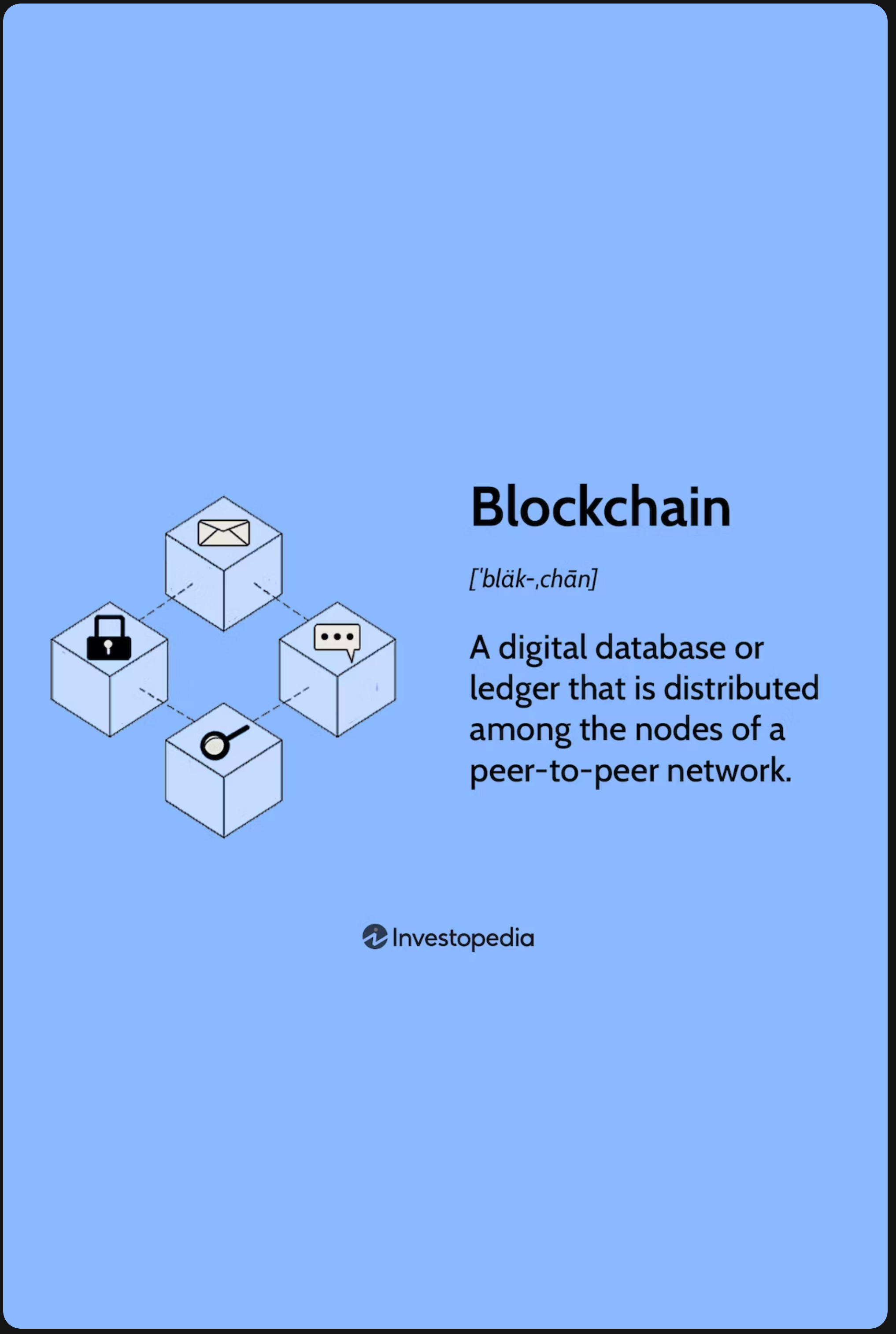
Technical Analysis and Its Effectiveness in Cryptocurrency Markets

Introduction - Bitcoin (BTC)

Cryptocurrency, with Bitcoin being the pioneering digital asset, has established itself as a new and significant emerging asset class in the world of finance. Specifically, it's importance stems from its decentralized nature, which eliminates the need for a central authority or intermediary, enabling secure, peer-to-peer transactions.

Bitcoin's finite supply, with a fixed cap of 21 million coins makes a innovative hedge and store of value, garnering increasing attention from investors and institutions alike. In the past decade the blockchain has solidified it's position as an asset class with immense potential for growth and diversification in the global financial landscape.

However, the blockchains novelty and unique features also make it subject to significant risks and uncertainties. It is an unpredictable space for traditional investors, making it difficult to predict price movements. To be successful in trading cryptocurrency, investors must stay informed about market trends and developments, understand risk management, and be disciplined in their investment strategies.



Research Question

Therefore,

The primary focus of my research was to help explore such strategies and asses effectiveness of traditional technical analysis methods in predicting price movements in the cryptocurrency markets.

"Can historical technical indicators be used to reliably speculate price movements in cryptocurrency markets, and to what significance are trading strategies based on technical indicators effective?"

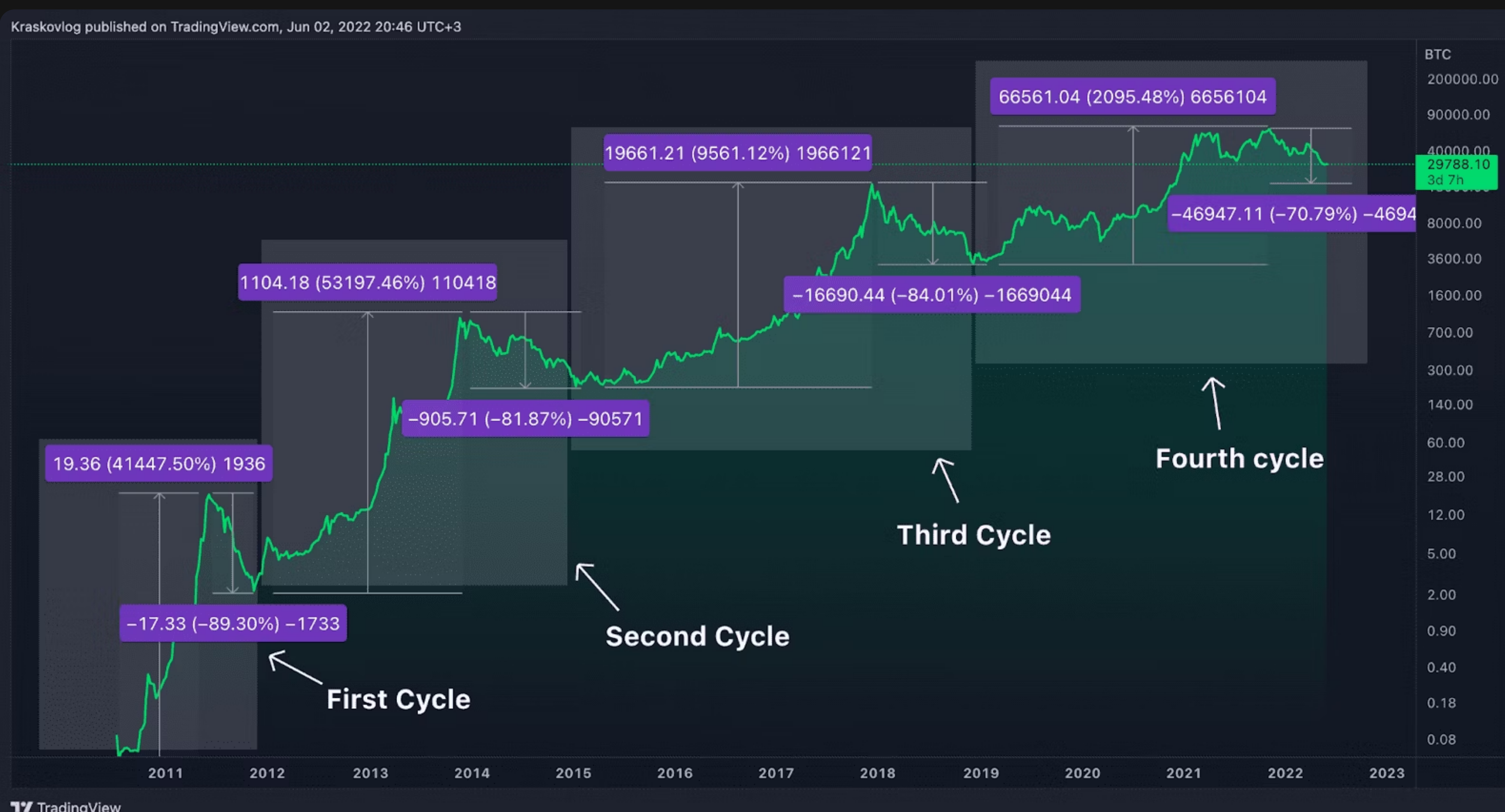
To do so I will compare the performance of significant market indicators, such as Moving Averages, RSI, MACD, and Market Cycles to historical price action. This will provide insight on whether speculative predictions on can be somewhat explained by historical technical analysis or if the moves in the crypto market are mainly driven by “the noise”.

