Analyzing Moving Average Models in Forecasting High-Volatility Stocks

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AGENDA

- Background
- Methodology
- Visualizations
- Analysis
- Conclusions

OVERVIEW

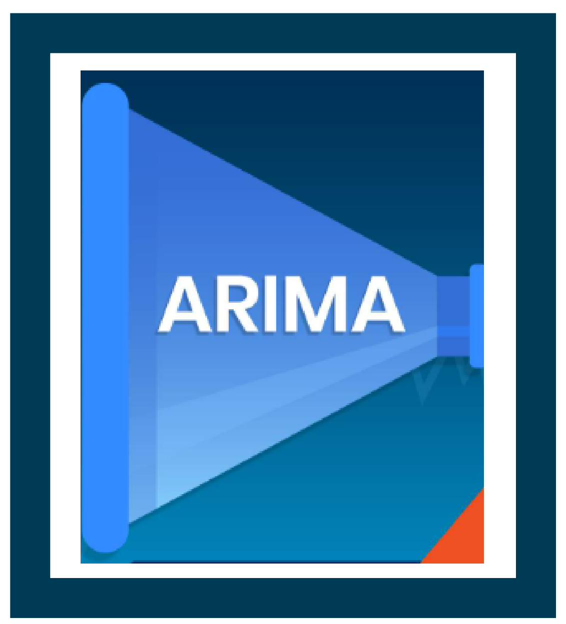
QUESTION: Will there be any statistically significant change in ARIMA's performance in forecasting stock prices based on their volatilities?

HYPOTHESIS: Yes, ARIMA will work better on forecasting stocks of low volatilities to an extent where it can be considered to be of statistical significance.

KEY TERMS

Volatility

- Rate at which a stock price changes over time
- Measured in β, which is a relative indicator
- β greater than 1, more volatile than S&P 500



ARIMA

- AutoRegressive Integrated Moving Average
- Used to forecast, analyze or model time series
- Works through timelagging of moving averages

Background Methodology Visualizations Analysis Conclusions

COMPANY OVERVIEW

AMD

- Computer chip producer based in California
- Produces consumer desktop chips such as CPUs and GPUS
- High volatility stock (β=1.95)

General Mills

- Food manufacturer based in Minneapolis
- Primarily produces breakfast cereals, but also snacks
- Low volatility stock (β=0.31)

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DATASET SUMMARY

Daily Stock Prices

- Open, Close, High, Low, Adj Close, Volume
- Via Yahoo Finance

Daily info from 11/1/2021 to 11/1/2022

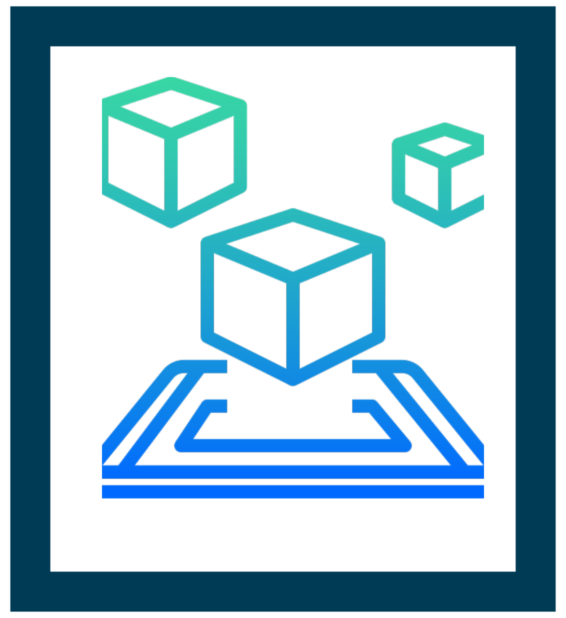
- No weekend or holiday info
- Indexed for lower load on machine

250 Rows | 7 Columns

APPROACH

Returns

- Primarily focusing on a change of Close Prices (Returns)
- Implemented via pct_change function
- Returns is a time series that ARIMA can forecast on



Testing Method

- Simple simulation with ARIMA for both stocks
- Parameter of time lag with highest autocorrelation
- Compare returns of both stocks

