Evaluating Cryptocurrencies as Modern Haven Assets

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Introduction

This document examines the role of cryptocurrencies as potential stabilizers in the digital age. While initially met with doubt, cryptocurrencies are now being seriously considered for their long-term value, similar to traditional assets like gold. The study utilizes advanced data analysis techniques to evaluate how cryptocurrencies perform during economic downturns, understand investor sentiment, analyze the effects of regulation, and explore different investment approaches. The objective is to determine whether cryptocurrencies can serve as reliable assets during financial uncertainty, earning the title 'Digital Gold' and potentially redefining safe-haven assets for contemporary investors by offering a balance between potential growth and risk management.

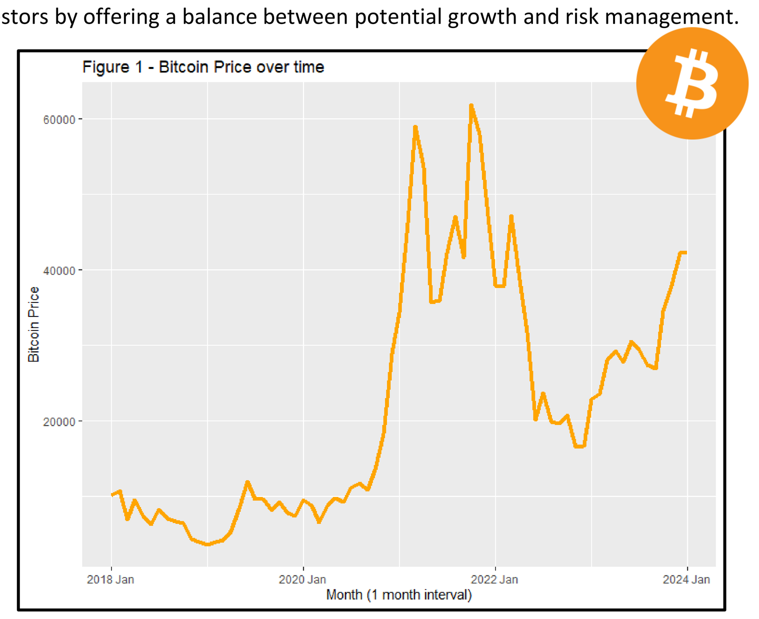
Figure 1 - Bitcoin Price over time

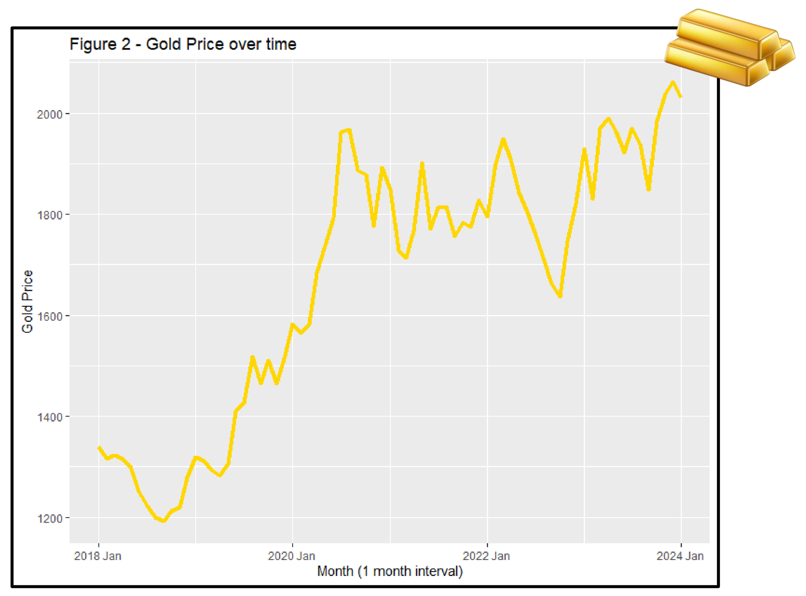
Figure 2 - Gold Price over time

In Figure 1 we can see how the Bitcoin price (USD $) has evolved during different months, more specifically from January 2018 to January 2024. In Figure 2 we can see how the Gold price (USD $) has evolved during the same period. The graphs depict Bitcoin's significant price fluctuations and Gold's steadiness, reflecting varied reactions to economic shifts. This disparity underlines the importance of evaluating how digital and traditional assets perform amid financial uncertainty, potentially offering insights into evolving market sentiments and the nature of value in today's digital economy.

