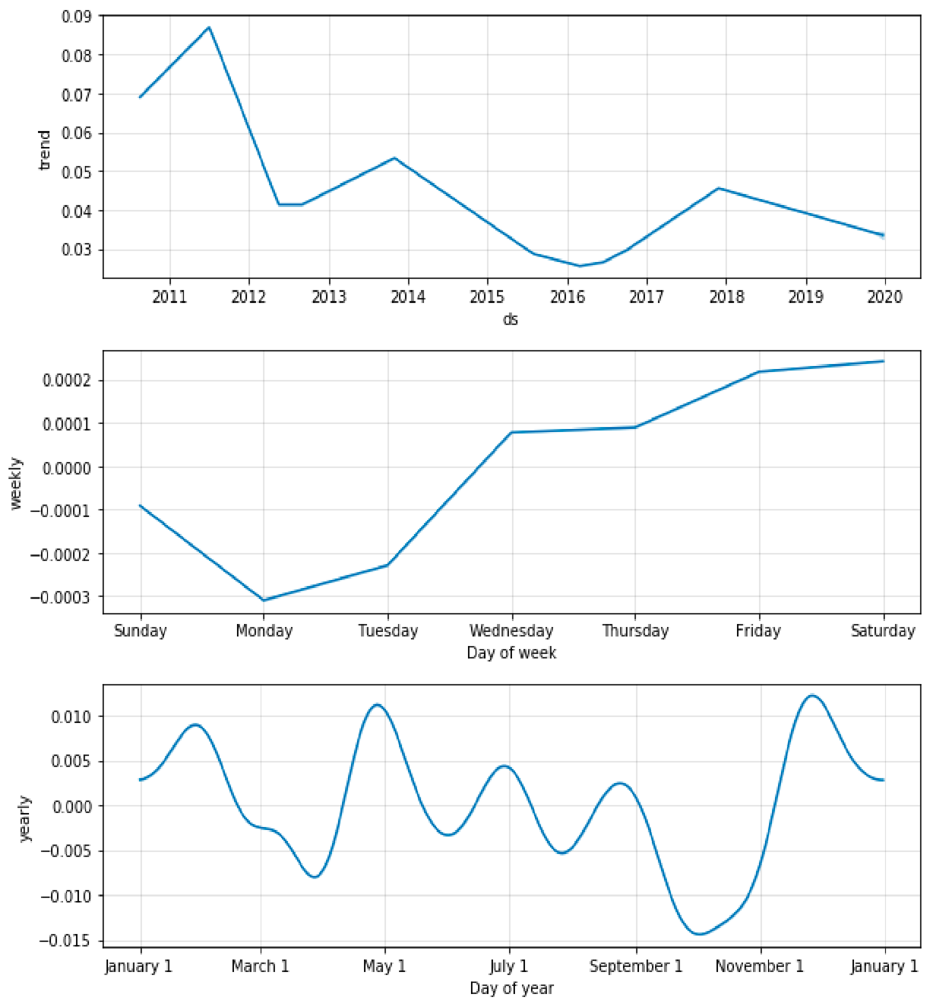
The chart below plots the 30-day moving average (MA) of bitcoin's daily price volatility. There are two primary levels which ignite large volatility spikes, 2% (the black line) and 1% (the red line). The recent spike in volatility from the "flash crash" initiated from the 2% trigger level.

SEASONAL INVESTMENT CYCLES



The below charts breakdown bitcoin's historical 30-day MA of daily volatility into their seasonal components. First chart, "historical trend," shows the overall trend in daily volatility, which has steadily decreased since inception, which is common as a financial asset matures. The second chart, "weekly," demonstrates a predictable and logical pattern to volatility growth throughout the week with a steady increase Monday to Saturday. The third chart, "yearly," maps volatility cycles on a month by month basis with clear patterns, e.g. increasing April to May and October to early December (Q4).

SEASONAL INVESTMENT CYCLES



coinmetrics.io

Currently, the 30-day MA daily volatility is ~3% and beginning to plateau. Given volatility has already begun to stabilize, compression back towards the "trigger zone" between 1% and 2% is likely over the coming weeks and months. The closer volatility drifts towards 1% in Q4, the greater the magnitude of the resulting volatility spike.

The goal of the remainder of this research report is to articulate a quantitative approach to probabilistically discerning which direction bitcoin's Q4 volatility is likely to manifest itself in 2019.

Quantitative Analysis

INTRODUCTION

Despite bitcoin's volatility patterns conforming to the historical imperative, softening price, sentiment, and technical indicators are producing directional uncertainty for the upcoming Q4 breakout. In order to discern the direction with the highest probability, we must engage quantitative analysis. In particular, change point detection analytics that can spot market cycle inflection points.

HURST EXPONENT

The Hurst exponent (H) is rooted in mathematics founded by Benoit Mandelbrot, to determine if a financial market is trending or not. The Hurst Exponent, H, has a value range from 0 to 1.

- H > 0.5 – Market persistence, i.e. trending market
- H = 0.5 – No persistence, i.e. random walk market
- H < 0.5 – Anti-persistence, i.e. mean reverting market

There are several ways to calibrate the Hurst exponent and we use a proprietary calibration that has been an early indicator of price inflection points for bitcoin. Interestingly, our analysis uncovered an opposite dynamic compared to the traditional theory articulated above.