Null Hypothesis (Ho)

No single technical indicator alone can predict the price of a cryptocurrency, but a combination of indicators and signals might provide better insights for the cycle.

Alternative Hypothesis(Ha)

At least one of the prominent technical indicators and signals can predict the price of a cryptocurrency with a high degree of certainty.



Here you can see a screenshot of Crypto Market growth, the similarities in cycles is undeniable.

Gaps in Literature

The market is still relatively new, a little more than a decade ago was it created. Not only that but it is constantly evolving. Value is based on innovative utility blockchain technology can produce. Being such a new tech it is constantly evolving and being improved upon.

As a result, there are many factors that influence cryptocurrency prices and market dynamics. Their influence is still not well understood when compared to other asset classes.

Hence, regulatory and legal environment surrounding cryptocurrencies is also constantly evolving, as governments and financial institutions grapple with the implications of this new asset class. As new laws and regulations are introduced, this can impact the growth and adoption of cryptocurrencies, as well as the attitudes of investors and the general public towards the asset class.

Some under researched factors:

- **Liquidity**: Referring to the ease with which an asset can be bought or sold on the market. Just like we see with USD. The liquidity of the cryptocurrency market has been shown to impact price action, but there is still much to be learned about the specific ways in which liquidity affects prices. More research is needed to identify the mechanisms through which liquidity impacts cryptocurrency prices and to develop models that can better predict how changes in liquidity will impact prices.
- Cross-asset correlations: Cryptocurrencies are a relatively new asset class, and their relationship with traditional assets such as stocks, bonds, and commodities is not well understood. The performance of traditional assets can impact cryptocurrency prices, and vice versa.
- Jurisdictional discrepancies: Different countries may have different levels of regulatory oversight and enforcement when it comes to cryptocurrencies. This means that the perceived value of a cryptocurrency may be impacted by the regulatory environment in a particular country. One challenge in researching the impact of regulatory changes on cryptocurrency prices is the lack of standardization and consistency in regulatory approaches across different jurisdictions.

Scope of Study and Key Variables

To outline the scope of the study, including the specific cryptocurrencies we are analyzing, key variables, and the time frame of our analysis.

In my analysis I am using Bitcoin, Ethereum, and Solana's price fluctuations for roughly the span of 3 months [3/13/2023-5/08/2023]. These three coins together make up more than 50% of the markets capitalization. Thus they are give a good glimpse of historical price action.

Key variables we are investigating:

- Price, Moving Average, RSI, MACD, and Bollinger Bands

Brief synopsis of their significance

<u>RSI (Relative Strength Index):</u> RSI is a widely respected technical indicator that measures the speed and change of price movements. It ranges from 0 to 100 and helps identify overbought or oversold conditions in a market. Generally, an RSI above 70 indicates overbought conditions, while an RSI below 30 indicates oversold conditions.

<u>MACD (Moving Average Convergence Divergence):</u> MACD is a trend-following momentum indicator that calculates the difference between two moving averages, typically a 12-day and a 26-day exponential moving average (EMA). It is used to signal potential trend changes or reversals and to identify buying or selling opportunities.

<u>Bollinger Bands:</u> Bollinger Bands are a popular volatility indicator that consists of a simple moving average (usually 20-day) with two bands above and below it. These bands are typically set two standard deviations away from the moving average. Bollinger Bands can help traders identify potential price breakouts and reversals, as well as overbought or oversold conditions.

<u>Moving averages:</u> MA's are calculated by taking the average price of an asset over a certain period of time (e.g. 10 days, 50 days, etc.), and plotting this value on a chart. The resulting line shows the average price of the asset over that period of time. Moving averages can also be used to identify potential support and resistance levels in cryptocurrency prices. For example, if the price of a cryptocurrency is currently below its 50-day moving average, this may indicate that the 50-day moving average is acting as a resistance level

These indicators are highly respected due to their ability to provide traders with useful insights into market trends, potential reversals, and overbought/oversold conditions. By incorporating these indicators into our analysis, we aim to assess their effectiveness in predicting price movements in the cryptocurrency markets.

Data Source - Fetching Desired Variables

In this study, the CoinGecko API was utilized as a data source for fetching cryptocurrency price data and various technical indicators. By closely following CoinGecko's API documentation, a Python script was developed to access the necessary data. After retrieving the data as dictionaries, they were transformed and sorted as needed to fit the research objectives. Subsequently, the data was converted into data frames using Python's popular library, pandas. These data frames were then saved as CSV files for further analysis.

The CSV files were imported into RStudio, where the majority of the statistical analysis took place. Although not all of the functions initially written in the Python script were used, the data obtained through the CoinGecko API and the pre-processing steps performed in Python provided a solid foundation for the R-based analysis. This streamlined approach allowed for efficient and accurate examination of the effectiveness of various technical indicators in predicting cryptocurrency price action.

To the right is my custom Python script for the main Data Frame in my Analysis.