SIMULATION DETAILS

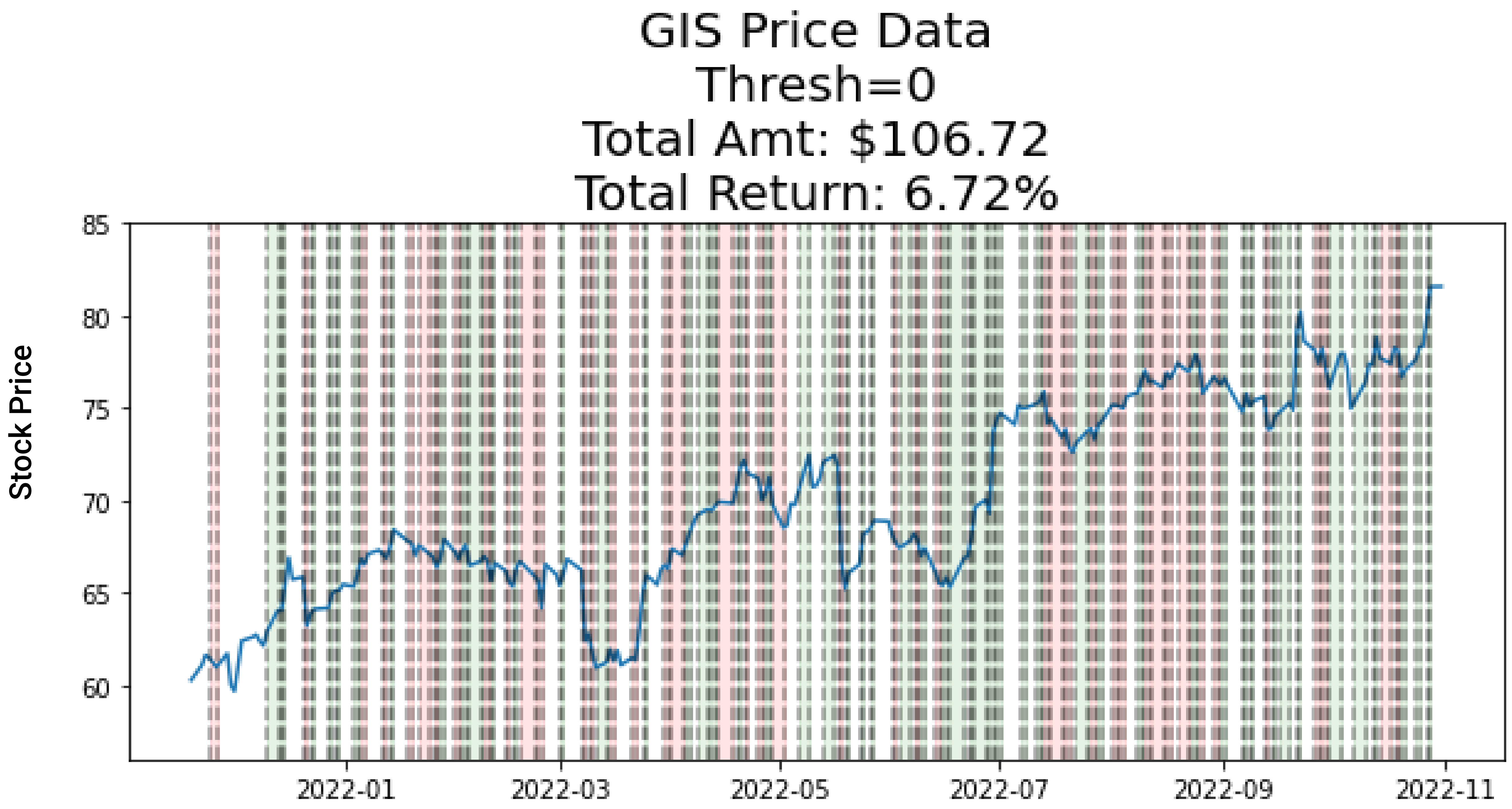
Simple Simulation

- A buyer has $100
- Will buy when ARIMA predicts expected returns to be over 0
- Plots each trade and returns after the given time period

Assumptions

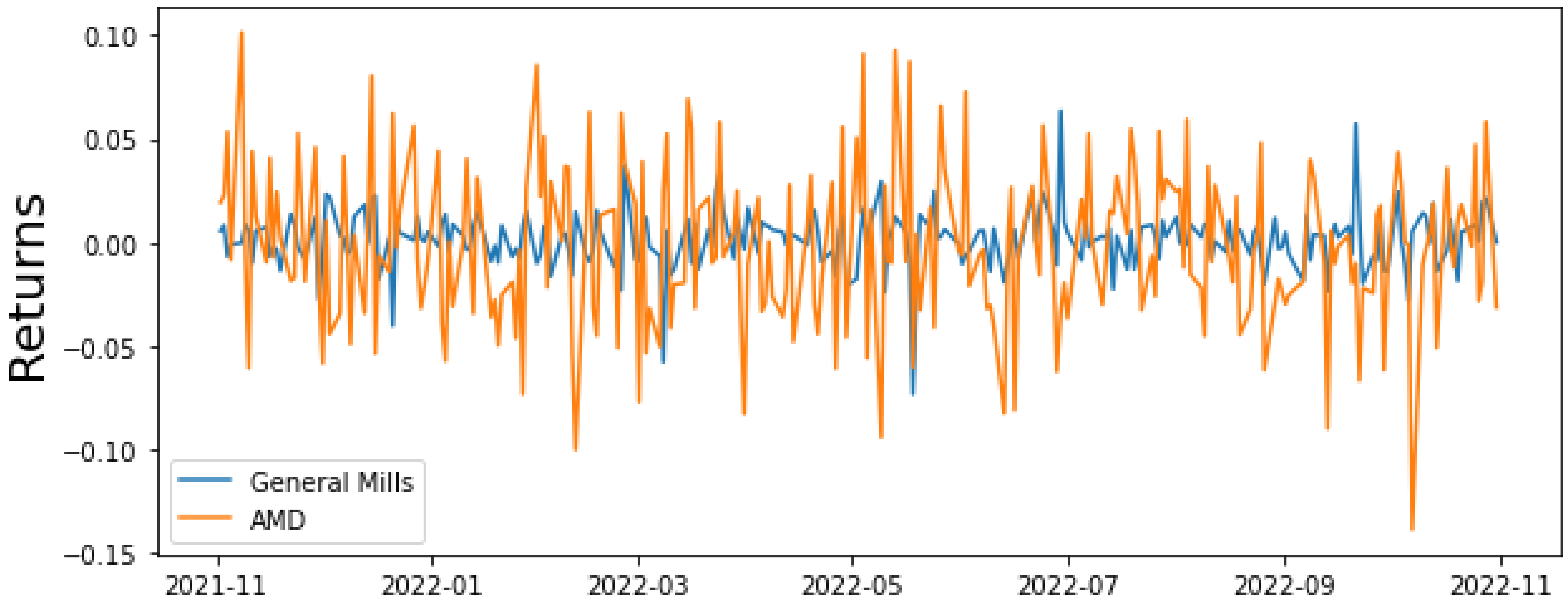
- The buyer will immediately sell
- The buyer is rational
- The time series is stationary