In the case of bitcoin:

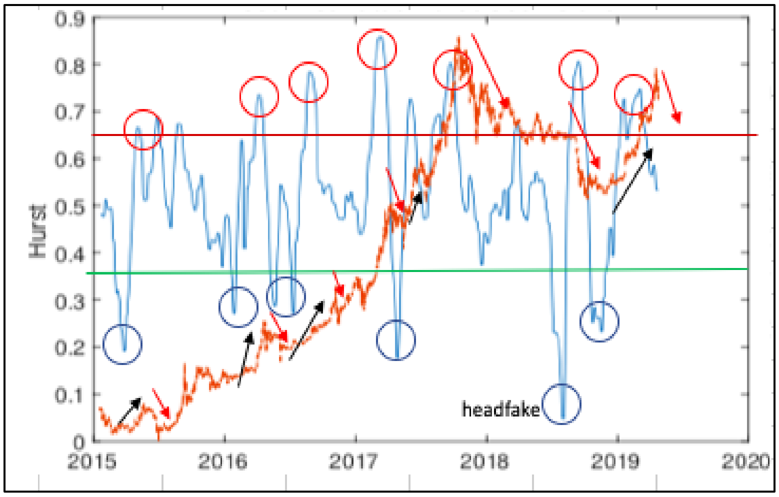
- H > 0.65 – Signals a price decline is forthcoming
- H < 0.35 – Signals a price increase is forthcoming

HISTORICAL HURST FOR BITCOIN

If one tracks the chart's key ranges, beneath 0.35 and above 0.65, one will see its consistency as a leading indicator for price movements; especially large inflection points.

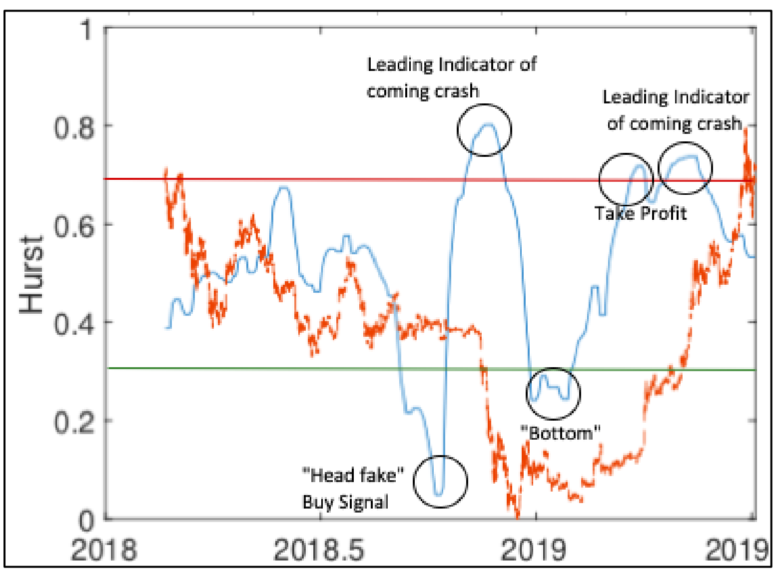
The graphic below shows:

- Historical plot (2015 to 2019) of bitcoin price (orange line)
- Hurst exponent (blue line)
- Level beneath 0.35 (green line)
- Level above 0.65 (red line)
- Buying inflection points (black circles with black arrows to track price growth)
- Selling inflection points (red circles with red arrows to track price fall)



*blocktap.io

In 2018, bitcoin offered a “head fake” with a low H that signaled a strong buy, but quickly saw that opportunity reverse. At the beginning of 2019, the low H correctly signaled a buy opportunity, but the high H in early-summer would have signaled profit-taking well before bitcoin reached its year to-date highs near $13,000. Despite early profit-taking and periodic “head fakes,” the Hurst exponent accurately called not only the 2019 bottom, but also the two price crashes of Q4 2018 and Summer 2019.



*blocktap.io

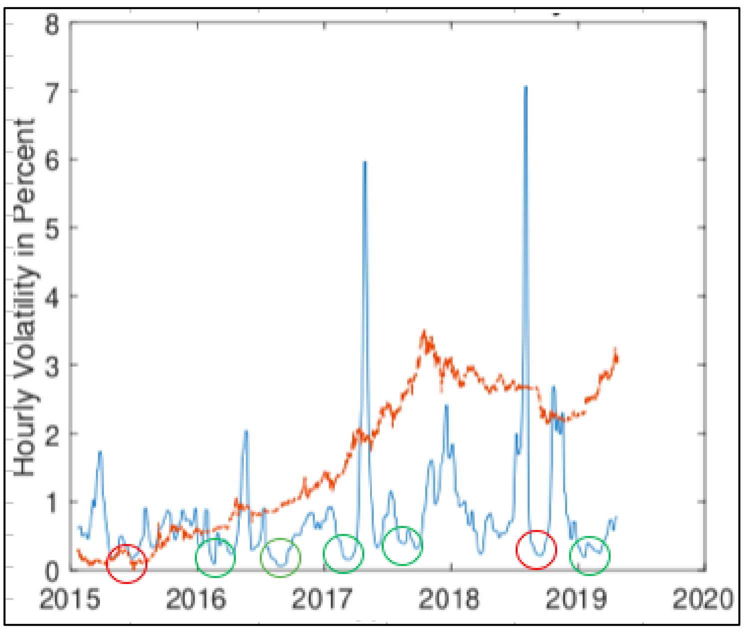
QUANTITATIVE ANALYSIS

The beauty of this indicator is its simplicity and leading nature. However, given it is a leading indicator, the specific timing of entering or exiting investment positions needs to be guided by other mechanisms. For example, combining Hurst with hourly volatility can aid entry and exit timing.

HOURLY VOLATILITY + HURST

The graphic below shows:

- Historical plot (2015 to 2019) of bitcoin price (orange line)
- Hourly volatility (blue line)
- Hourly volatility beneath 0.50% resulting in negative breakouts (red circles)
- Hourly volatility beneath 0.50% resulting in positive breakouts (green circles)



*blocktap.io

Hourly volatility levels beneath 0.50% identify likely breakout events both positive and negative. Thus, combining the Hurst exponent with a low volatility reading, increases the odds of correctly predicting the direction and timing of price breakouts.