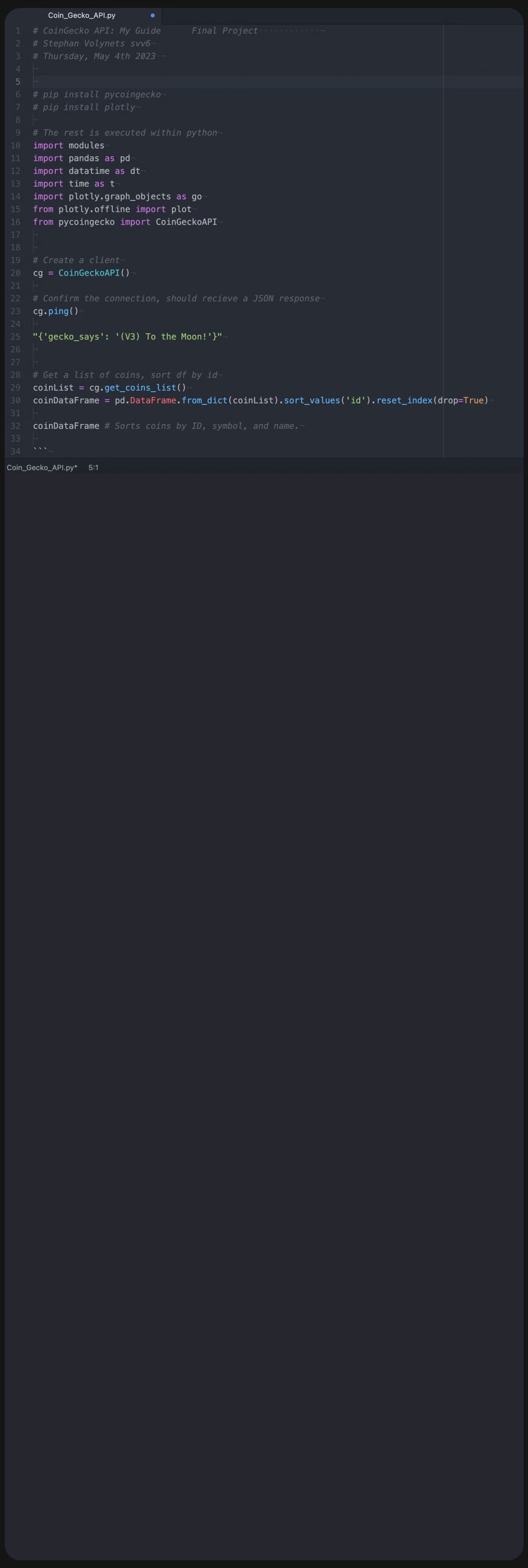
The three below show my first attempt, you can see here I was more surgical, fetching categorical and continuous variables. However, once discovering Coin Geckos 50 req/minute for their free API I realized many of the dictionaries were too large to be pulled.

