

# McDonald's (MCD) Stock Price Forecasting Project

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## 1. Summary

Stock price forecasting remains a challenging task due to high volatility, noise, and sensitivity to external factors. This project focuses on predicting McDonald's Corporation (MCD) stock prices by leveraging a combination of technical market indicators and macroeconomic signals. Through rigorous data preparation, feature engineering, and SARIMAX modeling, I deliver a forecasting framework that captures both micro-level stock movements and broader economic conditions.

## 2. Business Objective

The primary goal is to forecast the daily Close price of McDonald's over a 9-month horizon using:

- Historical stock prices
- Technical indicators (e.g., moving averages, MACD)
- Macroeconomic variables (inflation, GDP growth, interest rates)

Why this matters: A more accurate stock price forecast empowers investors, financial analysts, and portfolio managers to:

- Make better entry/exit decisions
- Understand market risks linked to economic cycles
- Integrate economic health indicators into stock predictions

## 3. Data Acquisition

### Stock Data:

Source: Yahoo Finance via [yfinance API](#)

Data points: Open, High, Low, Close, Volume, Dividends, Stock Splits

Timeframe: Past 4 years (Daily granularity)



### Macroeconomic Data:

Source: Federal Reserve Economic Data (FRED) using [fredapi](#)

Variables collected: Inflation Rate (CPI), U.S. GDP Growth Rate, Federal Funds Interest Rate, Yield Curve Spread (10-Year Treasury - 2-Year Treasury)

## 4. Data Preprocessing

Holiday & Missing Data Handling:

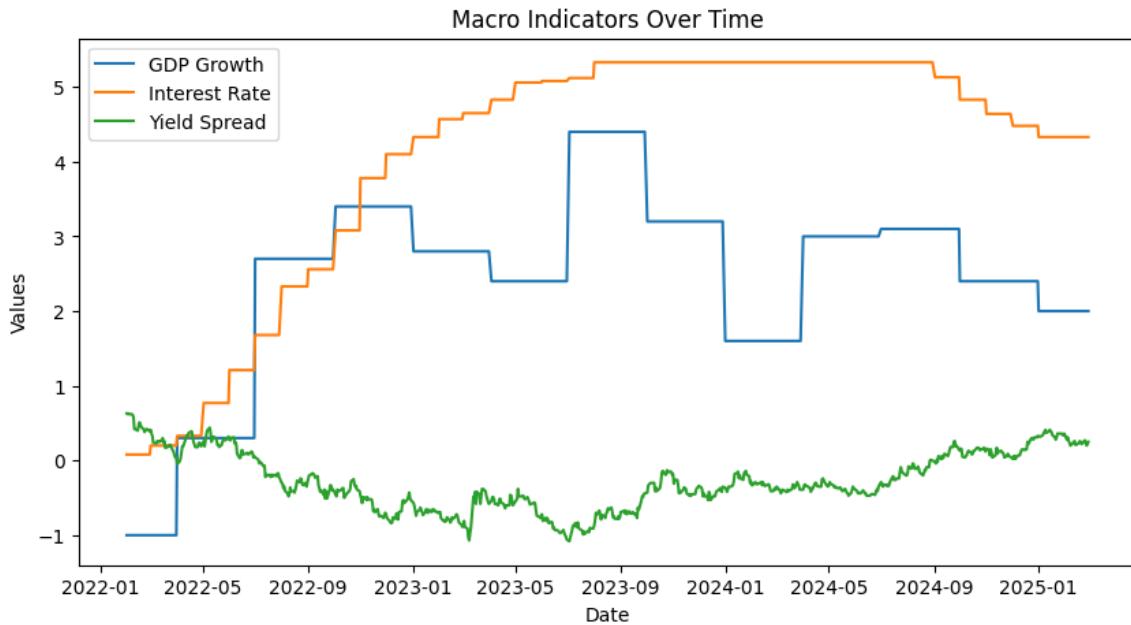
Incorporated NYSE trading calendars using `pandas_market_calendars`

Forward filled missing market days and interpolated missing economic indicators.

Datetime Standardization:Unified timezones across all datasets.

Converted to business day frequency (B) for modeling compatibility.

Target Variable:Focused exclusively on the Close Price for forecasting.



