Time Series Analysis for Stock Price Prediction

Combining Holt-Winters and ARIMA Models

Background

Context

- The stock market, a dynamic ecosystem of buying and selling, poses inherent challenges and risks.
- Investors often grapple with the unpredictability of stock prices, making accurate predictions vital for financial success.

This study

- Delves into the realm of time series analysis, offering a strategic approach to mitigate risks and optimize profits.
- Focuses on combining the strengths of two powerful forecasting models—Holt-Winters and ARIMA—unveiling a new perspective for stock price prediction.

Introduction

Aims to predict stock prices using various time series analysis techniques, specifically focusing on generating a range of prices beneficial for buyers.

Data Dependency:

 Investors rely on historical stock prices but need a more robust solution beyond past prices.

Time Series Analysis Role:

 Optimal solution due to its ability to work with numerical data and generate future values based on past data points.

Practical Applications:

• Widely applicable across domains like economics, e-commerce, finance, and banking.

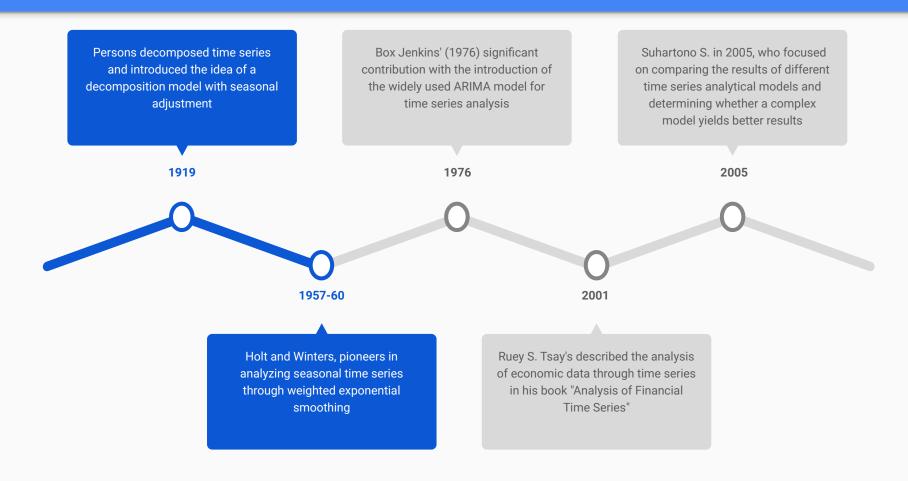
Data Source:

Yahoo Finance

Focus on Apple Inc:

 Analysis conducted on Apple Inc (AAPL) for its popularity, longevity, and abundant online information.

Literature Review



Decoding Seasonal Trends in Stock Prices

Seasonal Nature:

 Generally, stock prices follow a rising trend at the beginning, contrasting with a fall during August and September.

Reasons Behind Seasonal Trends:

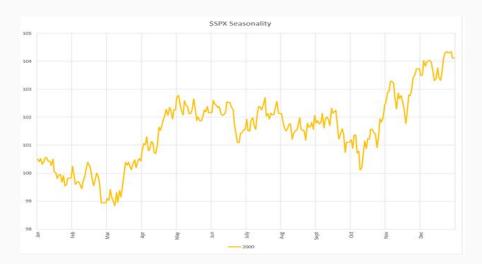
 Seasonal patterns are not coincidental but rooted in various factors.

Year-End Improvements:

 Stock funds strive to enhance performance at the end of the year, leading to increased stock prices.

Bond Coupon Payments:

 Year-end bond coupon payments flow partially into the stock market due to interest payments in December.





Decoding Seasonal Trends in Stock Prices

Holiday Season Influence:

 Buyer preferences are influenced by the holiday season, creating positive investment moods.

Market-Specific Reasons:

 Different markets exhibit seasonality with various reasons, including payments, emotional factors, and aberrations in finance reporting.