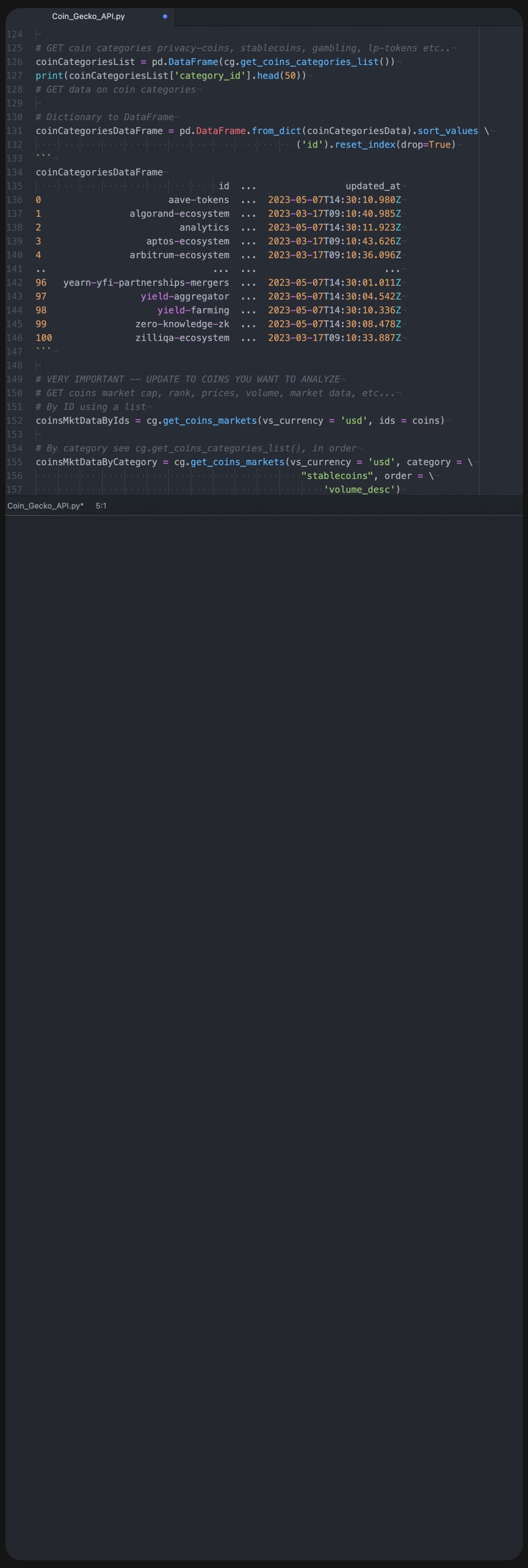
Coin_Gecko_API.py | Models.py

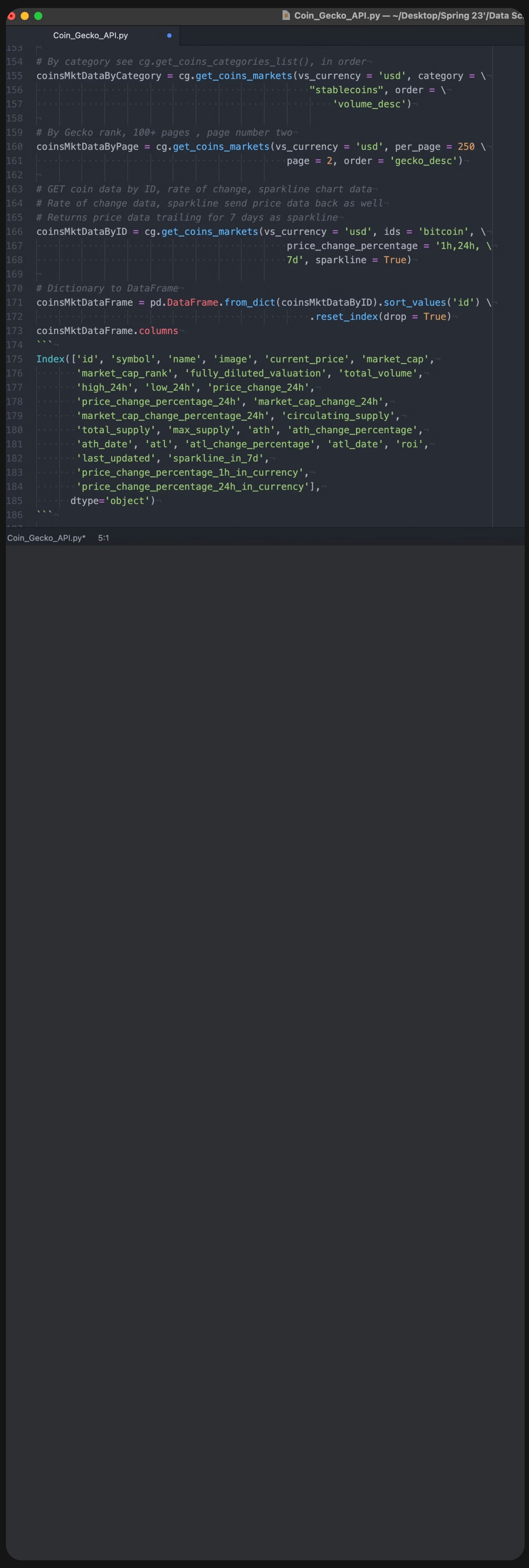
```python
# Price on 'ma', 'rsi', 'macd', 'bollinger', 'date' DataFrame
# Written by Stephan Volynets
import requests
import pandas as pd
import talib as ta
import numpy as np

def get_historical_data(coin_id, days):
    url = f"https://api.coingecko.com/api/v3/coins/{coin_id}/market_chart?vs_cur\
    rency=usd&days={days}&interval=daily"
    response = requests.get(url)

    if response.status_code != 200:
        print(f"Error {response.status_code}: {response.text}")
        return None

    data = response.json()

    if 'prices' not in data:
        print(f"Unexpected response: {data}")
        return None

    prices = data['prices']
    timestamps = [price[0] for price in prices]
    price_values = [price[1] for price in prices]

    df = pd.DataFrame(price_values, columns=['price'], index=pd.to_datetime\
    (timestamps, unit='ms'))

    # Add other columns: 'ma', 'rsi', 'macd', 'bollinger', 'date'
    # ...
    return df

coin_id = 'bitcoin', 'ethereum', 'solana', 'matic-network'
days = '90'
PopularIndicators = get_historical_data(coin_id, days)
print(PopularIndicators)

# 2. Calculate Technical Indicators
PopularIndicators['ma'] = ta.SMA(PopularIndicators['price'].values, timeperiod=20)
PopularIndicators['rsi'] = ta.RSI(PopularIndicators['price'].values, timeperiod=14)
macd, macdsignal, macdhist = ta.MACD(PopularIndicators['price'].values, fastperi\
od=12, slowperiod=26, signalperiod=9)
PopularIndicators['macd'] = macd
PopularIndicators['bollinger_upper'], PopularIndicators['bollinger_middle'], \
PopularIndicators['bollinger_lower'] = ta.BBANDS(PopularIndicators['price'].values,\
 timeperiod=20)
PopularIndicators['date'] = PopularIndicators.index
# Drop missing values
# Drop rows with missing values
PopularIndicators.dropna(inplace=True)

# Display the DataFrame
print(PopularIndicators)
# Save as CSV and move to R Studio
PopularIndicators.to_csv('PopularIndicators.csv', index=False)
```

Project/DesiredColumns.py* 39:36 LF

Main Data







Analysis Methodology - Variables and Their Correlation

Breakdown -

After identifying several key variables in my dataset my idea was to test for potential relationships between them.

For example, we may find that a strong correlation exists between moving averages and price, suggesting that moving averages can be a reliable tool for predicting price movements.

Or if the RSI is indicating that an asset is overbought, and the MACD is also showing signs of a potential trend reversal, this may suggest that it is a good time to sell the asset BUT we might discover that RSI and MACD have weaker correlations with price, indicating that these indicators may be less effective in forecasting price changes.

To evaluate the effectiveness I have employed a range of statistical methods:

- correlation analysis, linear regression, multiple linear regression, testing ANOVA, and interpreting residual plots.

My thought process behind selecting these methods was as follows

- Correlation analysis helps us identify the strength of the relationship between technical indicators and price, allowing us to assess the potential usefulness of these indicators in predicting price movements.
- Linear regression models enable us to quantify the relationship between each technical indicator and price, providing further insight into their predictive power.
- Multiple linear regression models, including those with interaction terms, allow us to compare the performance of different combinations of technical indicators in predicting price movements.
- ANOVA tests help us determine whether the inclusion of interaction terms significantly improves the predictive power of our multiple linear regression models.
- Residual plots allow us to assess the assumptions of linear regression and the overall reliability of our models.

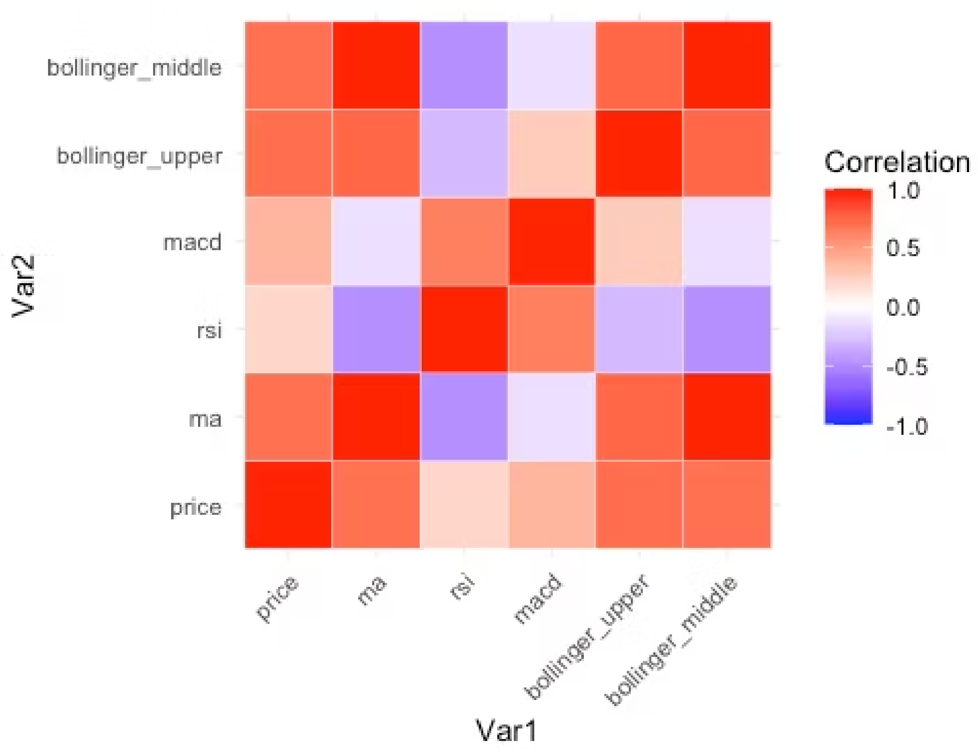
By employing these methods, you can build a comprehensive understanding of the effectiveness of technical analysis in strategizing cryptocurrency price movements and, ultimately, allow me to accept my null hypothesis.

Correlation Matrix and Heat map

Uncovering Relationships and running into redundancy

The intention behind this analysis was to visually explore the relationships between the variables and provide initial insights into the potential predictive power of the technical indicators.

However, it displayed redundancy due to its symmetrical nature. While the matrix is redundant, as it repeats information. The heat map was enough to analyze the correlations and new connections to support a null hypothesis.



Result Analysis

The higher correlations between variables Price and MA, Bollinger Upper, and Bollinger Middle could be due to these indicators being based on price averages, which indicated that they are more directly related to the price.