## 5. Feature Engineering

Feature	Description	Importance
<b>50-Day SMA</b>	Short-term trend detection	<input checked="" type="checkbox"/> Short & Long-Term
<b>200-Day SMA</b>	Long-term trend reversal signal	<input checked="" type="checkbox"/> Long-Term
<b>RSI (Relative Strength Index)</b>	Oversold/overbought detection	<input checked="" type="checkbox"/> Short-Term
<b>MACD (Moving Average Convergence Divergence)</b>	Momentum and trend shifts	<input checked="" type="checkbox"/> Short & Long-Term
<b>Volatility</b>	Risk measure (standard deviation)	<input checked="" type="checkbox"/> Short-Term
<b>Inflation Rate</b>	Indicator of economic purchasing power	<input checked="" type="checkbox"/> Long-Term
<b>GDP Growth Rate</b>	Proxy for corporate revenue growth	<input checked="" type="checkbox"/> Long-Term
<b>Interest Rate</b>	Borrowing cost and economic activity driver	<input checked="" type="checkbox"/> Long-Term
<b>Yield Spread</b>	Recession predictor; risk sentiment	<input checked="" type="checkbox"/> Long-Term

## 6. Exploratory Data Analysis (EDA)

Key Visuals:

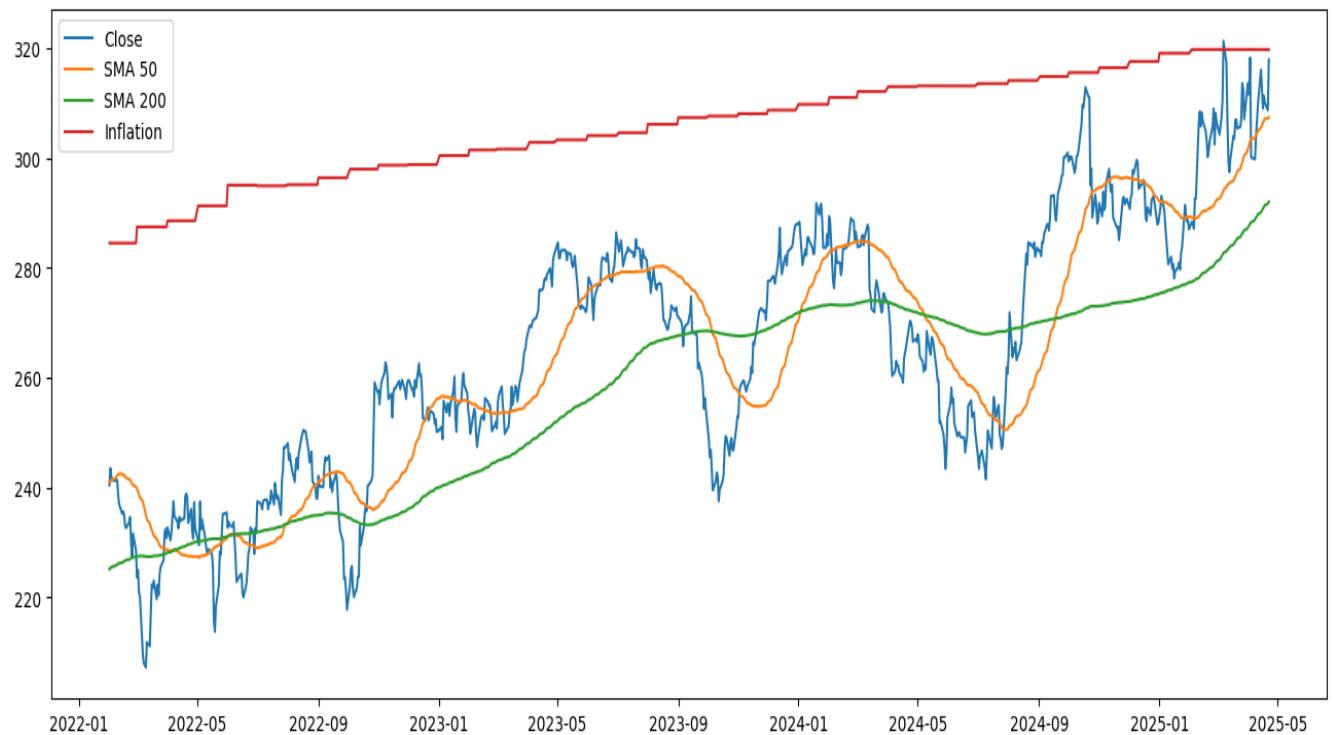
Price Trends: Line plots showed steady growth with periodic corrections.