SIMULATION EXAMPLE



- Model of each trade that the simulation performs
- Red indicates a negative trade, green indicates a positive trade
- Given parameters: Time lag, threshold (0), and starting money of 100

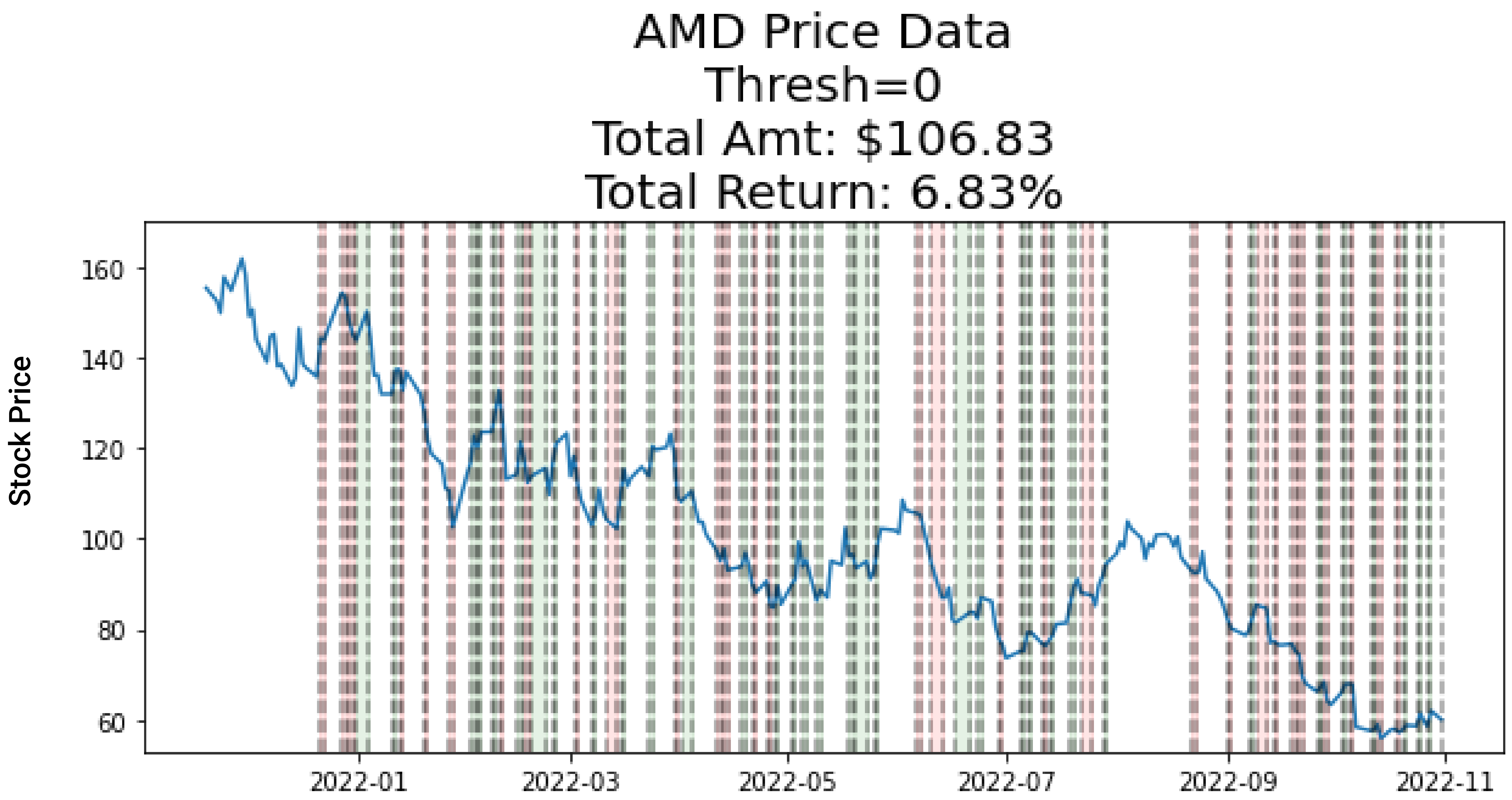
RETURNS