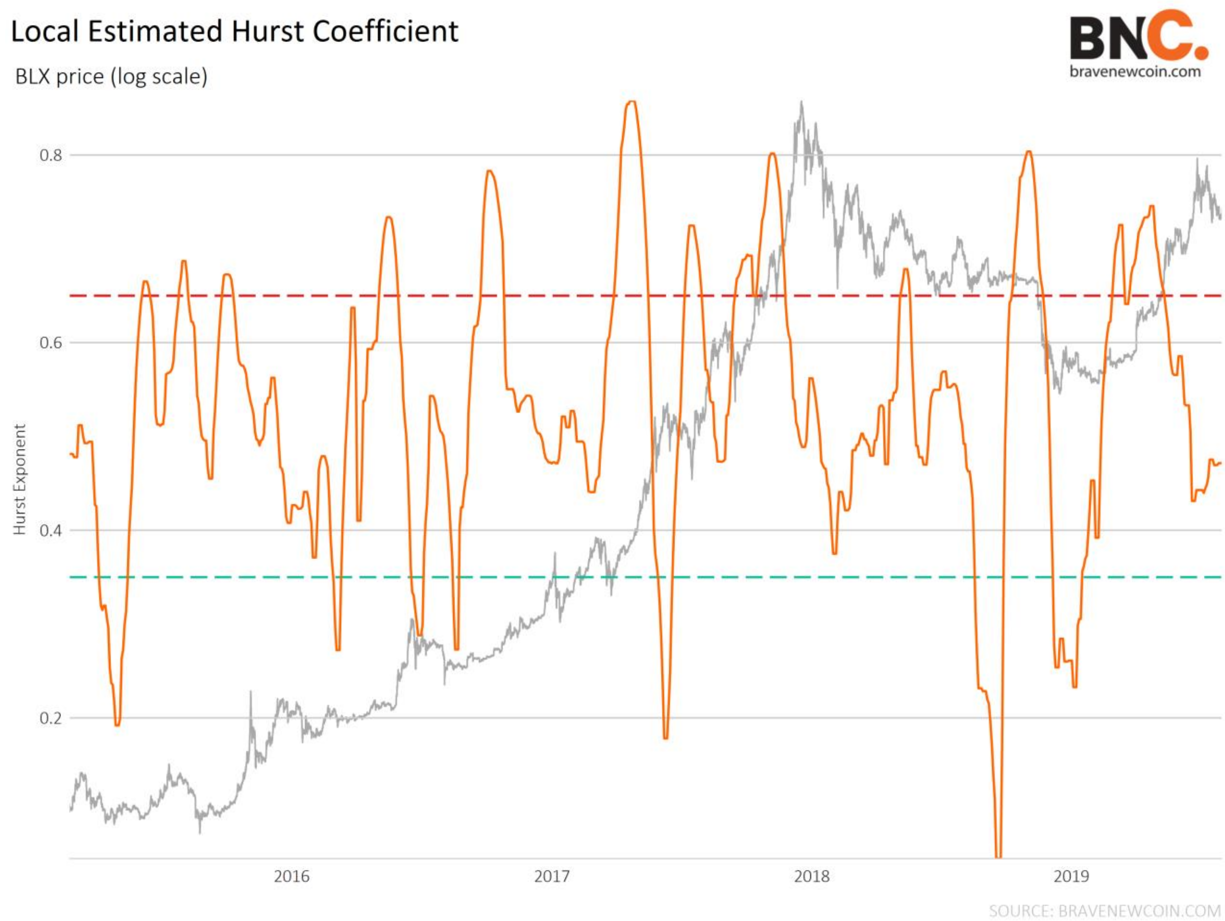
For example:

- H > 0.65 and V < 0.50%, indicates a high likelihood of a negative price breakout.
- H < 0.35 and V < 0.50%, indicates a high likelihood of a positive price breakout.

QUANTITATIVE ANALYSIS

CURRENT BITCOIN HURST EXPONENT

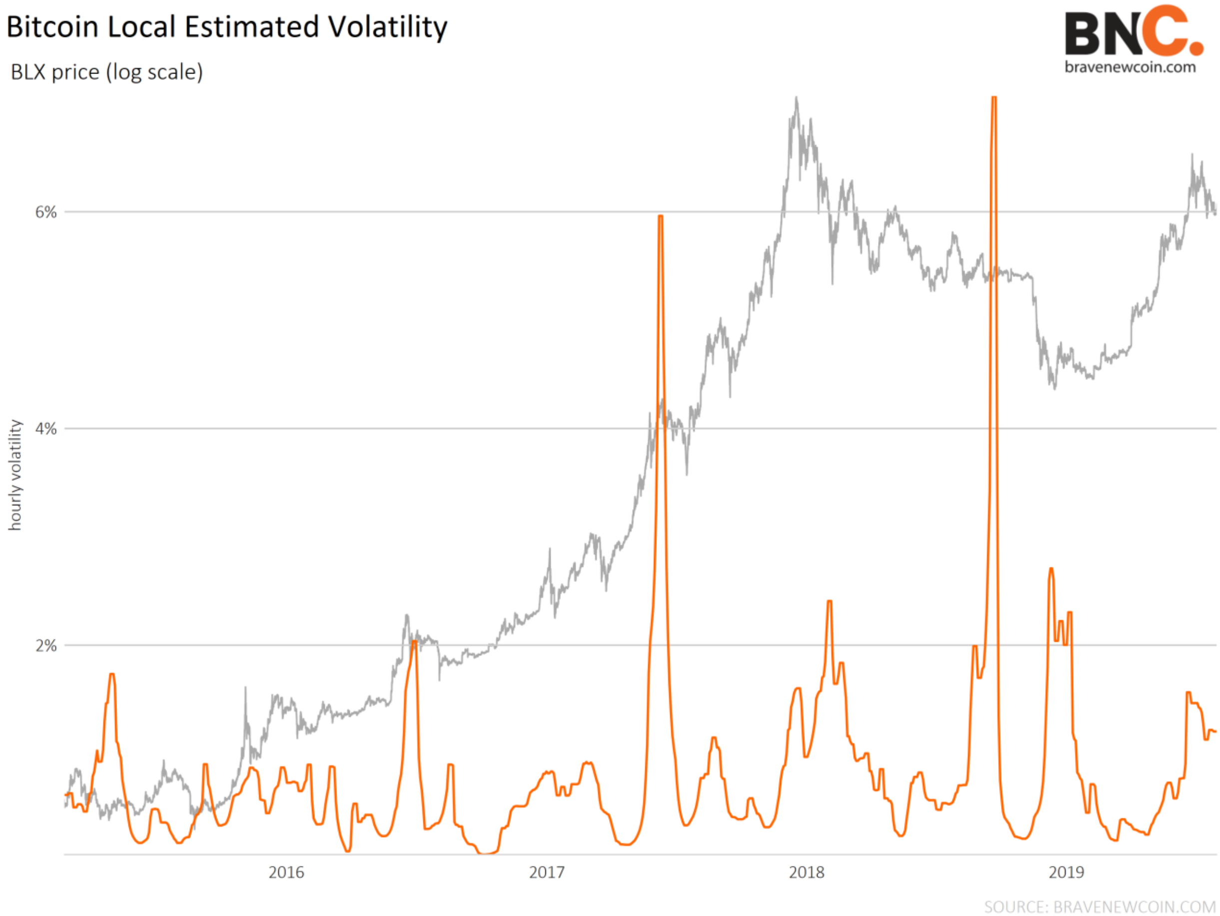
The current Hurst exponent value is 0.47 and trending upward. The huge 40% one day rally following China's President stating its intention to utilize blockchain technology, reversed Hurst's prior descent into the "buy zone." Hurst is still technically in "limited signal land" between "buy" and "sell" zones, which enhances uncertainty. However, despite the premature reversal, price and Hurst have trended upward without needing to touch the "buy zone" in some historical instances. Given the current directional trend, if Hurst could surpass and maintain above 0.50, i.e. the barrier for a "trending market," that would indicate bitcoin is in an uptrend and has further room to run.