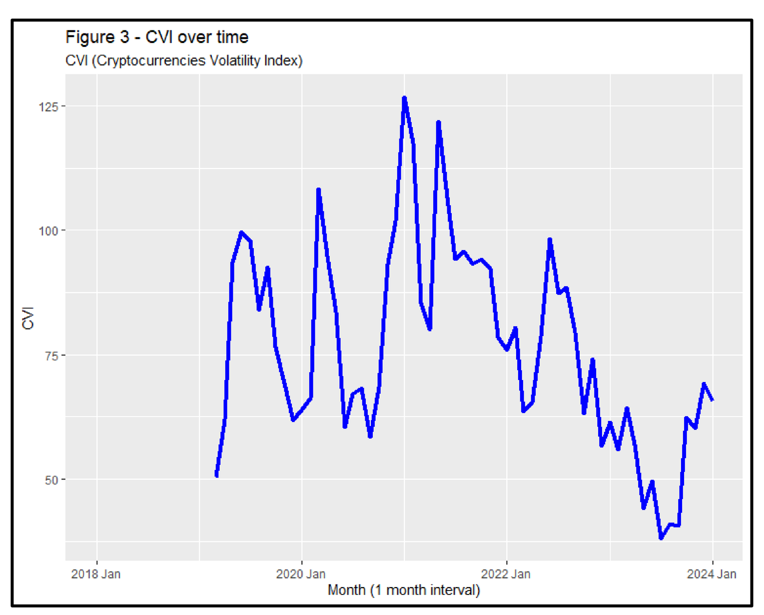
Figure 3 - CVI over time

Figure 3 depicts the Cryptocurrencies Volatility Index (CVI), which measures the expected price volatility of cryptocurrencies within a 30-day period. This tool translates complex market dynamics and investor sentiment into a percentage, predicting how widely crypto prices might fluctuate, thus aiding investors in gauging the risks of crypto investments. A declining CVI suggests a trend toward stabilization in the cryptocurrency market, indicating they may be evolving into more reliable investment vehicles, akin to traditional assets.

The decreasing pattern of the CVI reflects a maturing cryptocurrency market, potentially due to factors like broader market adoption, more precise regulatory frameworks, and institutional investments. This trend is promising for the crypto market, as it implies a shift away from its early, speculative phase to a period where cryptocurrencies are perceived as legitimate, dependable assets. Such a trend could lead to cryptocurrencies being viewed as stable as traditional safe havens like gold and government bonds, reshaping investment portfolios and strategies.

The fall in the CVI is significant as it indicates a transformation in the perception of cryptocurrencies from high-risk investments to assets with resilience and credibility. This evolution is key for their integration into conventional financial systems and for building the confidence of investors. Should this trend persist, it paves the way for broader acceptance of cryptocurrencies, possibly inaugurating a new era in which digital assets are recognized for their stability and reliability, comparable to traditional investment assets.

Data Preparation

Stationarity is a critical characteristic of time series data that allows for the application of models such as ARIMA for forecasting. Before modeling, we ensure our data is stationary, meaning its statistical properties do not vary with time. To ascertain stationarity, we examine the ACF plots of our cryptocurrency values and the Crypto Volatility Index (CVI). If the ACF shows significant correlations out to a high number of lags or a pattern that suggests a trend or seasonality, differencing the data may be required. This step transforms the original time series into one where the values represent the changes between consecutive observations, thereby stabilizing the mean and variance. It is this stationary series that we will then use for ARIMA modeling to forecast future values accurately.