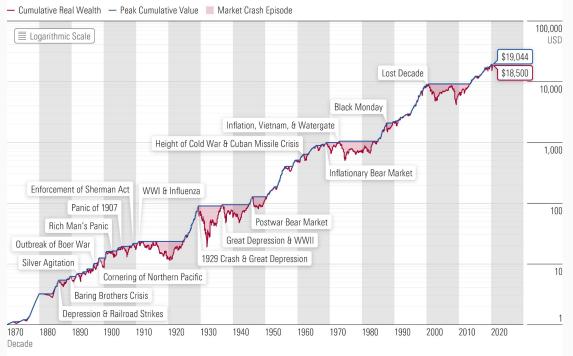
Non Seasonality Instances:

• Extreme moves, like the 1987 crash, showcase non seasonality, impacting the seasonal graph significantly.

Consecutive-Year Moves:

 Similar moves in consecutive years may form a series without true seasonal basis.

Market Crash Timeline: Growth of \$1 and the U.S. Stock Market's Real Peak Values



Data as of Jun 30, 2020. Sources: Kaplan et al. (2009); Ibbotson (2020); Morningstar Direct; Goetzmann, Ibbotson, and Peng (2000); Pierce (1982); www.econ.yale.edu/^shiller/data.htm, Ibbotson Associates SBBI US Large-Cap Stock Inflation Adjusted Total Return Extended Index.

Time Series Analysis Techniques

Holt-Winters Method:

- It incorporates three exponential smoothing methods to capture the level, trend, and seasonality of the data.
- Provides mathematical notations for the level (I), trend (b), and seasonal component (gamma), along with the forecasted value (y) and its representation.

ARIMA Model:

 Represents the ARIMA(p,d,q) model in mathematical notation, where p, d, and q denote the order of autoregression, the degree of first differencing, and the order of moving average, respectively.

$$l_x = \alpha(y_x - s_x - L) + (1 - \alpha)(l_x - 1 + b_x - 1)$$
 (1)

$$b_x = \beta(l_x - l_{x-1}) + (1 - \beta)b_{x-1}$$
 (2)

$$s_x = \gamma (y_x - l_x) + (1 - \gamma) s_x - L$$
 (3)

$$y_{x+m} = l_{x+m} + b_x + s_x - L + 1 + (m-1)modL$$
 (4)

$$y_t'=c+\varphi_1y_{t-1}'+\cdots+\varphi_py_{t-p}'+\theta_1e_{t-1}+\cdots+\theta_qe_{t-q}+e_t$$

Time Series Analysis Techniques

Determination of Model Parameters:

 Explains that the values of p, d, and q in the ARIMA model are determined by calculating the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF).

Autocorrelation and Partial Autocorrelation:

- Defines autocorrelation as the correlation between two variables and introduces the formula for calculating sample autocorrelations.
- Partial autocorrelation measures the linear dependency of one variable after removing the effect of another.

$$\rho = \frac{E[(y_1 - \mu_1)(y_2 - \mu_2)]}{\sigma_1 \sigma_2}$$

$$\rho(k) = \frac{\frac{1}{n-k} \sum_{t=k+1}^{n} (y_t - \bar{y}) (y_{t-k} - \bar{y})}{\sqrt{\frac{1}{n} \sum_{t=1}^{n} (y_t - \bar{y})} \sqrt{\frac{1}{n-k} \sum_{t=k+1}^{n} (y_{t-k} - \bar{y})}}$$

$$\bar{y_t} = \varphi_{21} \bar{y}_{t-1} + \varphi_{22} \bar{y}_{t-2} + e_t$$

Proposed Work

Emphasizes the goal of identifying a range of stock prices within which a buyer can secure profits.

Forecasting Models:

 Proposes the application of two forecasting models: Holt Winter exponential smoothing and ARIMA (Autoregressive Integrated Moving Average).

Target Data:

 Specifies the target data for analysis as the stock prices of Apple Inc.

Combining Results:

 Outlines the intention to combine the results of both forecasting models to derive a comprehensive range of stock prices.

Workflow

Data Extraction:

Analyzes monthly stock prices of Apple Inc from January 2000 to January 2018, sourced from Yahoo Finance, including open, high, low, close, and adjusted close prices, along with trading volume values.

Consistency Measure:

Utilizes close prices for consistent analysis.