CURRENT HOURLY VOLATILITY

The current hourly volatility is 1.20% and trending downward, which is the norm after large volatility spikes, e.g. early Q4 price action. If the downtrend persists, recompression back towards the 0.50% level is likely towards the end of Q4. Currently, hourly estimated volatility offers little definitive signal.

However, if estimated volatility recompresses to 0.50% and Hurst tracks above 0.50, the likelihood of a strong positive up move in bitcoin increases demonstrably.



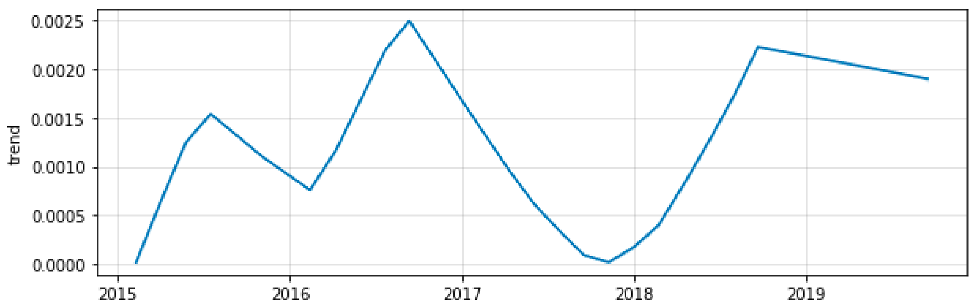
CYCLICAL TRENDS IN HURST

Lastly, we analyze the historical trend and seasonal components of the Hurst exponent, starting in 2015, by taking the first difference of the Hurst values. As discussed, a higher Hurst value is negatively correlated to price and vice versa, i.e. increasing first difference values are negative for price.

The first chart, “historical trend,” displays an interesting dynamic amongst bear and bull market cycles whereby bull market years see a declining trend in Hurst value and vice versa, with leading indicator inflection points being spotted at the “tops” and “bottoms” of market cycles. The largest swings were seen between 2017 and 2018.

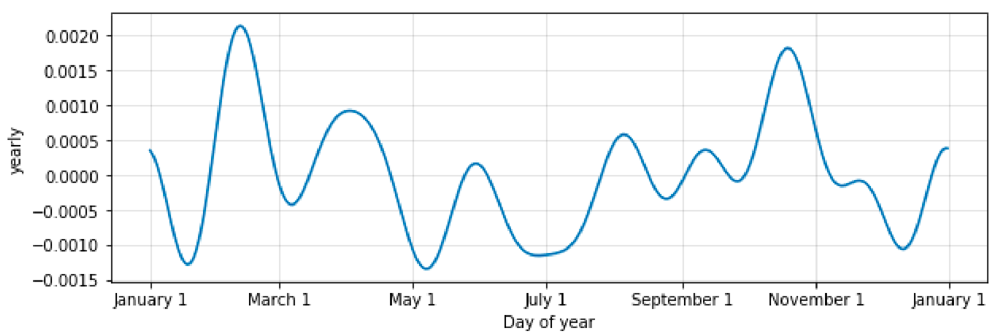
QUANTITATIVE ANALYSIS

In 2019, the trend has been downward, thus confirming the existing bull market. Additionally, the slope of the Hurst decline in 2019 has been quite temperate, potentially signaling that not only will 2019 remain bullish for price, but also has sufficient momentum to produce strong returns in 2020 as well.



*blocktap.io

Additionally, the "yearly chart," of the Hurst exponent confirms the same Q4 seasonality dynamic seen throughout this report, i.e. increasing Hurst (negative for price) until October, then a decreasing until December.



*blocktap.io

CONCLUSION

In this section, we have introduced a robust change point detection methodology that has successfully spotted market inflection points historically. The current readings of the Hurst exponent and hourly volatility seem to suggest, probabilistically, that a positive price breakout is on the horizon moving into Q4. However, as stated above, by extrapolating the current Hurst and hourly volatility values, we introduce a layer of risk into the analysis given both figures could change rapidly, and without warning over the coming 11-week period. Given that, we will provide updated Hurst exponent and hourly volatility figures, on an ongoing basis, to interested parties.