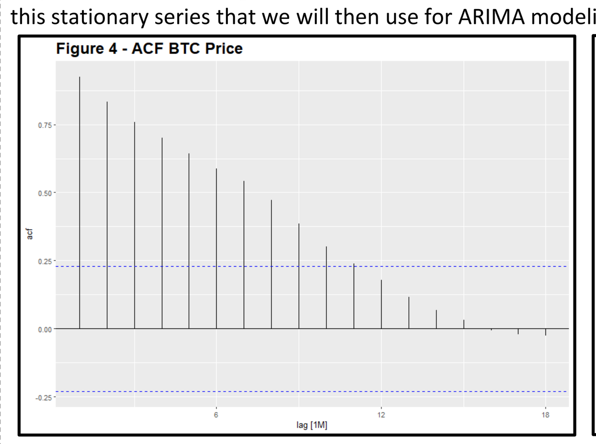
Figure 4 - ACF BTC Price

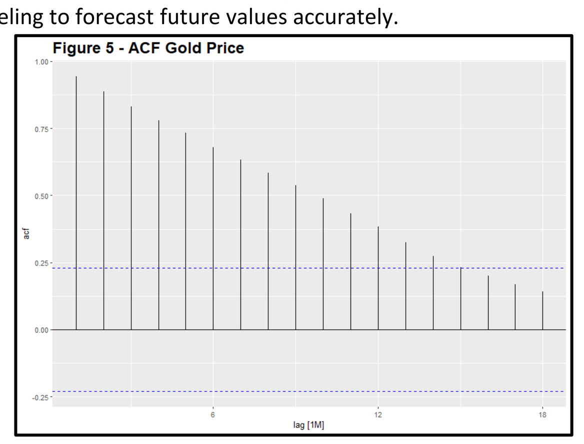
Figure 5 - ACF Gold Price

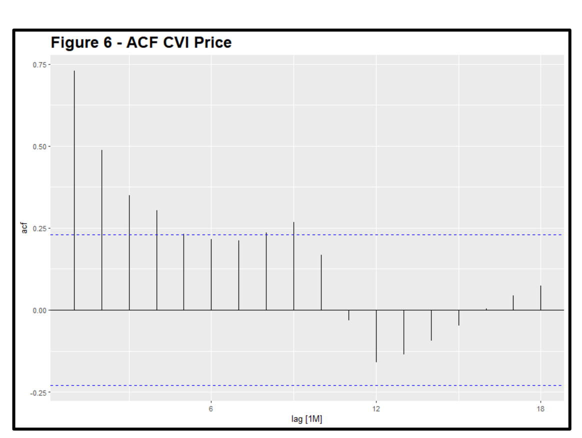
Figure 6 - ACF CVI Price

As indicated by the ACF plots, our data exhibits a non-stationary trend, with spikes that diminish gradually rather than dropping swiftly to zero, a clear sign that differencing is necessary, as it can be seen in Figures 4-7. To address this, we apply differencing to our dataset, where each value in the series is replaced by the difference between it and the previous value. This process is intended to remove trends and seasonality, leading to a stationary series where statistical properties such as mean and variance remain constant over time. Differencing is a prerequisite for the ARIMA model, as it relies on stationary data to produce reliable and accurate forecasts. By transforming our data accordingly, we lay a solid foundation for the subsequent modeling and forecasting steps.