RSI and MACD, on the other hand, are derived from price changes and consider more complex calculations, which may explain their lower correlations. This may make them less directly related to the current price level of the asset. While RSI and MACD are still useful indicators for identifying potential trend reversals and trading opportunities, their lower correlations with price may indicate that they have a more delayed or indirect impact on price action compared to MA and Bollinger Bands.

Overall, this analysis suggests that different technical indicators may have different impacts on price action, and that traders and analysts should use a variety of indicators to gain a more comprehensive understanding of market trends and potential trading opportunities.

This is evidence towards [Ho]

Linear regression models

Method

My focus was on implementing simple linear regression models for price with respect to each technical indicator (moving averages, RSI, and MACD). Subtle differences in visualization can be seen, for instance me keeping the legend on Moving average on Price was deliberate. Moving Averages unlike MACD and RSI are great signs of markets structure, like Resistance and Support Bands. In the last three months we see a clear resistance band at $30,000.

This is an infamous historical resistance band, if broken and held is big.

To add an extra element I fit a multiple linear regression model considering all the technical indicators. The visualizations for each of these models display the relationships between price and the respective indicators, with the red line representing the fitted regression line. I hoped this would help visualize potential patterns in the spread. Added visualization enhancements for appeal and removal of legend.

Lastly, assessing the fit of the individual linear regression models (R-squared, p-values, etc.) is crucial because a good fit and significant p-values would be in favor of the null hypothesis

Interpretation of Results

The single indicator models (price ~ ma, price ~ rsi, price ~ macd) have relatively low R-squared values, indicating that these individual indicators can't explain much of the price variation.

However, the combined model (price ~ ma + rsi + macd + bollinger_upper + bollinger_middle + bollinger_lower) has a much higher R-squared value (0.9522), suggesting that these indicators together can explain a significant proportion of price variation.

In the context of blockchain, this could mean that no single technical indicator is sufficient to predict the price, but a combination of them might provide better insights building upon