- AMD has far higher fluctuation compared to General Mills
  - Due to AMD's role as a tech manufacturer
  - Higher volatility market compared to food production

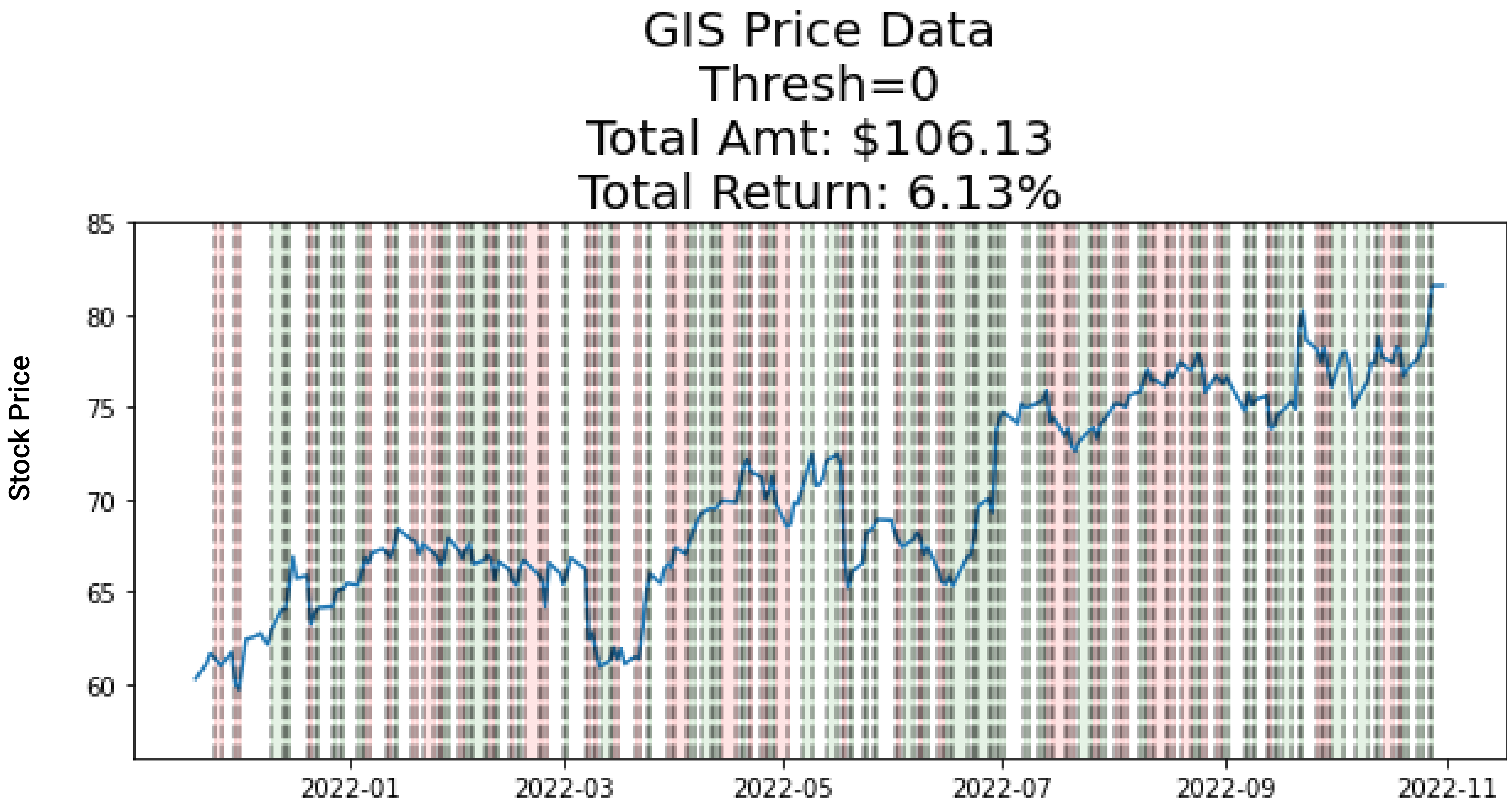
Background · Methodology · Visualizations · Analysis · Conclusions

