Stock Quant

Team:

- Constantinos Vogiatzis [cvogiatz@iu.edu (mailto:cvogiatz@iu.edu)](mailto:cvogiatz@iu.edu)
- Shubham Saurabh [ssaurab@iu.edu (mailto:ssaurab@iu.edu)](mailto:ssaurab@iu.edu)
- Seth Smithson [sesmit@iu.edu (mailto:sesmit@iu.edu)](mailto:sesmit@iu.edu)

Preliminary Analysis

Package installs

In [1]:
```
!pip install -q pmdarima
!pip install -q alpha-vantage
```

```
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```

In [2]:

```python
from alpha_vantage.timeseries import TimeSeries
import matplotlib.pyplot as plt
import matplotlib as mpl
import pandas as pd
from datetime import timedelta

import pmdarima as pm
from pmdarima import model_selection
from pmdarima.metrics import smape
from pmdarima.utils import acf, pacf
from sklearn.metrics import mean_squared_error, confusion_matrix
import numpy as np
from tqdm.notebook import tqdm

import plotly.graph_objects as go

mpl.rc('lines', linewidth=0.5)
VANTAGE_KEY = 'MUQXX1BUB5ZP3ZIC'    # Costas' free key
```

Get stock prices

In [3]:
```
stock_code = "AMZN"
date_range = 'full'     # 'full'/'compact' - 'full' gets the full stock history, 'compact'
                        # the last 100 trading days or so

def fetch_prices(stock_code, date_range='full'):
    ts = TimeSeries(key=VANTAGE_KEY,output_format='pandas', indexing_type='date')
    df_prices, meta_data = ts.get_daily_adjusted(stock_code,outputsize=date_range)
    df_prices.rename(columns={
        '1. open':'open',
        '2. high':'high',
        '3. low':'low',
        '4. close':'close',
        '5. adjusted close':'adj_close',
        '6. volume':'volume',
        '7. dividend amount':'dividend',
        '8. split coefficient':'split'
    }, inplace=True)

    # Adjust open, low, high the same way as adjusted close - all prices are now adjusted for splits
    split_ratio = df_prices['adj_close']/df_prices['close']
    df_prices['open'] = df_prices['open'] * split_ratio
    df_prices['high'] = df_prices['high'] * split_ratio
    df_prices['low'] = df_prices['low'] * split_ratio
    df_prices['close'] = df_prices['close'] * split_ratio

    return df_prices

df_prices = fetch_prices(stock_code)
df_main = df_prices.copy()

# Reset the index so it is now consecutive trading days since the start of the dataset
df_prices.reset_index(inplace=True)
# Sort from old to new data
df_prices.sort_index(ascending=False, inplace=True)
```

Time Series Visualization

Note: Sometimes google colab produces the same plots twice. Please ignore that. It will not impact the final UI.

OHLC plot

In [6]:
```python
def plot_ohlc(df_prices,log_plot=False):
    fig = go.Figure(data=go.Ohlc(x=df_prices['date'],
                        open=df_prices['open'],
                        high=df_prices['high'],
                        low=df_prices['low'],
                        close=df_prices['close']))
    fig.update_layout(
        title= 'OHLC Plot for ' + stock_code,
        yaxis_title= stock_code + ' Stock (Adjusted for splits)',
        autosize=False,
        width=1024,
        height=600)
    fig.update_yaxes(type=("log" if log_plot else "linear"))
    fig.show()