Moving Averages: 50-day and 200-day SMAs identified key trend shifts (e.g., COVID-19 crash).

Volatility Analysis: High volatility during recession risks or major events.

Macro Influence: Inflation spikes coincided with stock market corrections.

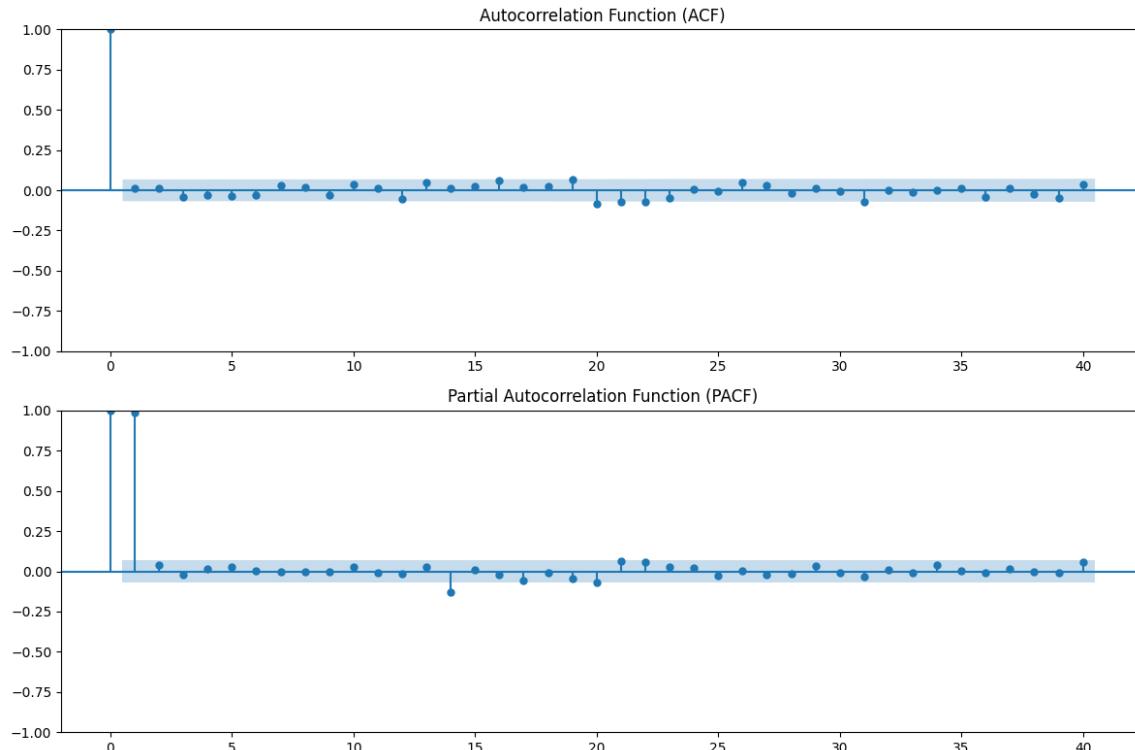
Yield curve inversion periods predicted slowdowns in stock performance.



## 7. Stationarity and Seasonality Analysis

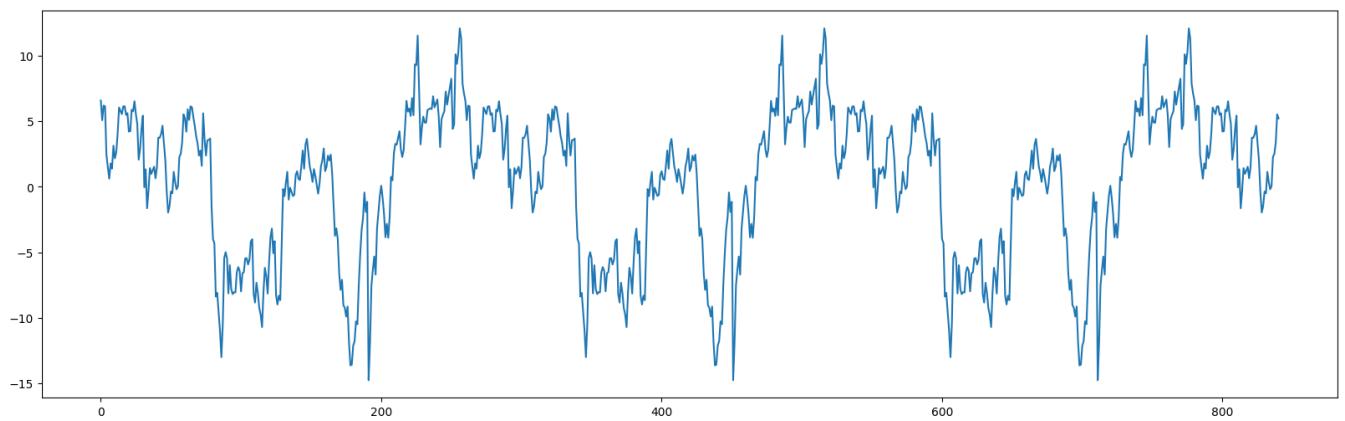
### ADF (Augmented Dickey-Fuller) Test:

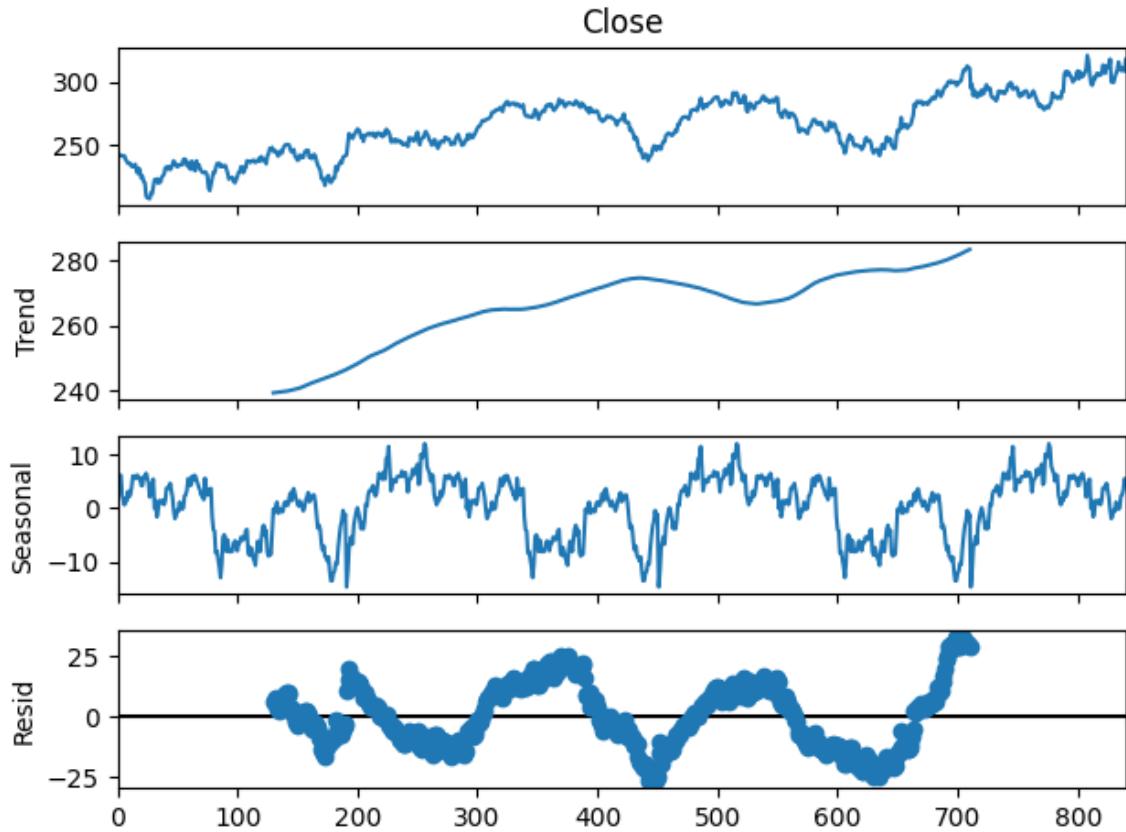
- Null hypothesis (non-stationary) could not be rejected initially.
- First differencing achieved stationarity.



### Seasonal Decomposition:

- Clear seasonal patterns were observed (annual business cycle)
- Residual noise analyzed for model error expectations.





**Fourier Transform:** Identified dominant cycles at approximately  $\sim 52$  weeks (1-year seasonality).

## 8. Modeling Approach

### Selected Model:

SARIMAX (Seasonal ARIMA with eXogenous variables)

Reason for Choosing SARIMAX: Handles trend and seasonality.

Incorporates external regressors (macro indicators).