AMD SIMULATION



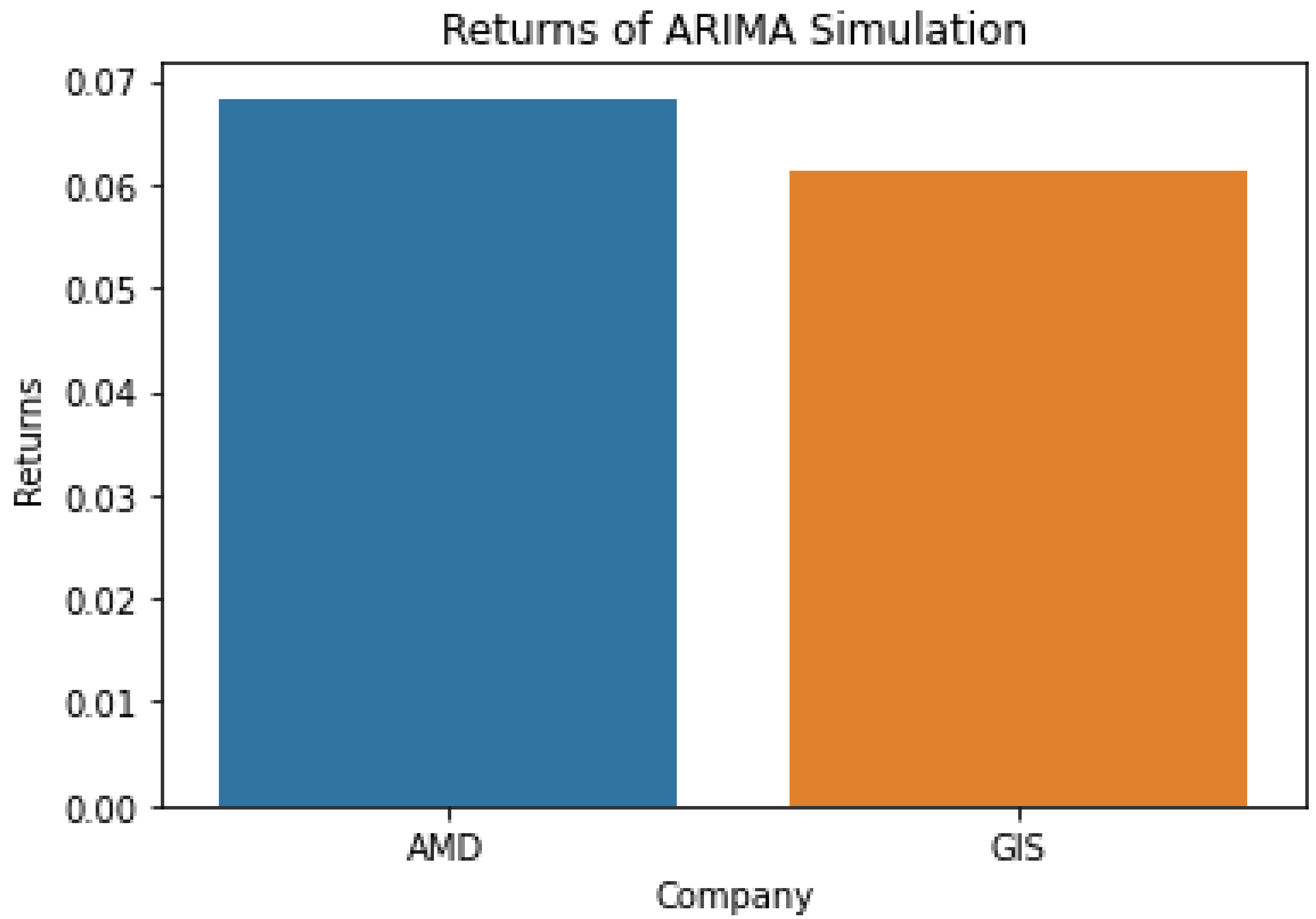
- Mix of negative and positive trades performed over the year
- Performs more accurately earlier in the year
- Implemented via a timelag of 21 days