plot_ohlc(df_prices,log_plot=False)
```

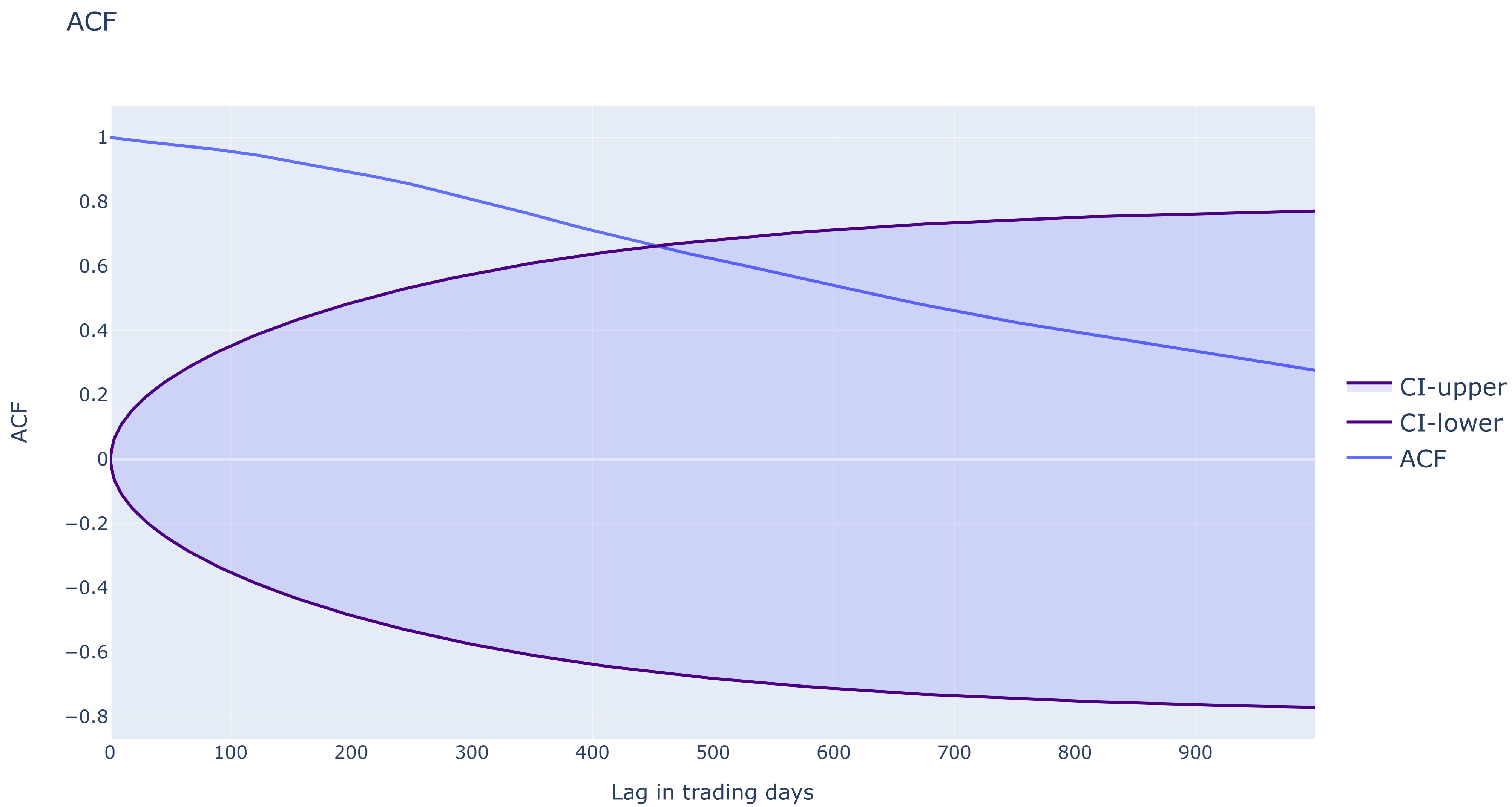
In [7]:

```
plot_ohlc(df_prices,log_plot=True)
```

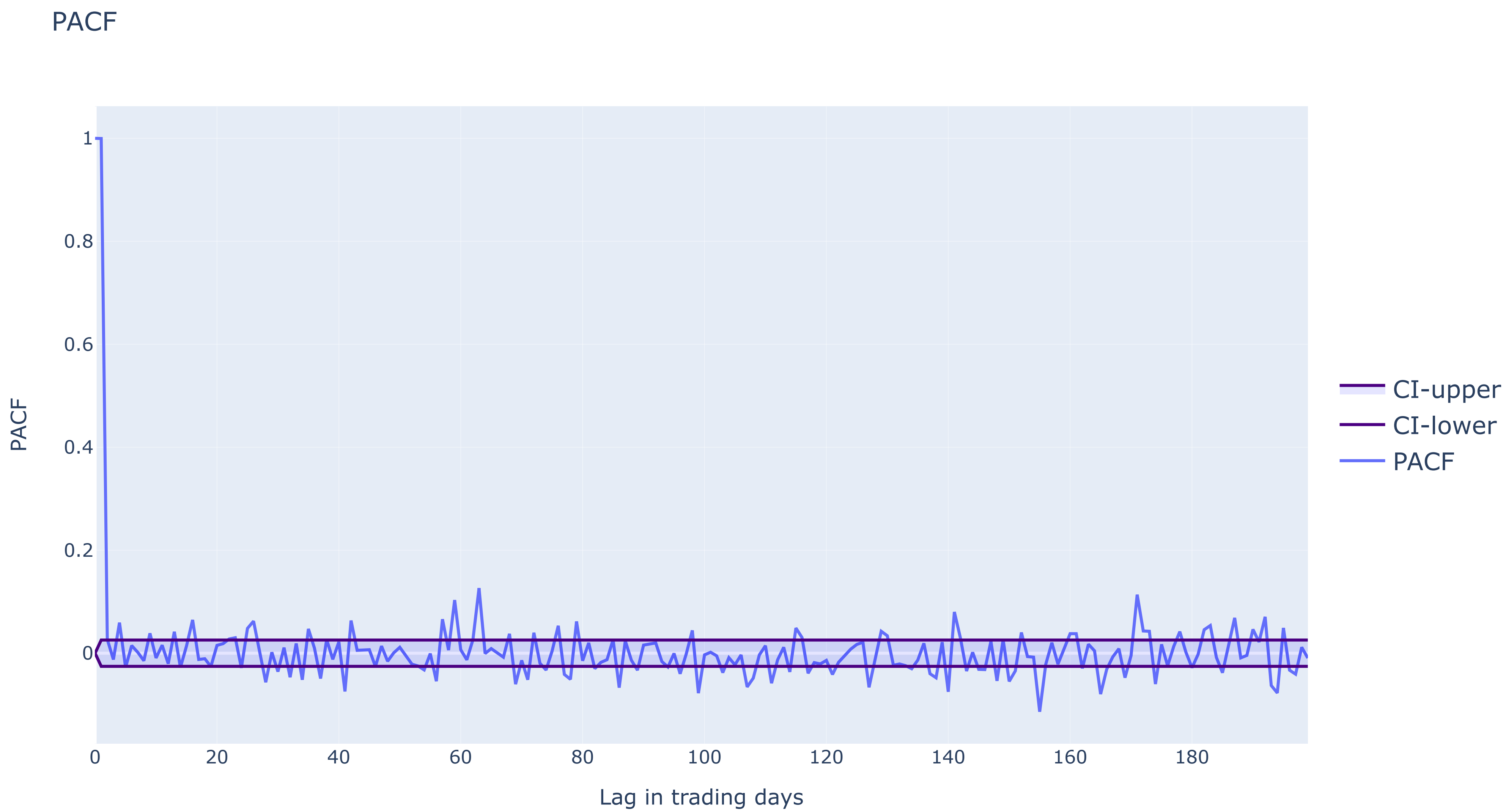
ACF, PACF plots

In [8]:

```
# yacf, ci_acf, qstat, pvals =
def plot_cf(prices, cf_type='ACF', nlags=100):

    yacf, ci_acf = ( acf(prices, alpha=0.05, nlags = nlags) if cf_type.lower()=='acf' else
                    pacf(prices, alpha=0.05, nlags = nlags) )
    ci_upper = ci_acf[:,1] - yacf
    ci_lower = ci_acf[:,0] - yacf

    fig = go.Figure()
    fig.add_trace(go.Scatter(x=np.arange(nlags), y=yacf, name=cf_type,
                        line_shape='linear'))

    fig.add_trace(go.Scatter(x=np.arange(nlags), y=ci_lower,
        fill=None,
        mode='lines',
        line_color='indigo',
        name="CI-lower"
        ))
    fig.add_trace(go.Scatter(
        x=np.arange(nlags), y=ci_upper,
        fill='tonexty',
        fillcolor='rgba(0, 0, 255, 0.1)',
        mode='lines', line_color='indigo', name="CI-upper"))