PRICE RETURN SCENARIOS

Price Return Scenarios

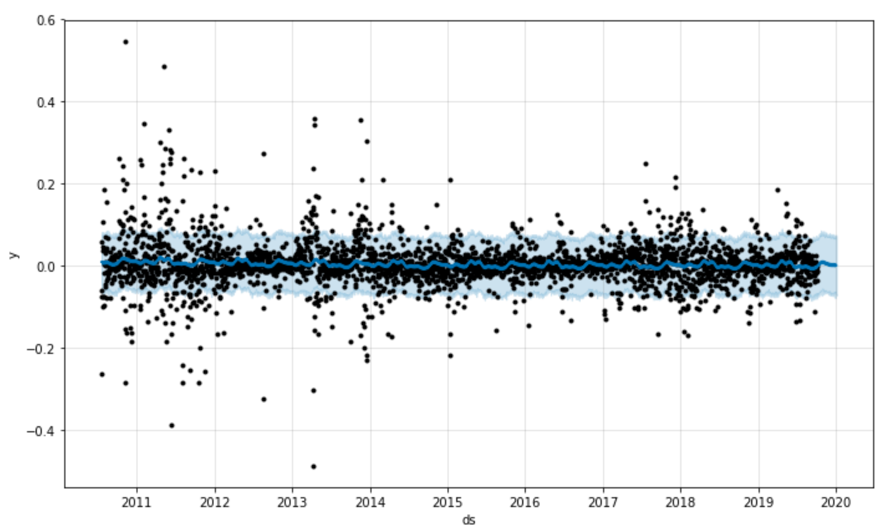
INTRODUCTION

In the prior section, we used the Hurst exponent to identify the likely direction of bitcoin's Q4 breakout. Although Hurst is excellent as a leading indicator for inflection point changes, it does not provide a framework for determining the magnitude of change, i.e. price forecasts. Given this shortcoming, we must leverage an additional quantitative model that can produce a range of price forecasts over the next 3 months, using both price return seasonality and stock to flow (S2F)[4] data for bitcoin.

It is important to note that the goal of this exercise is not to produce exactly correct (or incorrect) price forecasts, but rather generate a conceivable range of expected values for the anticipated breakout. From there, that range may be scrutinized for risk to reward characteristics.

RETURN SEASONALITY

Leveraging our time series model, we are able to dissect the seasonal and trend components of bitcoin's daily price returns since 2010, i.e. first difference change in price, shown in the chart below.

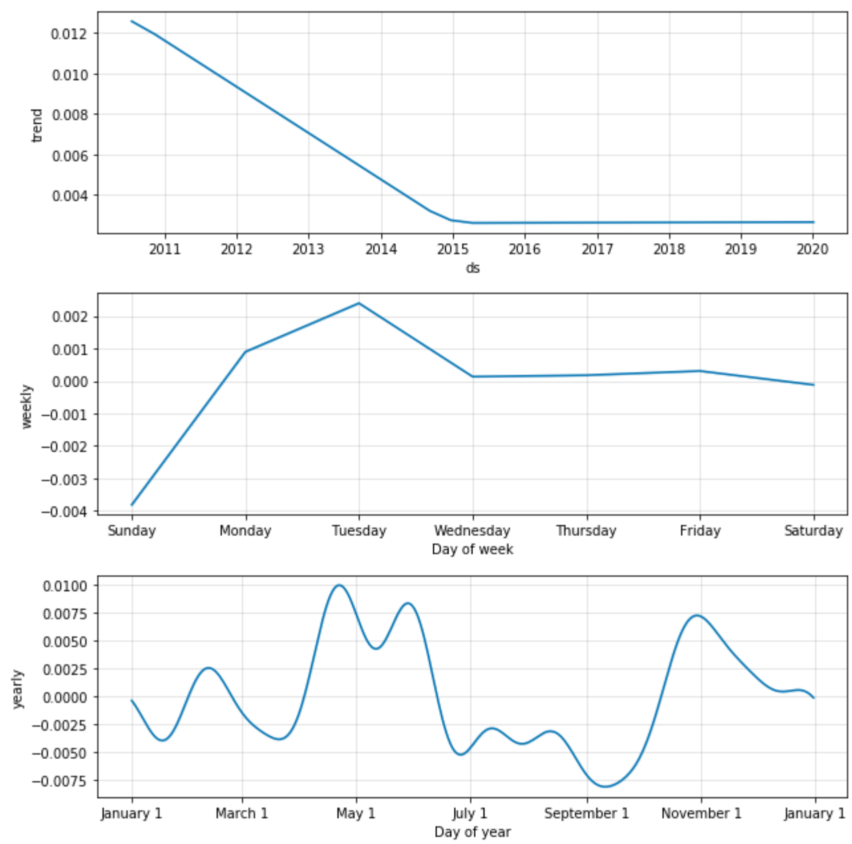


coinmetrics.io

Just as our analysis in the Price Seasonality section, the model offers a three-chart breakdown of the seasonal components. The first chart, "historical trend," shows the overall negative linear trend of first difference returns since inception, which makes sense given the asset's maturation, i.e. diminished

[4] https://medium.com/@100trillionUSD/modeling-bitcoins-value-with-scarcity-91fa0fc03e25

magnitude of returns and volatility. The second chart, "weekly," displays a fairly repeatable return trend, consistent with our prior analysis. The last chart, "yearly," articulates the yearly price return breakdown, which aligns with our prior analysis, i.e. March to June and October to December (Q4) coincide with positive price return periods.



*coinmetrics.io

STOCK TO FLOW RATIO

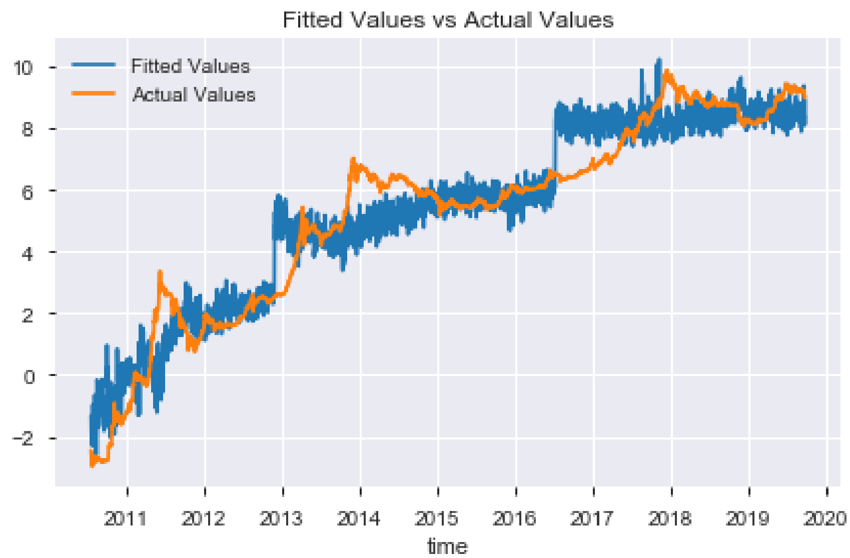
The stock to flow (S2F) ratio, i.e. the current supply divided by the number of new coins emitted, has long been a metric touted by many crypto social media influencers as the *only* driver of bitcoin price change. Personally, we have shown flaws in these assumptions in several ways, but in Summer 2019, a Crypto Analyst, Marcel Burger[5], offered a more rigorous approach to verifying S2F's effect on bitcoin's price via a statistical term called Cointegration.