GIS SIMULATION



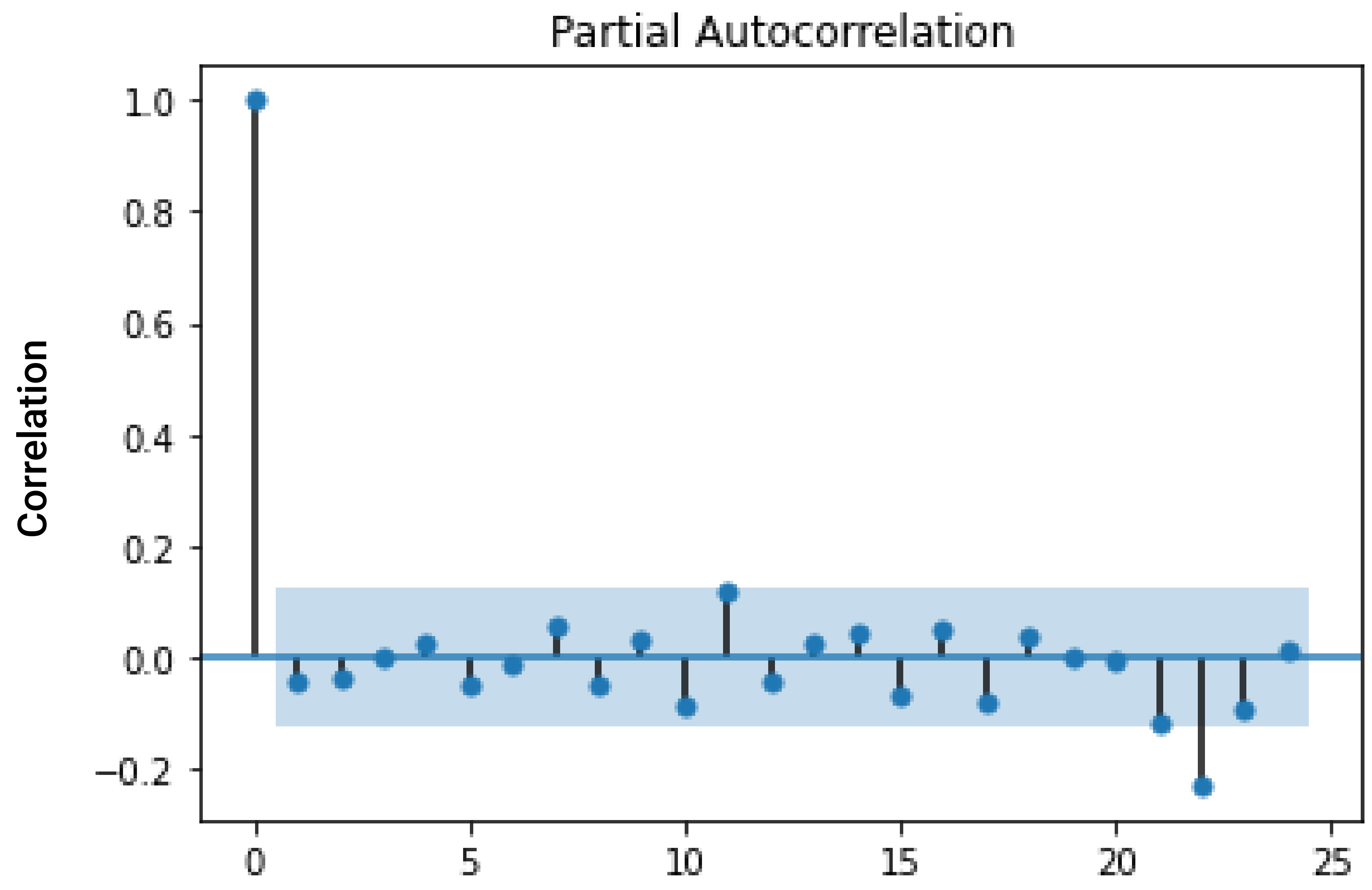
- Mix of negative and positive trades performed over the year
- Performs more accurately early/middle of the year
- Implemented via a timelag of 11 days