    fig.update_traces(hoverinfo='text+name')
    fig.update_layout(legend=dict(y=0.5, traceorder='reversed', font_size=16),
                    xaxis_title= 'Lag in trading days',
                    yaxis_title= cf_type,
                    title = cf_type,
        autosize=True,
        width=1024,
        height=600)

    fig.show()

plot_cf(df_prices['close'], cf_type='ACF', nlags=min(1000,df_prices.shape[0]))
plot_cf(df_prices['close'], cf_type='PACF', nlags=min(200,df_prices.shape[0]))
```



ACF
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
−0.8
0
100
200
300
400
500
600
700
800
900
Lag in trading days
CI-upper
CI-lower
ACF

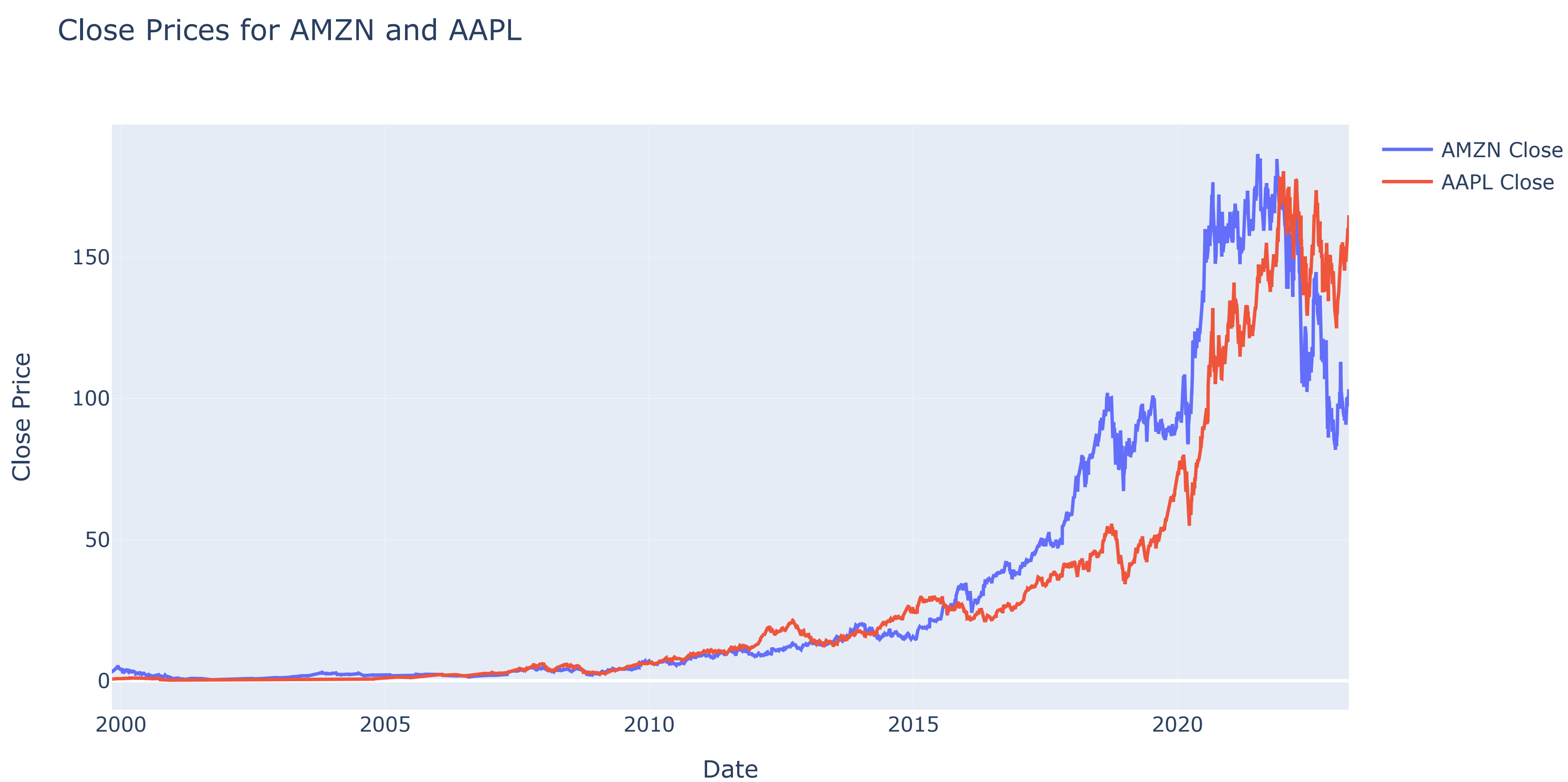


Stock Price Comparison plot

This functionality will allow users to compare the prices of any two stocks by plottting both on the same graph.

In [9]:

```
def plot_two_stocks(stock1_df, stock2_df, q_plot, stock1_name='Stock 1', stock2_name='Stock 2'):
    if q_plot not in ['open', 'close', 'low', 'high']:
        raise ValueError("q_plot must be one of 'open', 'close', 'low', or 'high'")

    # Assuming the date column in the DataFrames is named 'date'
    fig = go.Figure()

    fig.add_trace(go.Scatter(
        x=stock1_df['date'],
        y=stock1_df[q_plot],
        name=f'{stock1_name} {q_plot.capitalize()}',
        line=dict(width=2)
    ))

    fig.add_trace(go.Scatter(
        x=stock2_df['date'],
        y=stock2_df[q_plot],
        name=f'{stock2_name} {q_plot.capitalize()}',
        line=dict(width=2)
    ))

    fig.update_layout(
        title=f"{q_plot.capitalize()} Prices for {stock1_name} and {stock2_name}",
        xaxis_title="Date",
        yaxis_title=f"{q_plot.capitalize()} Price"
    )

    fig.show()

stock_code_other = "AAPL"
df_prices_other = fetch_prices(stock_code_other)
df_prices_other.reset_index(inplace=True)
df_prices_other.sort_index(ascending=False, inplace=True)

plot_two_stocks(df_prices,df_prices_other,'close',stock_code,stock_code_other)
```


Close Prices for AMZN and AAPL
AMZN Close
AAPL Close
Close Price
0
50
100
150
2000
2005
2010
2015
2020
Date

Time Series Decomposition

Decomposition using Prophet model

In [10]:
```
!pip install -q prophet
```