Data

1. Linear Model price ~ ma

R-squared: 0.5022

P-value: 4.847 e-10

2. Linear Model price ~ rsi

R-squared: 0.04293

P-value: 0.1186

3. Linear Model price ~ macd

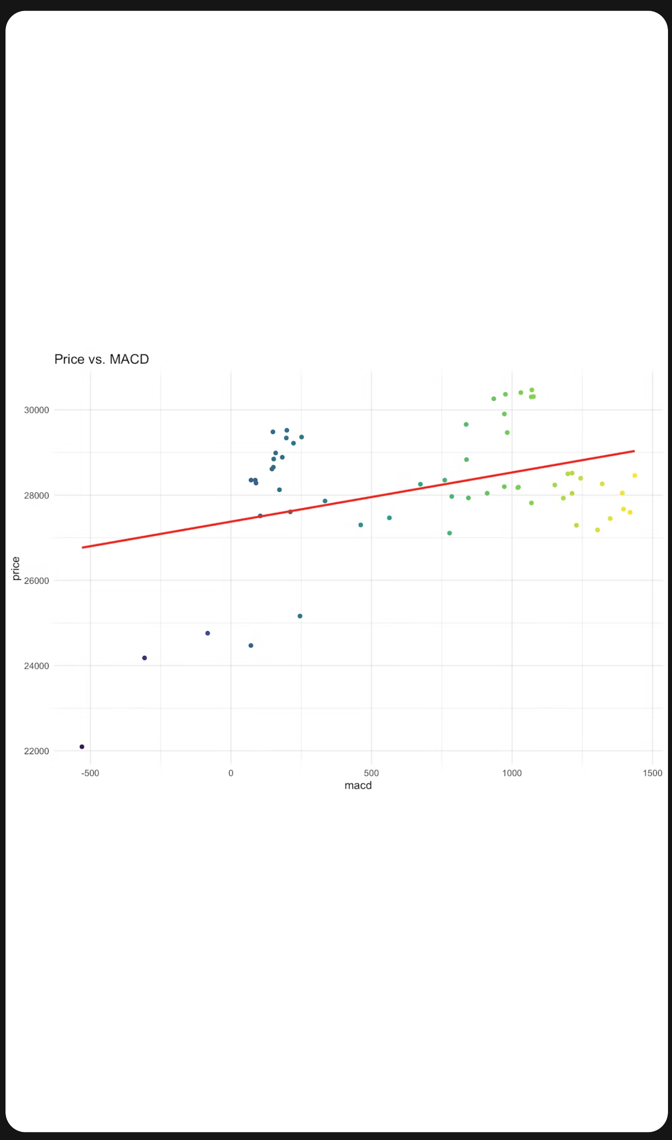
R-squared: 0.1431

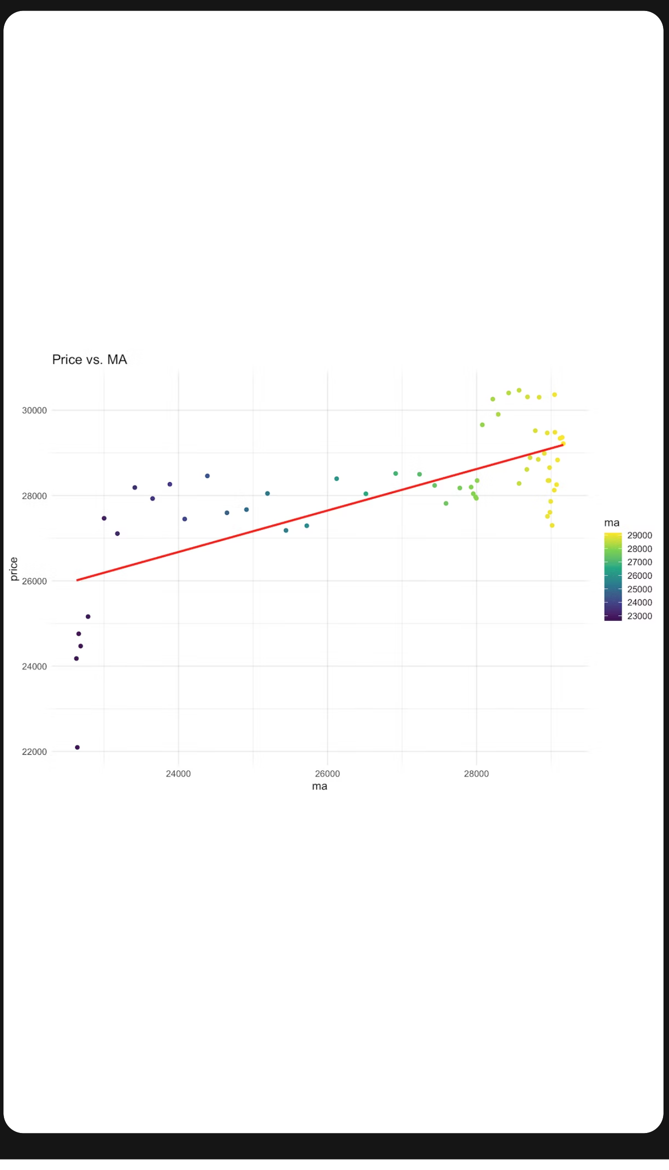
P-value: 0.003411

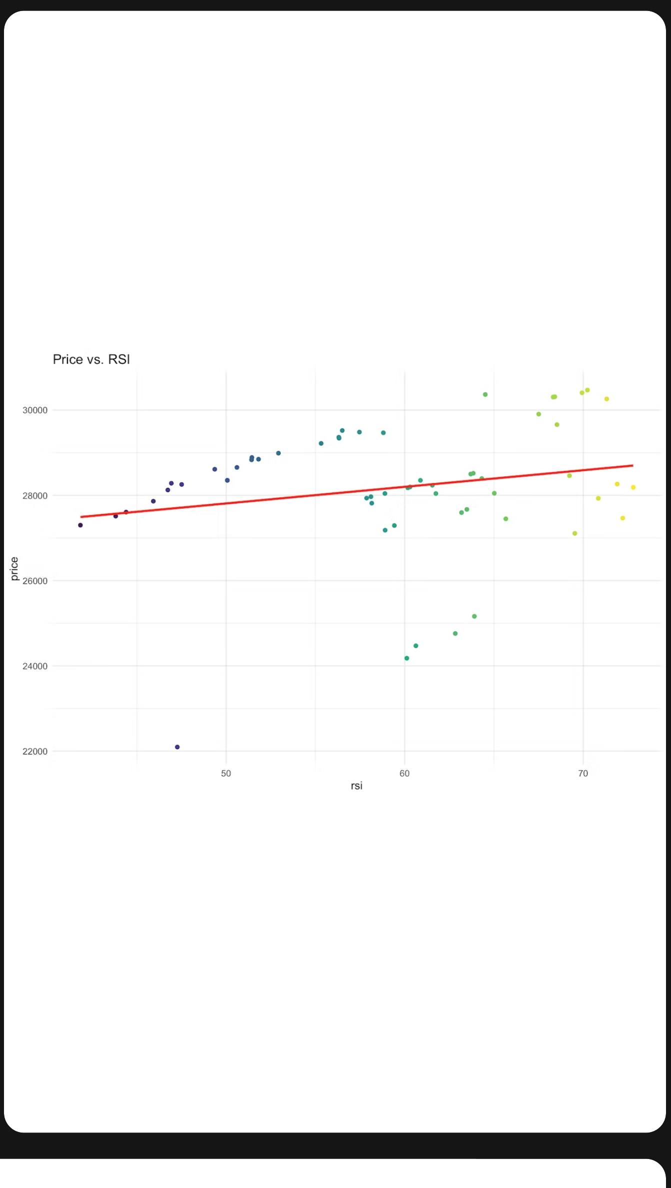
4. Linear Model price ~ ma + rsi + macd + bollinger_upper + bollinger_middle + bollinger_lower

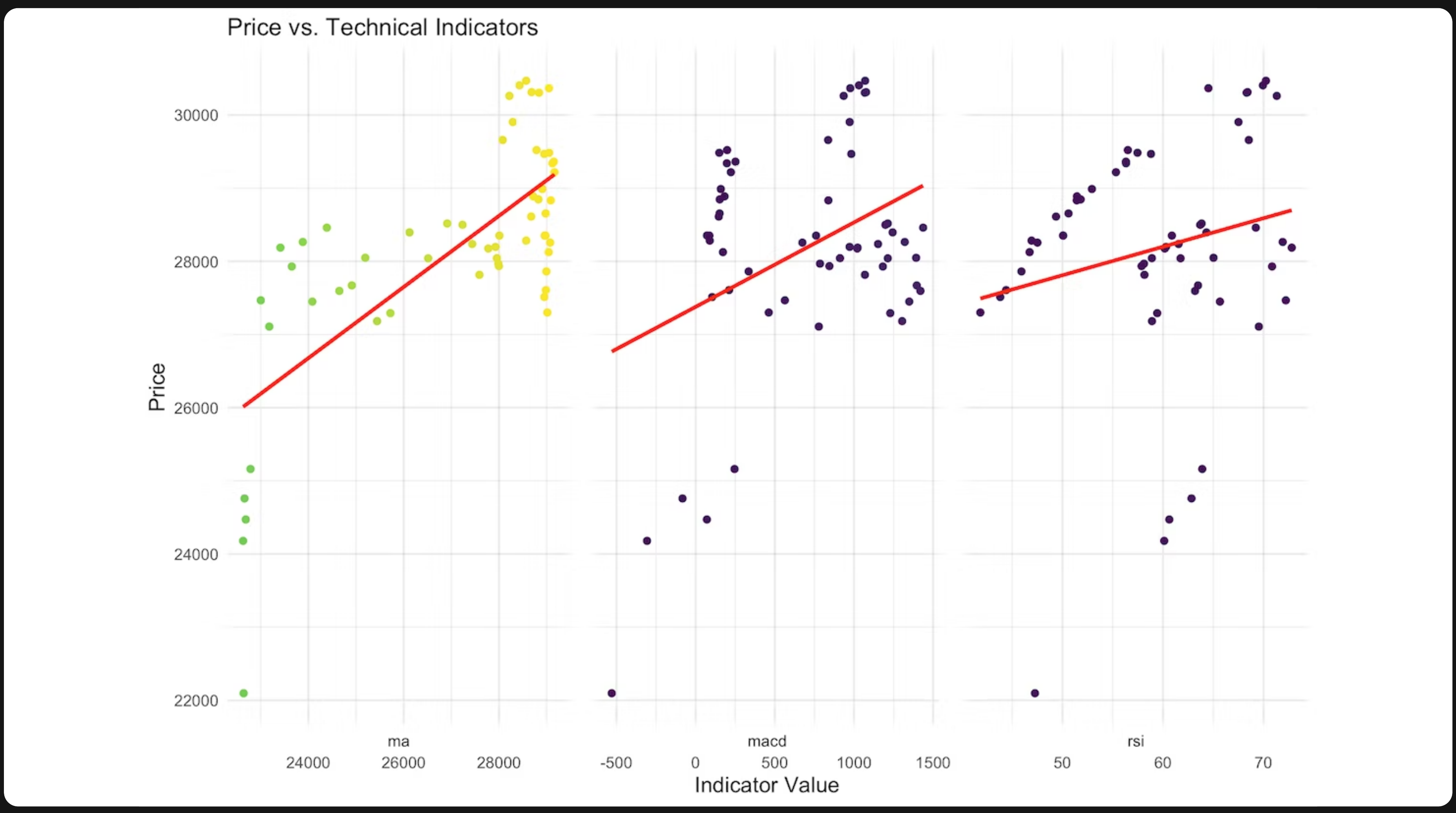
R-squared: 0.9522

P-value: < 2.2 e-16









Multiple linear regression models

Reasoning

I was looking to compare the performance of the multiple linear regression models, including the one with interaction terms. In a blockchain context, the multiple linear regression model without interaction terms (lm_multi) represents a model that predicts cryptocurrency price based on a combination of several technical indicators, such as moving average, RSI, and MACD. This model assumes that the effect of each technical indicator on the price of the cryptocurrency is independent of the other indicators.

Better performance would support the null hypothesis.

The multiple linear regression model with interaction terms (lm_multi_interaction), on the other hand, represents a more complex model that includes interaction terms between the technical indicators. This model assumes that the effect of one technical indicator on the price of the cryptocurrency may depend on the level of another technical indicator. For example, the effect of the RSI on price may depend on the level of the moving average.