COMPARING RETURNS

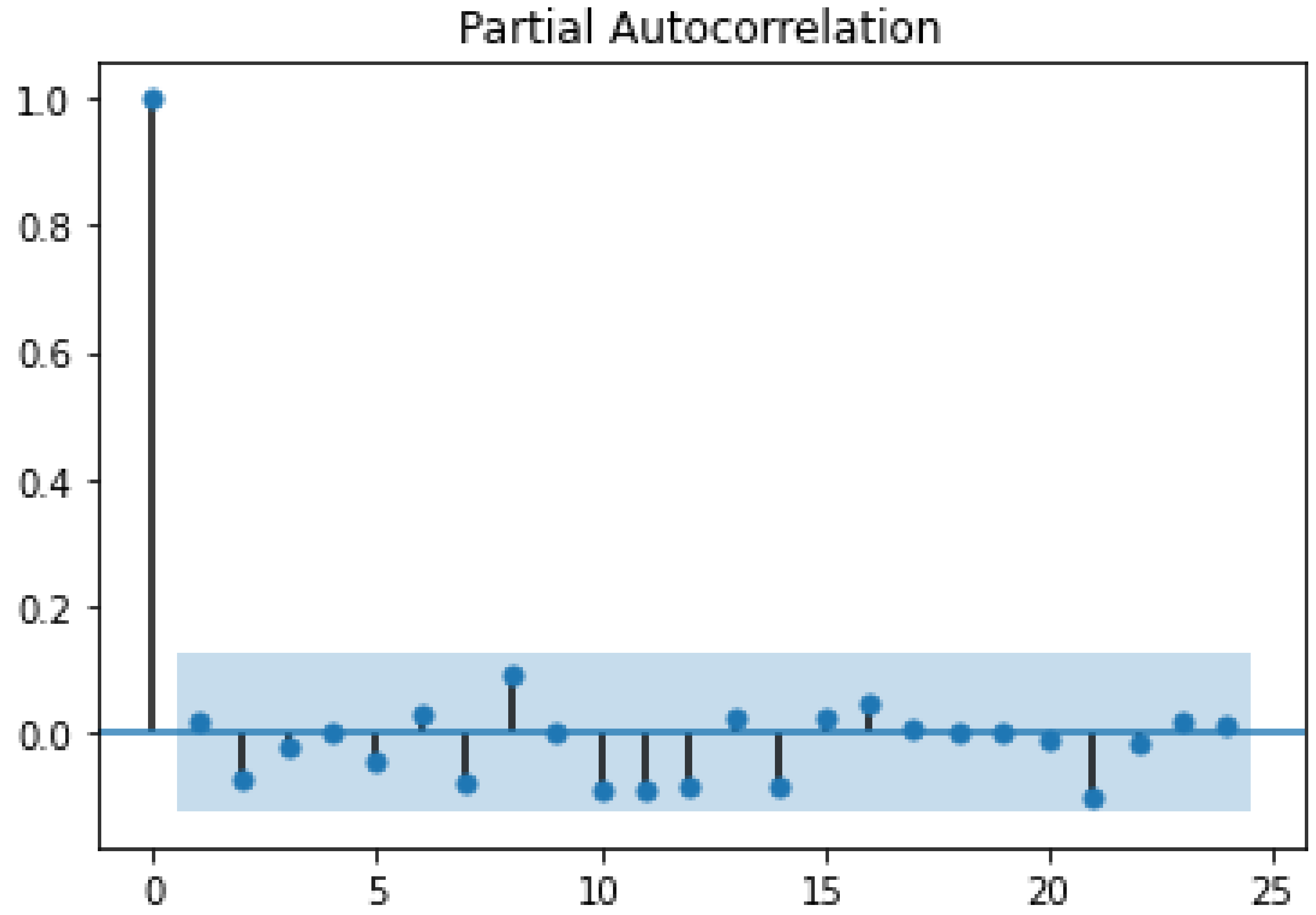


- AMD returns are slightly higher than GIS
- Indicates little/no correlation between ARIMA performance and returns
- Could have been accounted due to different timelags

GENERAL OBSERVATIONS



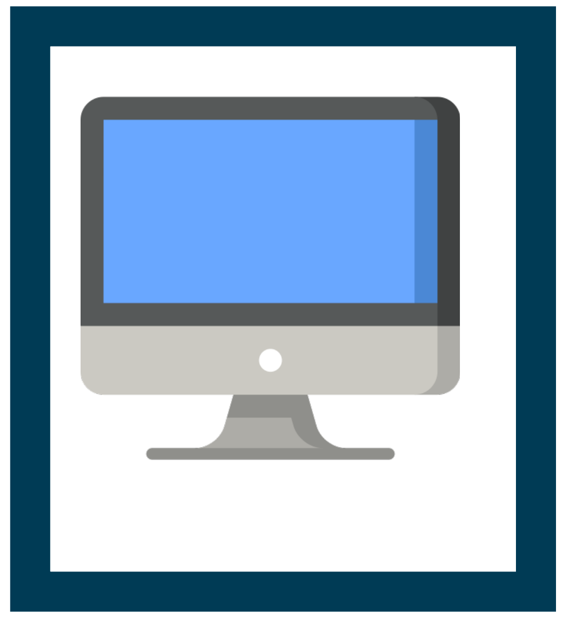
AMD Autocorrelation



GIS Autocorrelation

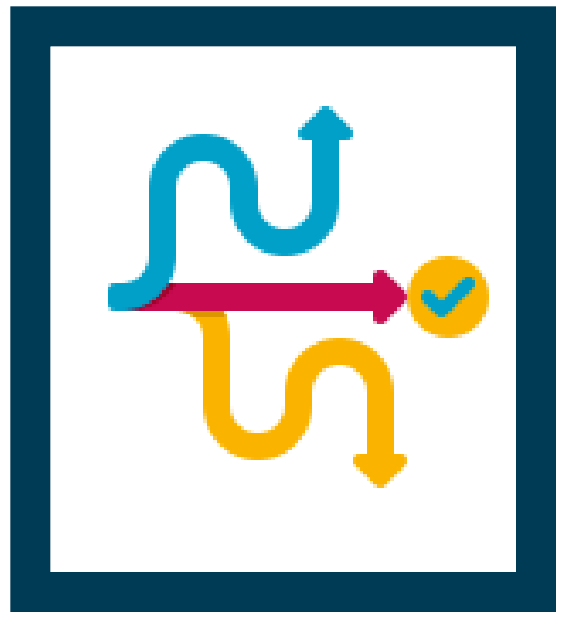
- Autocorrelation indicates what timelag we should use in the model
- Higher volatility stocks required more timelag for accurate predictions
- Those high volatility stocks also had notably larger correlation values