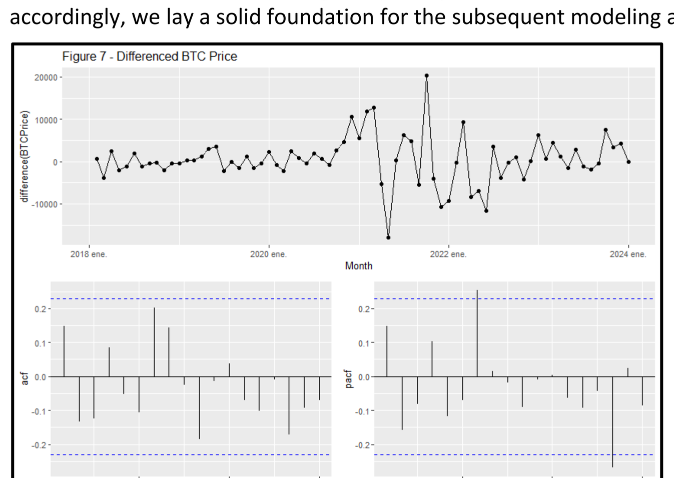
Figure 7 - Differenced BTC Price

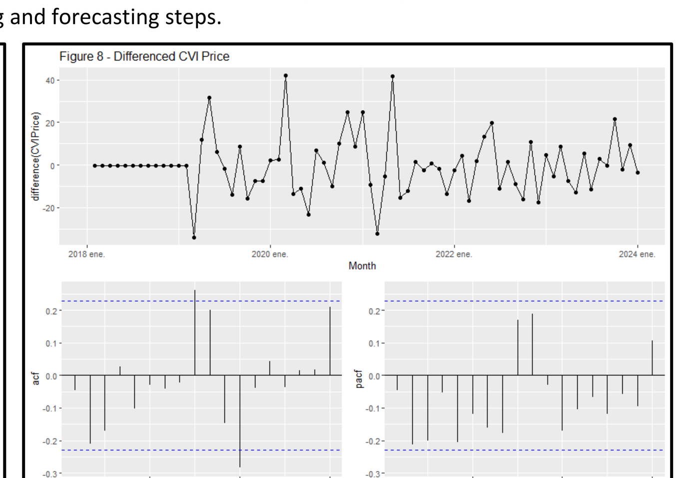
Figure 8 - Differenced CVI Price

Through first-order differencing, we transformed the original non-stationary data, as illustrated in Figures 7 and 8, into a stationary series ready for forecasting. This step effectively mitigated the trends and seasonality, evidenced by the now-stabilized autocorrelation in the ACF plots. Our data is now primed for ARIMA modeling to forecast future cryptocurrency price movements.

Model Analysis

In the Model Analysis phase, we utilize the ARIMA model to conduct our forecasting analysis, focusing on its robustness in handling different forms of time series data. ARIMA stands out for its flexibility in modeling data that has been rendered stationary through differentiation, as demonstrated with our cryptocurrency prices and the CVI. To benchmark the effectiveness of our ARIMA model, we compare its performance against simpler models: the mean model, which predicts the average past value, and the naive model, which assumes the last observed value as the next. These benchmarks represent our baseline for minimum accuracy. The accuracy of our ARIMA model will be quantified by measuring forecast errors, ensuring that our model can effectively capture the underlying patterns within the data. This step is crucial, as we are investigating the CVI's ability to reach a stability comparable to traditional safe haven assets like gold, potentially redefining the role of cryptocurrencies in financial security.

1 We first need to get the ARIMA model. To do this, we will compute the calculations manually to obtain the model. Here is an example of the model used:

```
Series: BTCPrice
Model: ARIMA(2,1,0)

Coefficients:
         ar1      ar2
      0.1757  -0.1515
s.e.  0.1159   0.1157

sigma^2 estimated as 29833636:  log likelihood=-
720.79
AIC=1447.57   AICc=1447.92   BIC=1454.4
```

We will pay close attention at the values of AIC, AICc, and BIC, using the model ARIMA(2,1,0).

2 Now, we obtain the result from the model automatically, and then we compare which result is expected to give us a better value:

```
Series: BTCPrice
Model: ARIMA(0,1,1)

Coefficients:
         ma1
      0.1901
s.e.  0.1201

sigma^2  estimated  as  29914191:   log  likelihood=-
721.38
AIC=1446.75   AICc=1446.93   BIC=1451.31
```

After reviewing both of the models, we obtain an expected better performance with the ARIMA(0,1,1). These steps are applied to all of our vectors, and the better value will be the model that is going to be forecasted.

3 We need to check if the ljung_box test, gives us a lb_pvalue bigger than 0.05, to reject the null hypothesis that states that the data is not stationary

```
# A tibble: 1 × 3
  .model lb_stat lb_pvalue
  <chr>    <dbl>     <dbl>
1 auto      19.5     0.489
```

Since we got a value bigger than 0.05, our data presents to be stationary

4 Now, using the most accurate model, we forecast our data.

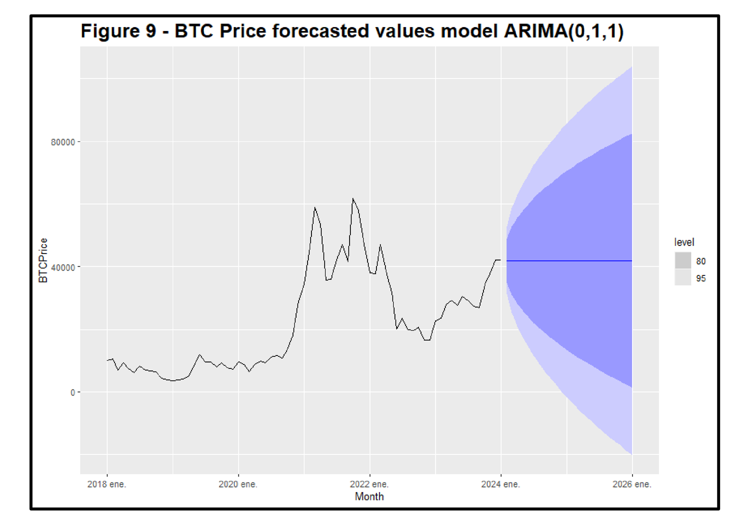
Figure 9 - BTC Price forecasted values model ARIMA(0,1,1)