[5] https://medium.com/burgercrypto-com/reviewing-modelling-bitcoins-value-with-scarcity-part-ii-the-hunt-for-cointegration-66a8dcedd7ef

PRICE RETURN SCENARIOS

ORDINARY LEAST SQUARES REGRESSION WITH COINTEGRATION (COLS) MODEL

Leveraging the Cointegration framework and our own data, we verified that S2F *is in fact* cointegrated to the price of bitcoin[6], which allows the COLS model to be utilized to describe price relationships between the two variables. Furthermore, the COLS model boasts an R2 equal to 0.89, i.e. a strong fit, evidenced by the plot of fitted versus actual values of the natural logarithm of bitcoin price.



coinmetrics.io

These results are interesting for two reasons. First, verifying Cointegration in financial time series is a rare event. Second, the emission schedule is programmatically fixed and known, which makes forecasting S2F and its long-term effect on price straightforward.

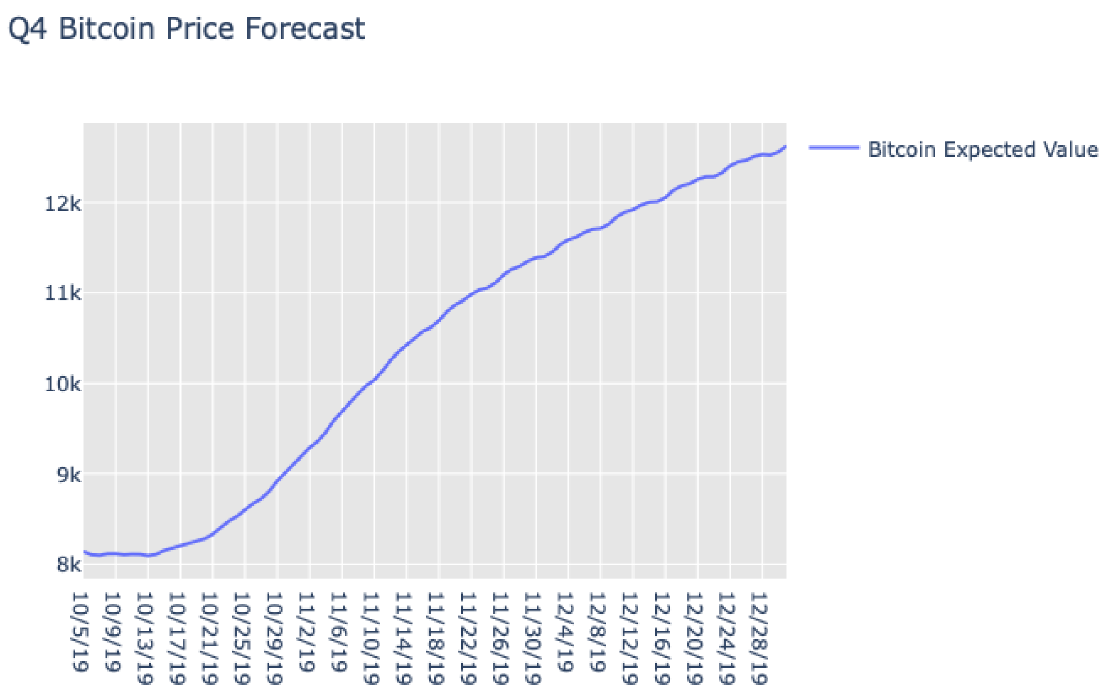
3 MONTH PRICE FORECAST

We generate the expected value for bitcoin on December 31, 2019, by combining the time series forecasting and COLS models, which leverage two key pieces of information, the seasonality of price returns and Cointegration effect of S2F. Again, the goal of the exercise is not to produce exactly correct price forecasts, but rather a conceivable range of prices and risk to reward characteristics.

Using the combined forecasting model, we generate bitcoin's expected mean value at $12,624.98 on December 31, 2019.

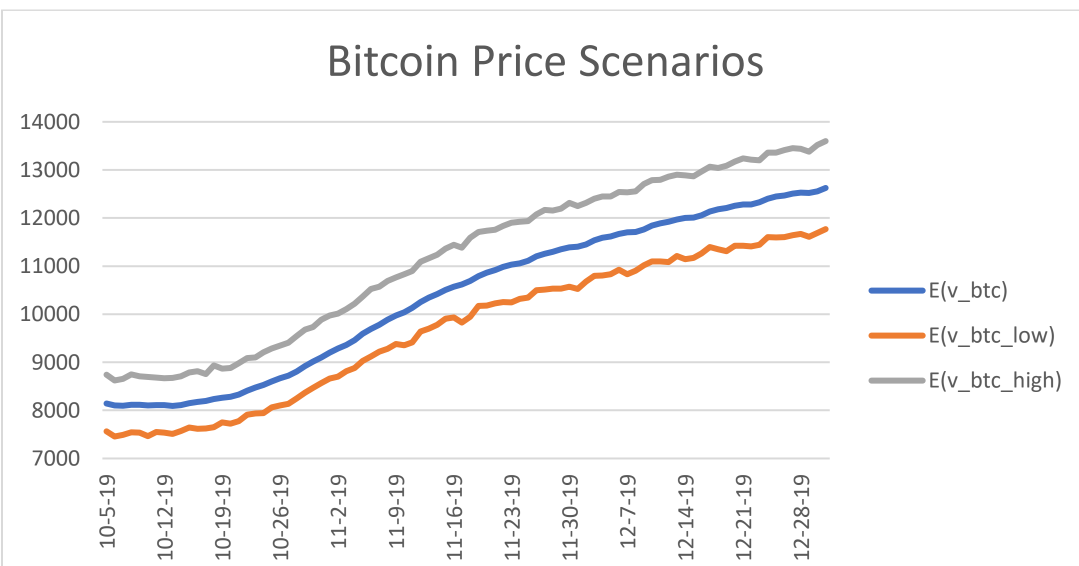
[6] See appendix for detailed Cointegration analysis of stock to flow and bitcoin price