Overfitting Risk

There is a risk of overfitting with the more complex model. This means that the model may be fitting the noise in the data rather than the underlying pattern, which could lead to poor predictive performance on new, unseen data. This is especially true when selecting insignificant / unimportant parameters.

However, I ensure that my key variables have already proven themselves in cycles prior. If I was basing this study on newer less accepted indicators it would completely illegitimatize my findings. Therefore, the risk of overfitting was minimal.

Values

- Summary (lm_multi)
  - Multiple R-squared: 0.9522
  - Adjusted R-squared: 0.9486
  - p-value: < 2.2e-16

- summary(lm_multi_interaction)
  - Multiple R-squared: 0.9991
  - Adjusted R-squared: 0.9984
  - p-value: < 2.2e-16

- AIC (lm_multi)

  852.4722
- AIC (lm_multi_interaction)

  662.9513
- BIC (lm_multi)

  864.8349
- BIC (lm_multi_interaction

  714.4623

Result Analysis

The multiple linear regression model with interaction terms (lm_multi_interaction) has a much higher adjusted R-squared value (0.9984) than the model without interaction terms (lm_multi, 0.9486). This indicates that including interaction terms improves the model's ability to explain price variations. Additionally, the lower AIC and BIC values for the model with interaction terms suggest better model performance.

It is still crucial to consider the possibility of overfitting, as the model with interaction terms might be too complex and fit the noise in the data rather than the underlying pattern. It's important to validate the model on new, unseen data to ensure its predictive performance is reliable.

Price action is easier studied when accounting for possible causal effects of indicators working together.