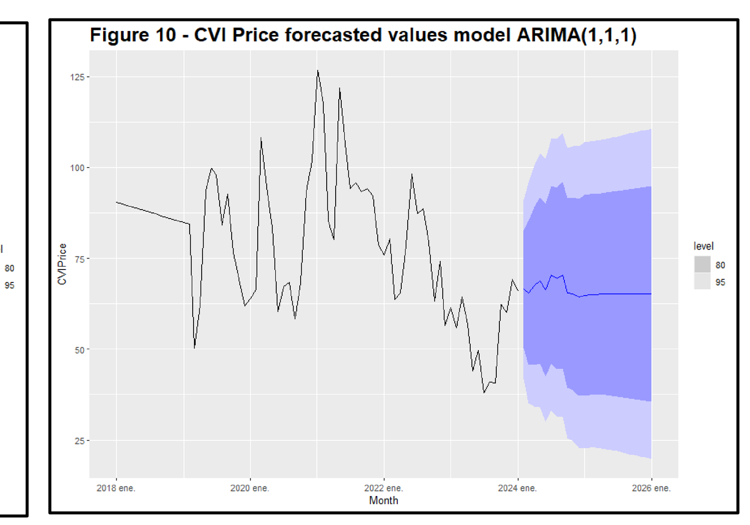
Figure 10 - CVI Price forecasted values model ARIMA(1,1,1)

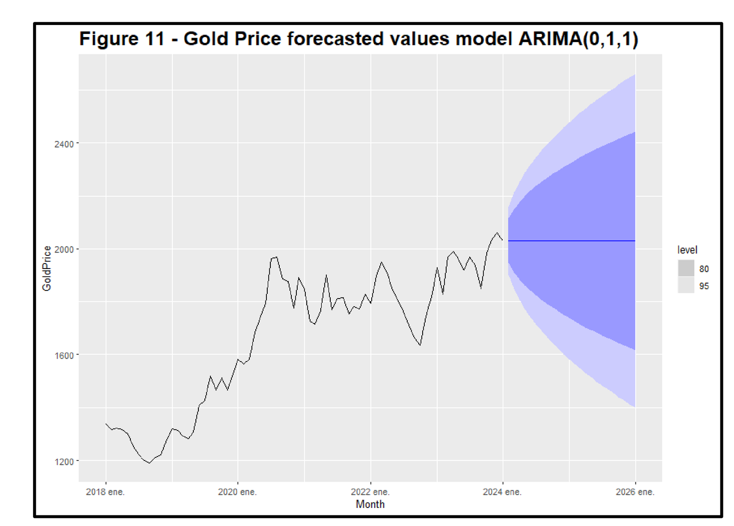
Figure 11 - Gold Price forecasted values model ARIMA(0,1,1)

5 Once we have obtained our forecasted values and graphs, we need to know if this forecasting is accurate. We run accuracy tests to measure how accurate our calculations are comparing with actual results that have been used as test. When looking at calculation, we will focus on the MAPE value, since it gives us a percentage of how accurate the forecasted values are with respect of the actual data:

```
  .model                                           .type     RMSE    MAE     MAPE  MASE  RMSSE
  <chr>                                            <chr>     <dbl>   <dbl>   <dbl> <dbl> <dbl>
1 ARIMA(BTCPrice, stepwise = FALSE, approx = FALSE)  Training 5.81e+3 3.78e+3 18.3  0.238 0.265
2 ARIMA(BTCPrice, stepwise = FALSE, approx = FALSE)  Test     1.56e+4 1.43e+4 44.3  0.903 0.710
3 ARIMA(GoldPrice, stepwise = FALSE, approx = FALSE) Training 6.22e+1 4.90e+1  2.94 0.265 0.268
4 ARIMA(GoldPrice, stepwise = FALSE, approx = FALSE) Test     1.55e+2 1.40e+2  7.04 0.759 0.666
5 ARIMA(CVIPrice, stepwise = FALSE, approx = FALSE)  Training 1.23e+1 8.72e+0 11.1  0.365 0.434
6 ARIMA(CVIPrice, stepwise = FALSE, approx = FALSE)  Test     3.02e+1 2.83e+1 57.5  1.19  1.07
```