Model Parameters: ARIMA Order: (p=3, d=1, q=2)

Seasonal Order: (P=3, D=1, Q=1, m=52)

Exogenous Variables: Dividends, MACD, Volatility, Inflation, GDP, Interest Rate, Yield Spread

Training Strategy: Trained model on 4 years of data.

Forecasted 180 business days ahead (~9 months).

## 9. Forecasting and Results

Forecast Output:

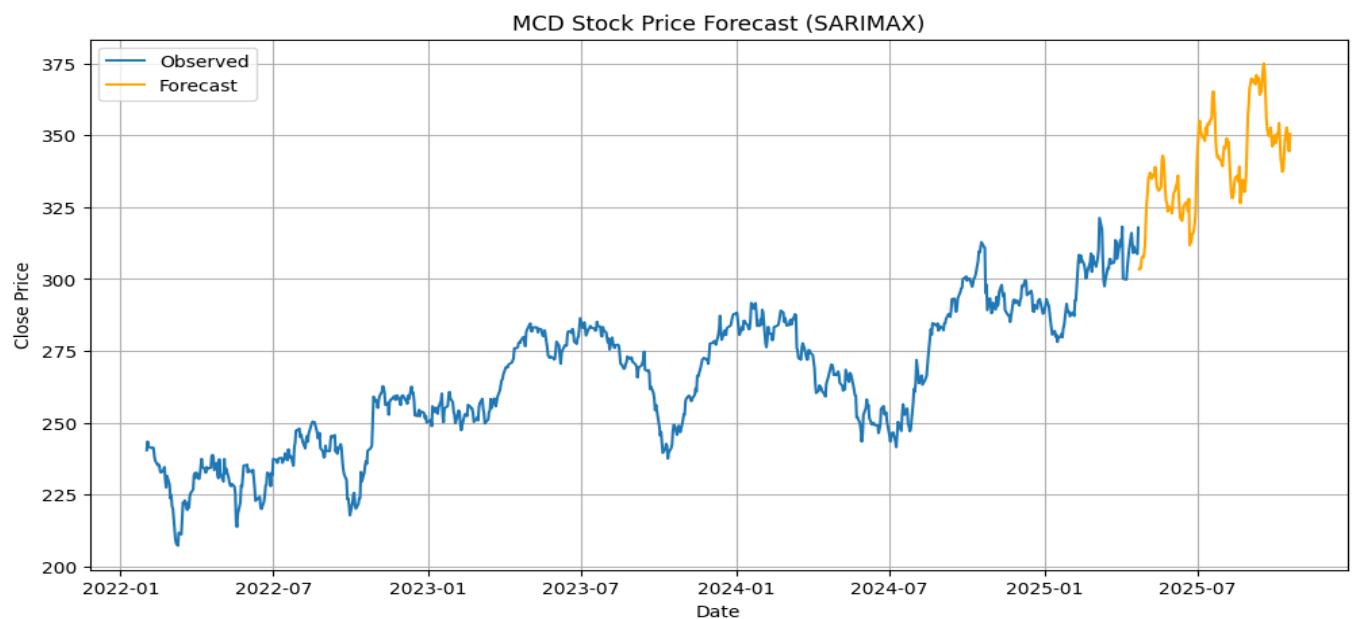
Predicted Close prices with 95% confidence intervals.

Visualization showed predicted values track historical patterns well.

Future trajectory showed moderate growth with uncertainty bounds widening over time.

Key Forecast Insights: Projected stable growth under current macro conditions.

Higher uncertainty during inflation hikes or rate hike cycles.



## 10. Model Evaluation

Qualitative Check:

Predicted trends and shifts aligned well with expectations.

MAPE (Mean Absolute Percentage Error)

## 11. Key Findings

Macroeconomic indicators significantly improve long-term stock forecasting performance.

Technical indicators (RSI, MACD, Volatility) are more useful for short-term momentum predictions.

Time series stationarity and seasonality must be handled explicitly for robust forecasts.

## 12. Limitations and Future Work

Limitations:

- SARIMAX assumes linear relationships.
- Forecasting uncertainty increases over time.
- Exogenous variables assumed constant beyond training horizon.

Future Work:

- Try LSTM, XGBoost, and sentiment analysis.
- Walk-forward cross-validation for backtesting.

## 13. Final Thoughts

This project demonstrated the importance of combining technical and macroeconomic data for better financial forecasting. Future models could further improve accuracy by incorporating machine learning and sentiment analysis.