PRICE RETURN SCENARIOS



*blocktap.io

Additionally, the combined model generated three scenario paths, i.e. mean, low, and high forecasts within a 90% confidence interval.



*blocktap.io

PRICE RETURN SCENARIOS

DATE	BTC MEAN VALUE	BTC LOW VALUE	BTC HIGH VALUE
12/31/2019	$12,624.98	$11,768.96	$13,599.32
CURRENT PRICE	EXPECTED RETURN	EXPECTED RETURN	EXPECTED RETURN
$8,200	53.96%	43.52%	65.84%

Using the model's potential price paths divided by the current price of bitcoin, we produce three expected return values. All of which, are quite bullish. However, given market nascency, small historical sample size, and extreme market reflexivity, one should discount these expected values by at least 50%.

RISKS AND MITIGANTS

Risks and Mitigants

HURST EXPONENT 'HEAD FAKE'

Risk: The Hurst exponent is a fluid indicator that is sensitive to extreme market conditions. As discussed prior, the Hurst exponent showed a bullish signal, then quickly reversed into a bearish signal in November 2018. This element of sudden reversal of signal still remains.

Mitigant: We are able to track the Hurst exponent in relative, real-time, thus our analysis is malleable enough to monitor for such sharp signal adjustments. Furthermore, we are offering updated Hurst exponent figures to any interested readers of this report on an ongoing basis.

COLS ASSUMPTIONS

Risk: If Cointegration exists, then S2F predominantly drives the long-term price trajectory for bitcoin. By accepting this premise, we also accept that bitcoin's price acts similar to a 'chaotic system' whereby the returns look stochastic, but are actually deterministic. This assumption could prove to be incorrect or diminish over time.

Mitigant: The rigorous statistical analysis used to validate Cointegration gives us confidence that S2F and bitcoin price are significantly cointegrated. Thus, the probability of some form of deterministic process influencing bitcoin's price is acceptably high, e.g. greater than 40%. Also, the additional variables effecting price from the demand side, e.g. active addresses, are positively correlated to price and trending upward currently.

INCORRECT FORECAST OF RETURNS

Risk: The time series forecasting model could produce incorrect or erroneous return predictions, which would severely diminish the reliability of our Q4 price forecasts.

Mitigant: Errors in time series forecasting are inevitable, but this particular model's efficacy has held up relatively well over time. For example, the model was originally implemented in July 2019 by Marcel Burger[7] and it correctly predicted a sharp decrease in price of bitcoin at almost the exact time that it occurred in late-September, with an error rate of ~9%, i.e. $8,800 predicted versus $8,000 actual. The delta of 9% might seem quite large, but considering the previously discussed unpredictable exogenous factors that contributed to a 3$\boldsymbol{\sigma}$ price drop, i.e. forced derivatives liquidation, the prediction result seems

[7] https://medium.com/burgercrypto-com/forecasting-bitcoin-returns-with-prophet-in-python-part-ii-b3e44b3de95

fairly strong if such event had not occurred. Thus, we have a good level of comfortability with the model's robustness.

EXOGENOUS MACROECONOMIC FACTORS

Risk: Cracks in the global macro-economy and Central Bank's ability to influence it have begun to show. In particular, it is largely expected that the U.S. will enter a recession in 2020 with record high debt levels. Additionally, overnight repo markets have recently shown instability not seen since the Great Financial Crisis, which could be the "canary in the coal mine" for severe macroeconomic issues. With that, recessionary environments driven by any bad deleveraging event will bode negatively for assets like bitcoin given in deflationary environments, all risk assets lose value, but fiat hedges are particularly hit hard due to "dollar swelling."

Mitigant: In a full and unabated deflationary environment, there will be no place to hide, so the only hope is that consumer price levels fall farther, percentage-wise, then bitcoin. However, if another crisis or regular recession unfolds, policymakers and Central Banks are likely to reinitiate easy money policies or outright stimulus, evidenced by the Fed's recent interest rate cuts and balance sheet expansion. This reflationary environment bodes well for fiat hedges and high yield assets like bitcoin.

MARKET MICROSTRUCTURE RISKS

Risk: The greater trend of increased use of derivatives will likely see the same phenomenon that caused the recent "flash crash" persist until the market microstructure matures. For example, BitMEX, the largest, unregulated exchange by daily volume, regularly has trading volumes 1x higher than the largest spot exchanges combined.

Mitigant: Market microstructure dislocations can also work in the portfolio manager's favor when sentiment reaches extreme highs, which may balance out the cumulative negative effects over time. Additionally, many institutional investors have been waiting for regulated derivatives (LedgerX and Bakkt) to gain exposure to bitcoin without needing to custody the asset themselves. Thus, derivatives may increase volatility for bitcoin in the short-term, but usher in a new wave of buying demand in the long-term.

SUMMARY

Summary

Throughout this report we have attempted to setup a robust quantitative framework whereby the data speaks for itself, devoid of opinions or biases – both in analyzing the recent "flash crash" and Q4 breakout direction. In doing so, the data appears to suggest that bitcoin will have a Q4 breakout, and the direction is likely to be to the upside.

Despite offering a range of positive price scenarios in the report, we acknowledge several inherent market and modeling risks. Given such risks, any educational insights gleaned from the analysis and price scenarios contained within the report should be discounted for conservatism.