6 To make sure that this model is above minimum levels of accuracy, we look into the benchmark's accuracy methods

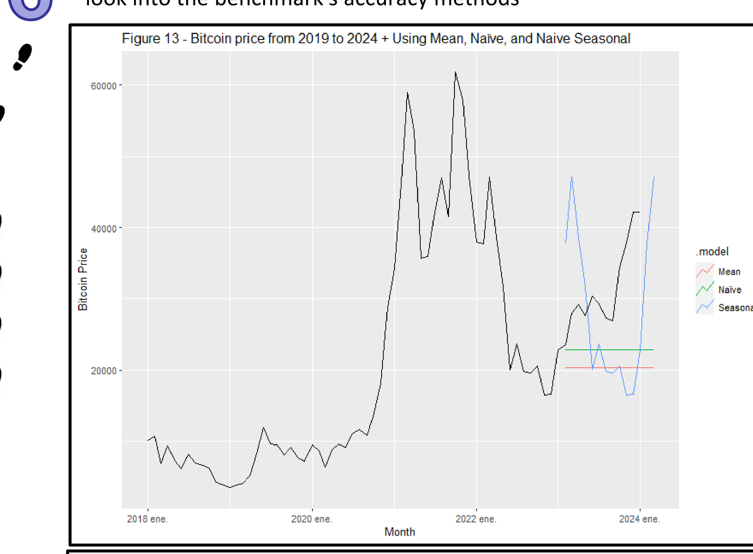
Figure 13 - Bitcoin price from 2019 to 2024 + Using Mean, Naïve, and Naive Seasonal

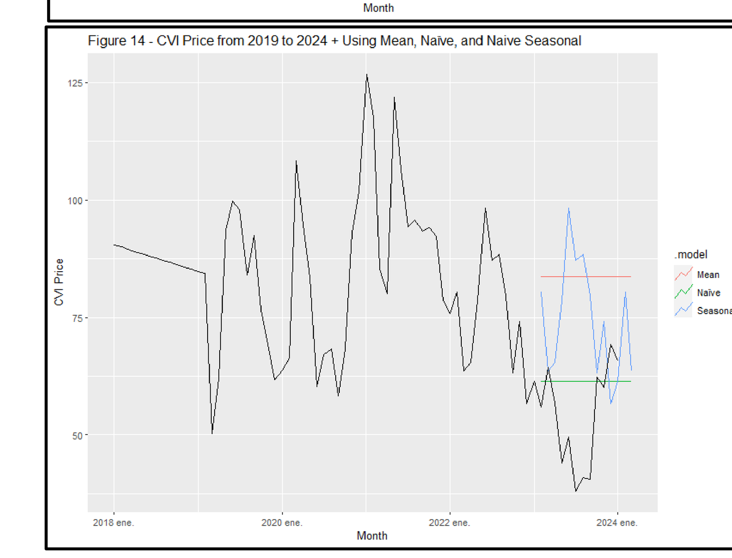
Figure 14 - CVI Price from 2019 to 2024 + Using Mean, Naïve, and Naive Seasonal

7 We now obtain the accuracy from the benchmark methods, to compare with the ARIMA models.

```
 .model-CVIPrice type   RMSE   MAE  MAPE  MASE RMSSE  ACF1
  <chr>          <chr> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
1 Mean           Test   31.5  29.7  61.5   NaN   NaN 0.554
2 Naïve          Test   12.8  10.1  22.5   NaN   NaN 0.554
3 Seasonal Naive Test   30.0  23.7  52.3   NaN   NaN 0.582

 .model-BTCPrice  .type   RMSE    MAE   MAPE  MASE RMSSE  ACF1
  <chr>          <chr>  <dbl>  <dbl>  <dbl> <dbl> <dbl> <dbl>
1 Mean           Test   12753. 11313.  33.7   NaN   NaN  0.639
2 Naïve          Test   10544.  8749.  25.4   NaN   NaN  0.639
3 Seasonal Naïve Test   14695. 13126.  40.5   NaN   NaN 0.753
```