```
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WARNING: Ignoring invalid distribution -rotobuf (c:\users\vishu\appdata\roaming\python\python39\site-packages)
```
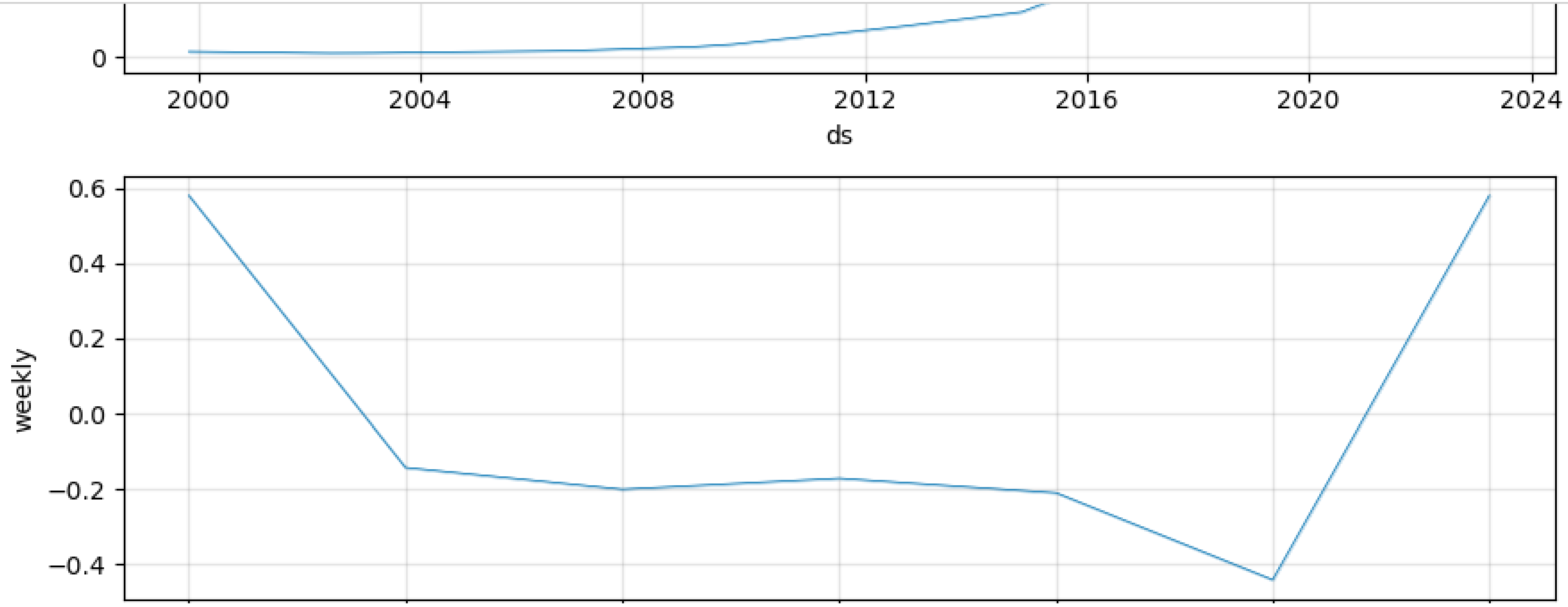
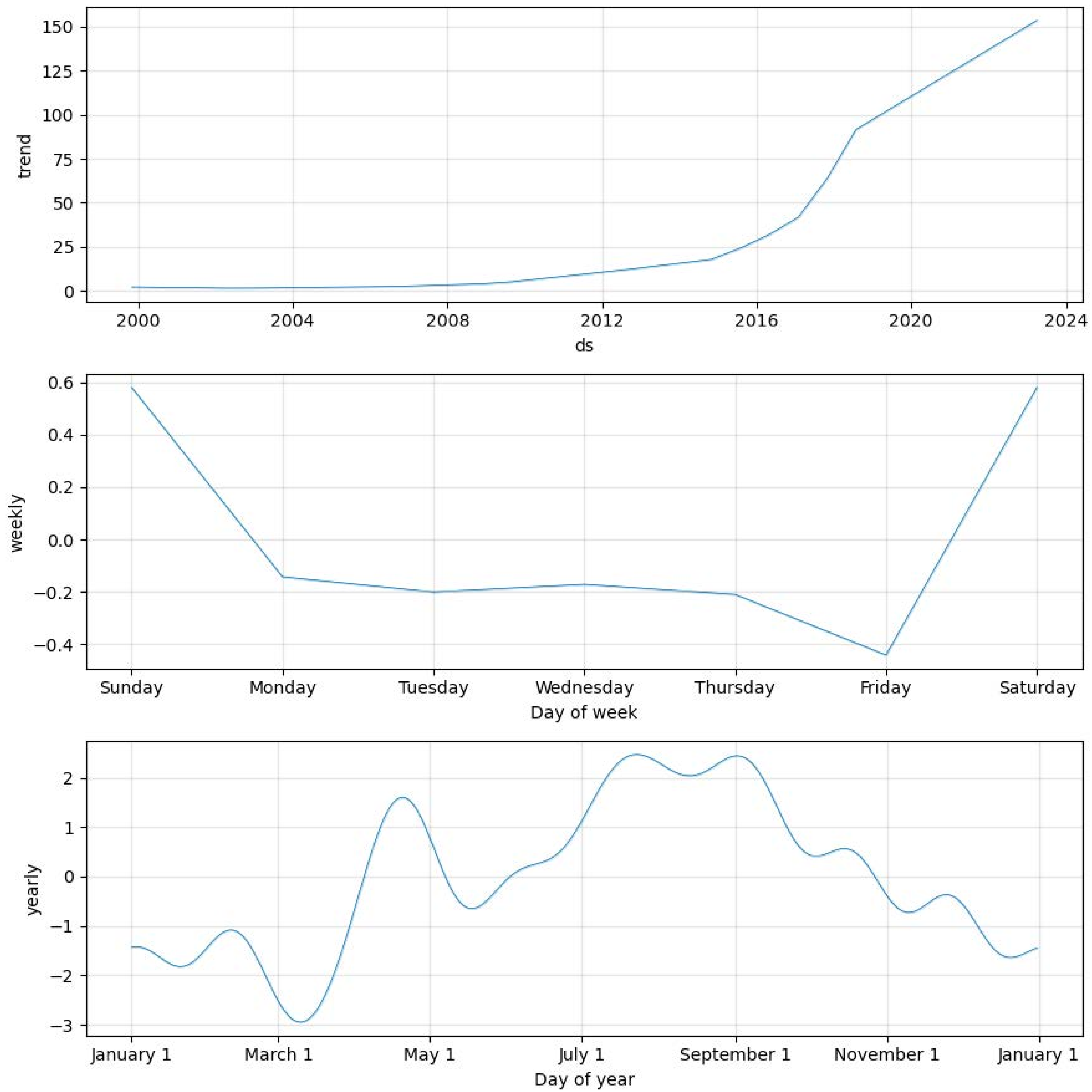

In [11]:
```
from prophet import Prophet