Last, we wanted to put this report out sooner rather than later given the speed in which this market moves. This means that the Hurst exponent and price range scenarios are likely to gyrate over the coming 11-week period. Thus, for anyone who found value in the report, we're willing to provide updated Hurst exponents and price forecasts on an ongoing basis. Interested parties should email **chris@valiendero.io** to sign up.

1.1 For educational purposes only. This is not investment advice nor a recommendation or solicitation of any kind.

CONTACT INFORMATION

Contact Information

CHRISTOPHER BROOKINS
FOUNDER AND CIO
CHRIS@VALIENDERO.IO

Valiendero Digital Assets LP
4765 Forbes Avenue
Pittsburgh, PA 15213
valiendero.io

Valiendero Digital Assets

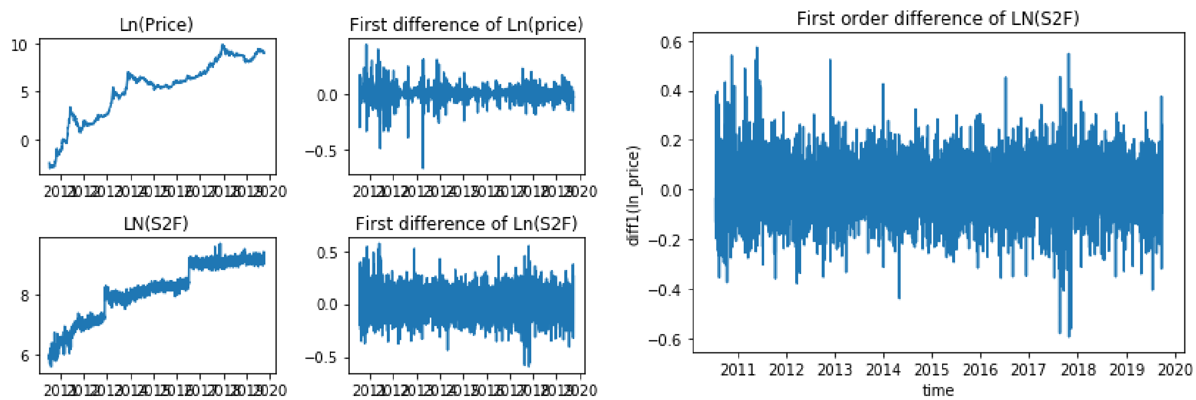
A quantitative cryptocurrency investment fund, founded out of Carnegie Mellon, leveraging machine learning and data-driven investment strategies over a variety of liquid digital assets.

APPENDIX

Appendix

STOCK TO FLOW MODEL COINTEGRATION

1. Determining if both time series are Stationary visually, which both appear to be, Engle Granger test.



2. Confirming the above Stationary assumption by performing the Augmented Dickey-Fuller (ADF) test on both time series (Engle Granger test). Both p values are ~0.00, which are highly significant, thus we can reject the null hypothesis that the time series are not Stationary, i.e. appropriate to perform OLS regression.

```
First order difference of ln(price)
ADF Statistic: -9.495815
p-value: 0.000000
Critical Values:
        1%: -3.432
        5%: -2.862
        10%: -2.567

First order difference of ln(S2F)
ADF Statistic: -16.050300
p-value: 0.000000
Critical Values:
        1%: -3.432
        5%: -2.862
        10%: -2.567
```

3. Ordinary Least Squares Regression results with Adjusted R2 = 0.89 and ln_S2F coefficient = 3.1.

APPENDIX

```
                            OLS Regression Results
==============================================================================
Dep. Variable:               ln_price   R-squared:                       0.890
Model:                            OLS   Adj. R-squared:                  0.890
Method:                 Least Squares   F-statistic:                 2.717e+04
Date:                Fri, 04 Oct 2019   Prob (F-statistic):               0.00
Time:                        09:36:04   Log-Likelihood:                -4854.0
No. Observations:                3358   AIC:                             9712.
Df Residuals:                    3356   BIC:                             9724.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept    -19.8862      0.153   -129.558      0.000     -20.187     -19.585
ln_sf          3.0994      0.019    164.840      0.000       3.062       3.136
==============================================================================
Omnibus:                       16.475   Durbin-Watson:                   0.145
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               21.832
Skew:                          -0.047   Prob(JB):                     1.82e-05
Kurtosis:                       3.384   Cond. No.                         71.7
==============================================================================
```

4. Running the Durbin-Watson test on regression residuals must be above 0 to confirm that the two variables are cointegrated. The Durbin_Watson test result is above 0, thus existence of Cointegration.

```
0.14460475464774625
```

5. Running the Augmented Dickey-Fuller test (Engle Granger test) on residuals, i.e. if residuals are non-stationary, then the time series are not cointegrated. The p value significance is greater than the 99% confidence level, which means the time series are cointegrated.

```
Regression residuals
ADF Statistic: -3.545338
p-value: 0.006896
Critical Values:
        1%: -3.432
        5%: -2.862
        10%: -2.567
```

6. Johansen test for Cointegration, i.e. if both test statistics (Trace and Maximum Eigenvalue) are higher than the critical values, we have to reject the null hypothesis of no Cointegration. Both test statistics are well above the 99% confidence level critical values, thus we have to reject the null hypothesis of no Cointegration.

APPENDIX

```
Trace Statistic:
[74.43728239  7.90874476]
Critical Values Trace Statistic [90% 95% 99%]:
[[13.4294 15.4943 19.9349]
 [ 2.7055  3.8415  6.6349]]

Maximum Eigenvalue Statistic
[66.52853763  7.90874476]
Critical Values Maximum Eigenvalue Statistic [90% 95% 99%]
[[12.2971 14.2639 18.52  ]
 [ 2.7055  3.8415  6.6349]]
```

7. We performed three separate statistical tests of Cointegration, i.e. Engle Granger, Durbin-Watson, and Johansen. The results of all three tests show strong statistical evidence (greater than 99% confidence) that Cointegration does exist between bitcoin price and stock to flow ratio.