Dataset Splitting:

Divides data into training (Jan 2000 - Jan 2016) and test (Feb 2016 - Jan 2018) datasets for validation.

Time Series Analysis:

Applies time series analysis to the training set, plotting the actual trend for historical stock price variations.

Logarithmic Transformation:

Applies logarithmic transformation for stability, addressing increased variance and volatility in prices at the end of 2015.

Holt-Winters Method:

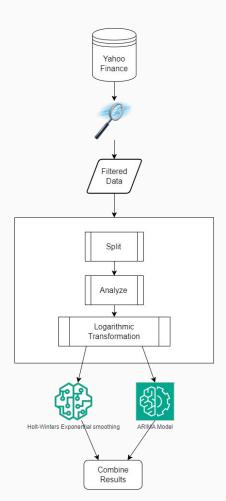
Applies Holt-Winters method for capturing seasonal trends, incorporating triple exponential smoothing.

ARIMA Model:

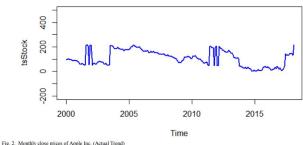
Utilizes ARIMA(2,1,0) based on differencing and ACF/PACF analysis to study price behavior when seasonality is disrupted.

Combination of Results:

Combines Holt-Winters and ARIMA outputs to establish a profitable stock price range for investors.

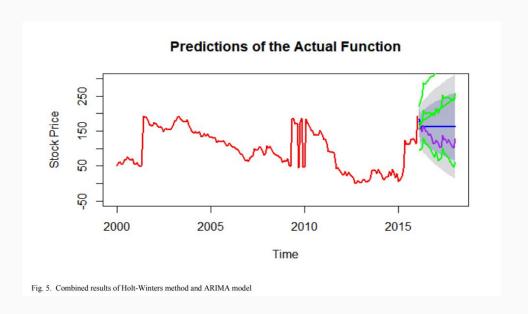


				Б	-	-	-
-4	Α	В	С	D	E	F	G
1	Date	Open	High	Low	Close	Adj Close	Volume
2	01-01-2000	3.745536	4.339286	3.089286	3.705357	2.508365	3138794400
3	01-02-2000	3.714286	4.283482	3.464286	4.09375	2.771291	1829945600
4	01-03-2000	4.234375	5.370536	4.071429	4.850446	3.283542	2174589200
5	01-04-2000	4.839286	4.982143	3.745536	4.430804	2.999461	2165601200
6	01-05-2000	4.459821	4.508929	2.919643	3	2.03087	2451937600
7	01-06-2000	2.919643	4.116071	2.870536	3.741071	2.532543	2026301200
8	01-07-2000	3.723214	4.330357	3.348214	3.629464	2.456989	1436692600
9	01-08-2000	3.59375	4.392857	3.160714	4.352679	2.946575	1409021600
10	01-09-2000	4.379464	4.580357	1.8125	1.839286	1.245116	3629232600
11	01-10-2000	1.90625	1.910714	1.25	1.397321	0.945926	5476447200



Results & Observations

- The red curve represents the actual trend, blue and green curves for Holt-Winters predictions, and a purple curve for ARIMA predictions.
- Dark grey portion highlights the range of prices where the investor incurs no losses.
- Dark grey portion is the safe range where the risk of investing in stocks is minimal.
 Moving away from this range increases the risk.



Key Takeaways

Precise Predictions:

 Depicts a fusion of Holt-Winters and ARIMA models for accurate stock market investment results.

Strength in Simplicity:

 Emphasizes the power of simplicity in Holt-Winters and ARIMA models, relying on historical stock prices for robust predictions.

Advantages:

• Simple and effective models leveraging historical stock prices for both seasonal and nonseasonal behaviors.

Limitations:

 Misses external factors; market policies, press releases, or news that might impact stock prices.

Areas for Growth:

- Focus on improving data collection and analysis methods.
- Suggests further research to enhance experimental results.

What is the significance of applying logarithmic transformation in the analysis?

- 1. It increases variance
- 2. It stabilizes variance
- 3. It removes outliers
- 4. It accelerates price volatility

В

It stabilizes variance

THANK YOU