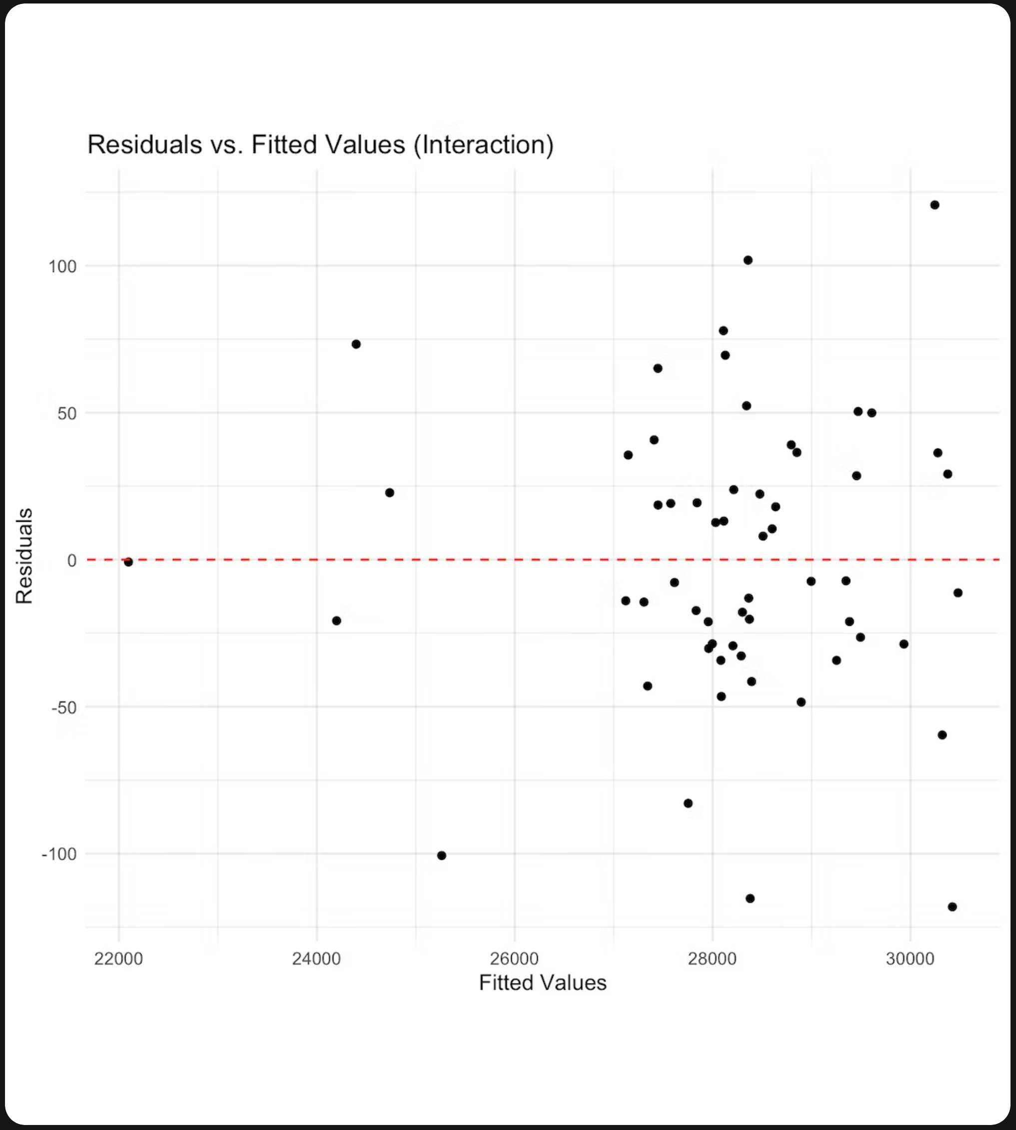
This supports the Null Hypothesis

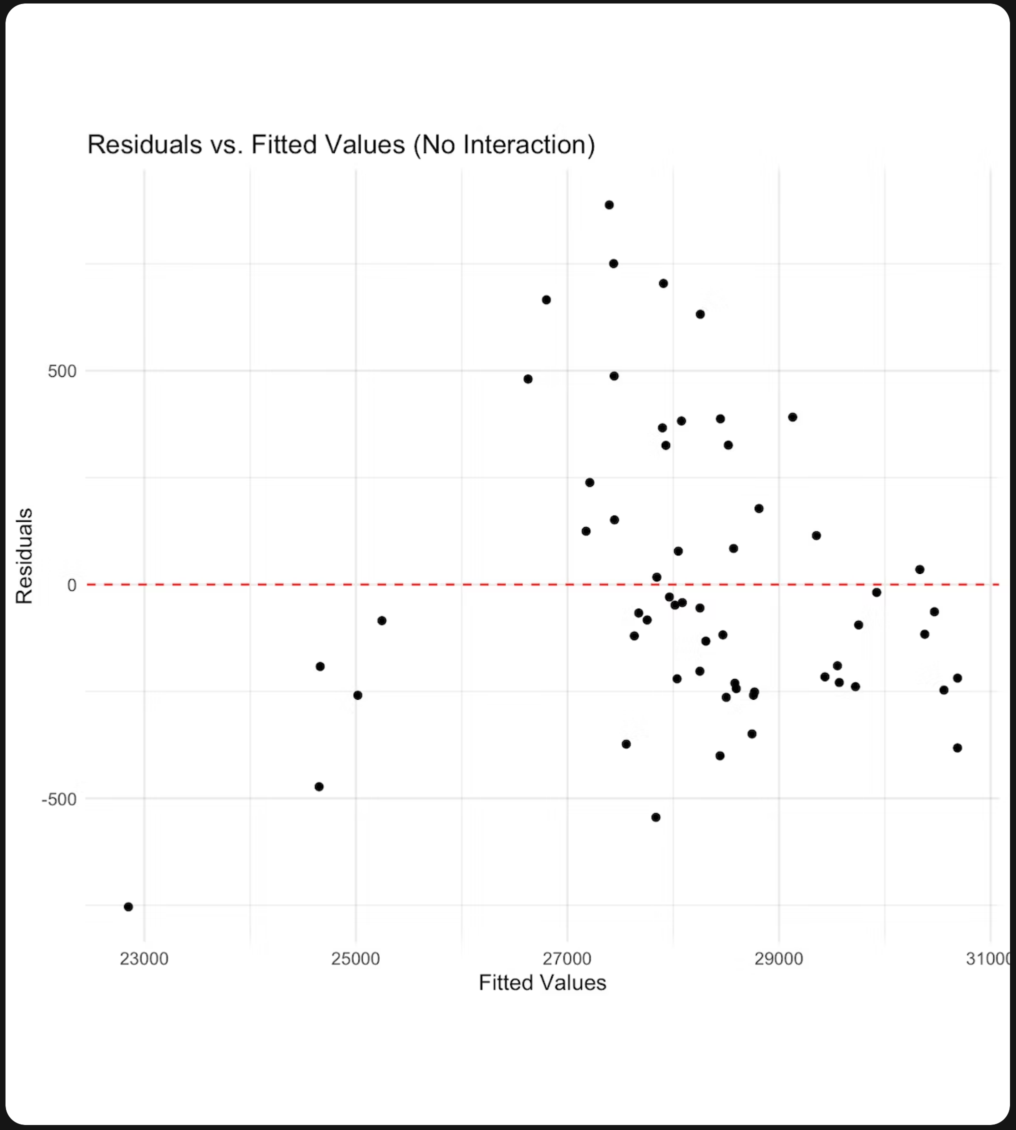
```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 62.31 on 34 degrees of freedom
Multiple R-squared:  0.9991,    Adjusted R-squared:  0.9984
F-statistic:  1561 on 23 and 34 DF,  p-value: < 2.2e-16

> AIC(lm_multi)
[1] 852.4722
> AIC(lm_multi_interaction)
[1] 662.9513
> BIC(lm_multi)
[1] 864.8349
> BIC(lm_multi_interaction)
[1] 714.4623
```

Residual plots:

The residual plots help us assess the assumptions of linear regression. It seems that the model without interaction terms exhibits a slight funnel shape, which could indicate ***heteroskedasticity*** (non-constant variance). The model with interaction terms seems to have less apparent funnel shapes, which is a positive sign for meeting the assumptions of linear regression.

The original plots are the actual price values, while the residual plots show the differences between the predicted price values and the actual price values. You can plot the actual price values using a simple line plot in R.





Discussion / Conclusion:

Importance and Findings of the Research

In this slide, I want to reemphasize the importance of our research in the context of the growing cryptocurrency market. With the rapid adoption of cryptocurrencies as an emerging asset class, understanding the effectiveness of traditional technical analysis methods is crucial for both experienced traders and newcomers to the market.

My findings support the null Ho

We found that no single indicator should be treated as foolproof. Instead, a combination of indicators and strong risk management strategies should be employed for more reliable results. One must be up to date with a multitude of price altering factors.

Broader Impacts and Risk Management

The broader impacts of your research findings lie in the potential for your study to provide valuable insights into the cryptocurrency market, which can be used to guide beginners in making safer investments. By demonstrating the usefulness of technical analysis as a tool for traders, your study can help beginners to better understand market trends and make more informed investment decisions. This has the potential to reduce the risks associated with cryptocurrency trading for beginners and to promote more responsible investment practices.

I want to place emphasis on the importance of risk management in trading strategies is critical for long-term success in the cryptocurrency market. As you noted, losing trades are inevitable, and effective risk management strategies are necessary to protect capital and ensure that gains are achieved with minimal risk. By highlighting the importance of risk management in trading strategies, your research can help to promote more responsible trading practices and reduce the likelihood of significant losses.

We will also emphasize the importance of risk management in trading strategies. Since losing trades are inevitable, managing losses effectively is crucial for long-term success. Risk management must be at the core of any strategy to protect capital and ensure that gains are achieved with minimal risk.

I believe my research has important implications for both traders and beginners in the cryptocurrency market. By providing insights into market trends and emphasizing the importance of risk management, your study can help to promote more informed and responsible investment practices, ultimately contributing to a more stable and sustainable cryptocurrency market.

Despite the enigmatic learning curve, with conviction, due diligence, and good strategy my study proves how investors were able to make serious money.

Limitations to This Study

It is important that I acknowledge the limitations of our study,

1. **API Rate Limit and Data Retrieval Time Constraints**

Fetching large time frames of historical data with thousands or hundreds of thousands of data points using a 50 requests per minute API could take quite some time on a laptop. To give you a rough estimate, let's consider the following scenario: - Suppose you have an API that returns 1,000 data points per request, and you have a limit of 50 requests per minute. If you need to fetch 100,000 data points, you would need to make 100 requests. With a rate limit of 50 requests per minute, it would take you at least 2 minutes (100 requests / 50 requests per minute) to fetch all the data.

Including the time-consuming process of fetching large amounts of historical data using the CoinGecko API with a 50 requests per minute limit. This can impact the efficiency and speed of our analysis.

If I had the resources I think to obtain even stronger results we could compare the performance of strategies based on technical indicators with other models, such as machine learning algorithms or time series models. Statistical tests, such as t-tests or ANOVA, can be used to determine the significance of the results and whether the null hypothesis can be rejected in favor of the alternative hypothesis.

2. **Pricing Data Inconsistencies and Exchange Rate Variability**

I will also mention the potential inaccuracies and unreliability in CoinGecko's pricing data due to its reliance on various cryptocurrency exchanges with differing levels of liquidity, security, and regulatory oversight.

This is due to the fact that data is collected based on the coins trading pair. he perceived value of a cryptocurrency can vary depending on the fiat currency used to value it. For example, if the price of Bitcoin is $50,000 USD and the exchange rate between USD and CNY (Chinese Yuan) is 1 USD = 6.5 CNY, then the price of Bitcoin when traded against CNY would be around 325,000 CNY. However, if the exchange rate changes to 1 USD = 7 CNY, then the price of Bitcoin when traded against CNY would be around 350,000 CNY, even if the underlying supply and demand dynamics for Bitcoin have not changed.

This means that the price of Bitcoin can appear to fluctuate differently when viewed in different fiat currency pairs. For example, if the price of Bitcoin is decreasing when viewed against CNY but increasing when viewed against USD, this could be due to fluctuations in the exchange rate between the two currencies, rather than changes in the underlying value of Bitcoin itself.

It is important for investors to be aware of these differences and to carefully consider the risks involved when investing in cryptocurrencies, particularly when trading against multiple fiat currency pairs.

Reference Documentation

> https://github.com/TA-Lib/ta-lib-python#dependencies

> https://github.com/man-c/pycoingecko

> https://www.coingecko.com/en/api/documentation