Conclusion

In synthesizing the forecast accuracy results derived from our empirical analysis, it is evident that while the Naïve model exhibits superior performance in terms of Mean Absolute Percentage Error (MAPE), this metric alone does not encapsulate the full spectrum of the predictive dynamics inherent in cryptocurrency markets. The Autoregressive Integrated Moving Average (ARIMA) models demonstrate enhanced proficiency in capturing absolute deviations, as indicated by lower Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) values, metrics that are critical when accounting for the magnitude of errors in a market characterized by pronounced volatility and non-linear price behaviors. These findings suggest that the ARIMA models, despite the relatively higher MAPE, offer a more comprehensive and realistic framework for forecasting in the domain of crypto-assets, aligning with our hypothesis of a maturation trajectory that sees cryptocurrencies evolving towards a semblance of stability akin to traditional safe-haven assets. This maturation is reflective of an emerging recognition of cryptocurrencies as viable components of diversified investment portfolios, potentially signaling a shift in investor sentiment and a redefinition of asset class stability in the digital age.

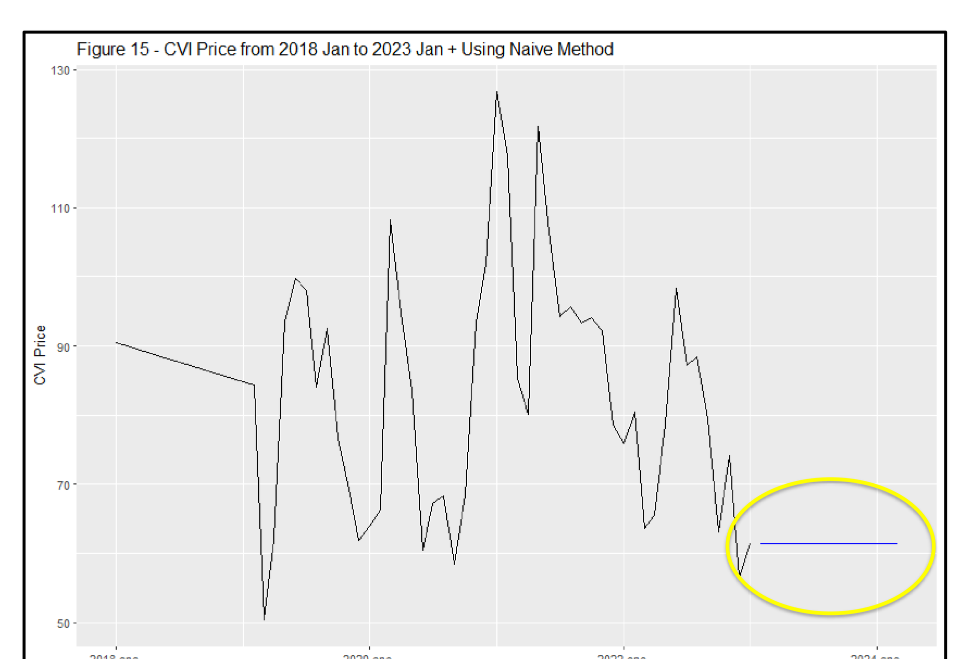
Figure 15 - CVI Price from 2018 Jan to 2023 Jan + Using Naive Method