LIMITATIONS



Model Limitations

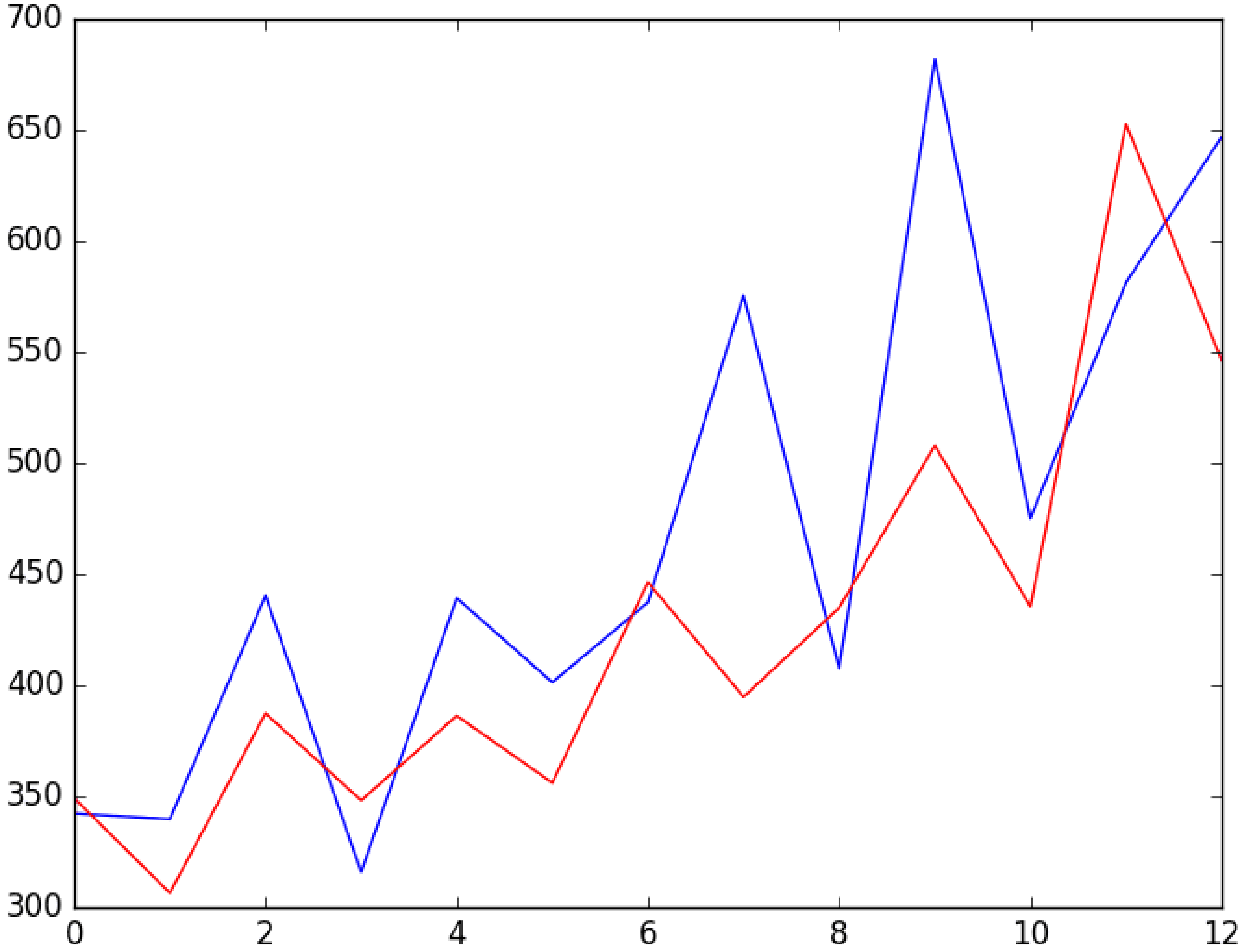
- Lack of Data Points (Possible Overfitting)
- Not enough computing power (Conducted via Colab Pro)
- Poorly optimized model



Simplification of Real-Life Observations

- Buyer is assumed to be rational and buys day to day
- Lots of variables set constant
- Only $100 (means incredibly low volume)

CONCLUSIONS



- ARIMA is simple and efficient
- Best works with stationary data
- Minimizes high overfitting
- Still captures relationships of data
- Volatility plays small role
- Not good for long-term forecasting

BUSINESS INSIGHTS

Use in the Business World

- Can help influence investing strategies via forecasts
- Effective on most stationary series to a certain extent
- Lots of potential in increasing accuracy of forecasts

Stepping Stone Model

- Used by banks such as Capital One to handle money
- Proper implementation can result in high accuracy forecasts
- Fully fledged ARIMA models can model nonstationary series!

APPENDIX

```
run_simulation(returns, prices, 100, (p,0,0), 0, verbose=False)
```

Code snippet to run the simulation - p is the timelag (ARMA model)

```
[ ]  tickerSymbol = 'GIS'
     data = yf.Ticker(tickerSymbol)
```

```
[ ]  prices = data.history(start='2021-11-01', end='2022-11-01').Close
     returns = prices.pct_change().dropna()
```

Code snippet to load financial data and turn into returns vs prices