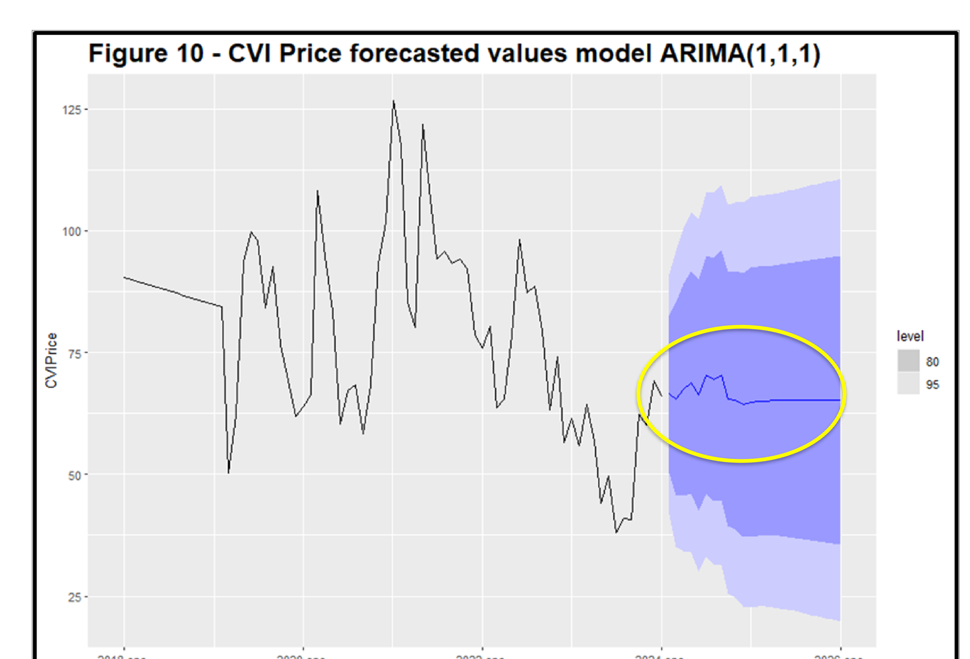
Figure 10 - CVI Price forecasted values model ARIMA(1,1,1)

In these 2 graphs we can observe the different forecasting methods, the Naïve method, which gives us a better MAPE accuracy. This accuracy has not been backed up by the other measurements, being the ARIMA model the more accurate when predicting financial movements. We can see in Figure 10 how the volatility will slowly decrease, as the mean of the forecasting, while the Naïve method maintains the same number over time.

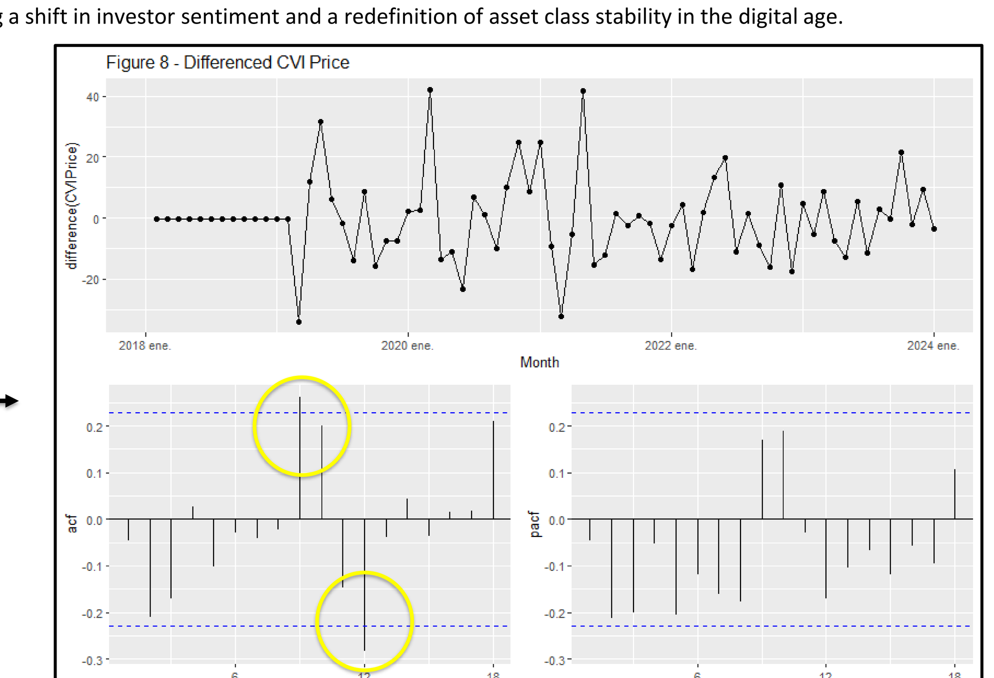
Figure 8 - Differenced CVI Price

Another important aspect of the ARIMA model, is the fact that it has been removed the seasonality and trend prior to the analysis and forecasting. These procedures only make this model more robust and more trustworthy. We can see in the ACF graph that only a couple spikes surpass the dashed line, indicating that this model does not present any relevant seasonality.