df_decompose = df_main[['adj_close']]
df_decompose = df_decompose.reset_index()
df_decompose.columns = ['ds', 'y']

# define the model
model = Prophet()

# fit the model
model.fit(df_decompose)

future = model.make_future_dataframe(periods=1)
forecast = model.predict(future)
```

```
17:05:11 - cmdstanpy - INFO - Chain [1] start processing
17:05:14 - cmdstanpy - INFO - Chain [1] done processing
```

In [12]:

```python
# Plot Components
model.plot_components(forecast)
```





trend
150
125
100
75
50
25
0
2000
2004
2008
2012
2016
2020
2024
ds
weekly
0.6
0.4
0.2
0.0
−0.2
−0.4
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Day of week
yearly
2
1
0
−1
−2
−3
January 1
March 1
May 1
July 1
September 1
November 1
January 1
Day of year

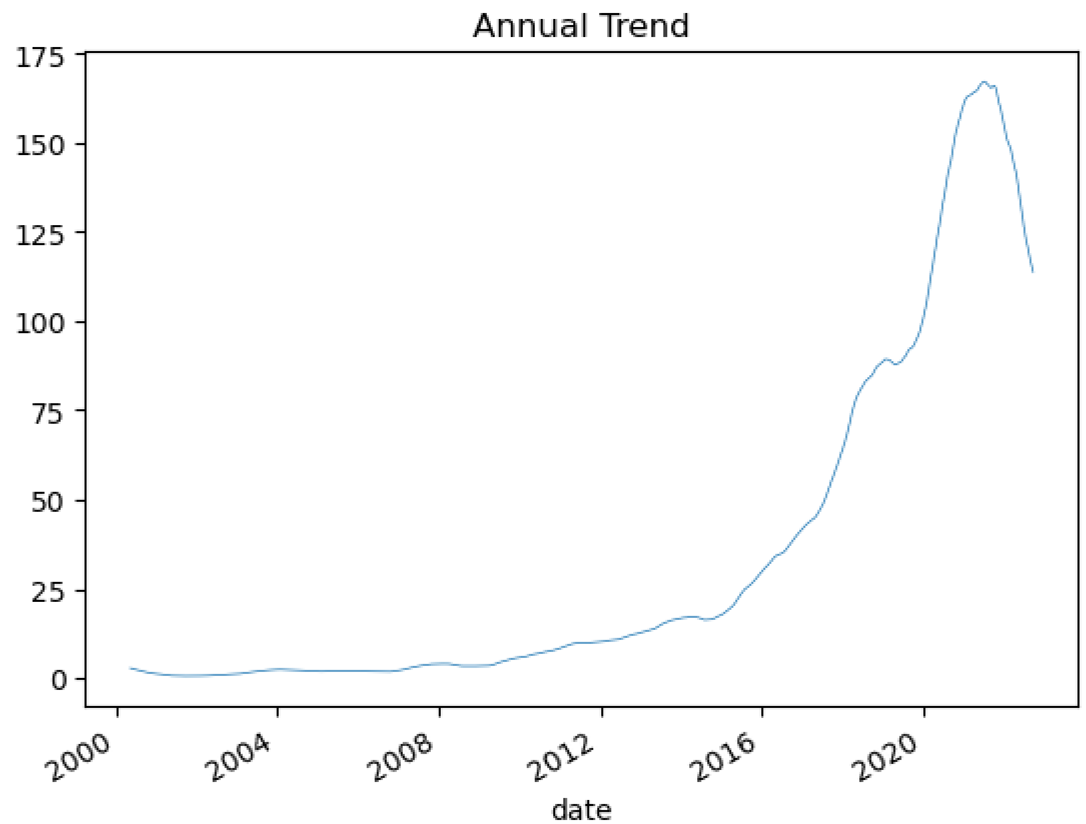
Decomposition using statsmodels.tsa

In [13]:

```
from statsmodels.tsa.seasonal import seasonal_decompose

decompose = seasonal_decompose(df_main['adj_close'], model='multiplicable', period=260) # assuming 260 business days in a year

decompose.trend.plot(title='Annual Trend')
```

Out[13]:

```
<AxesSubplot: title={'center': 'Annual Trend'}, xlabel='date'>
```

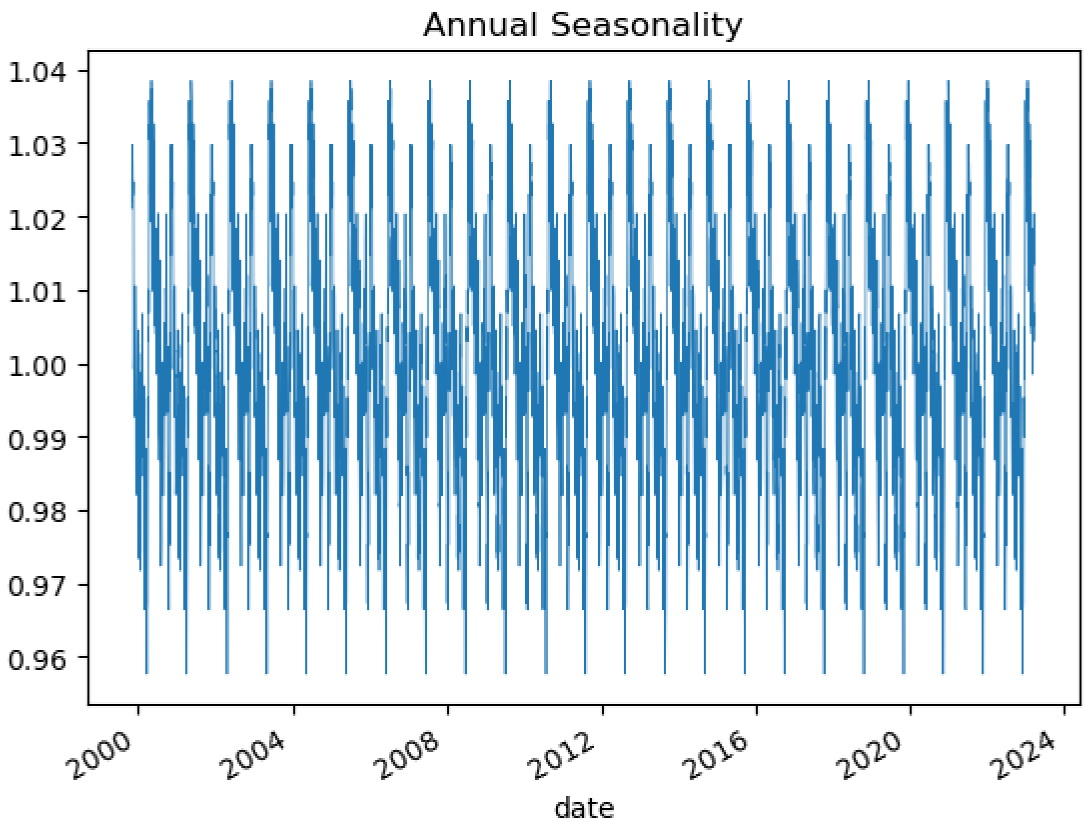


In [14]:

```python
decompose.seasonal.plot(title='Annual Seasonality')
```

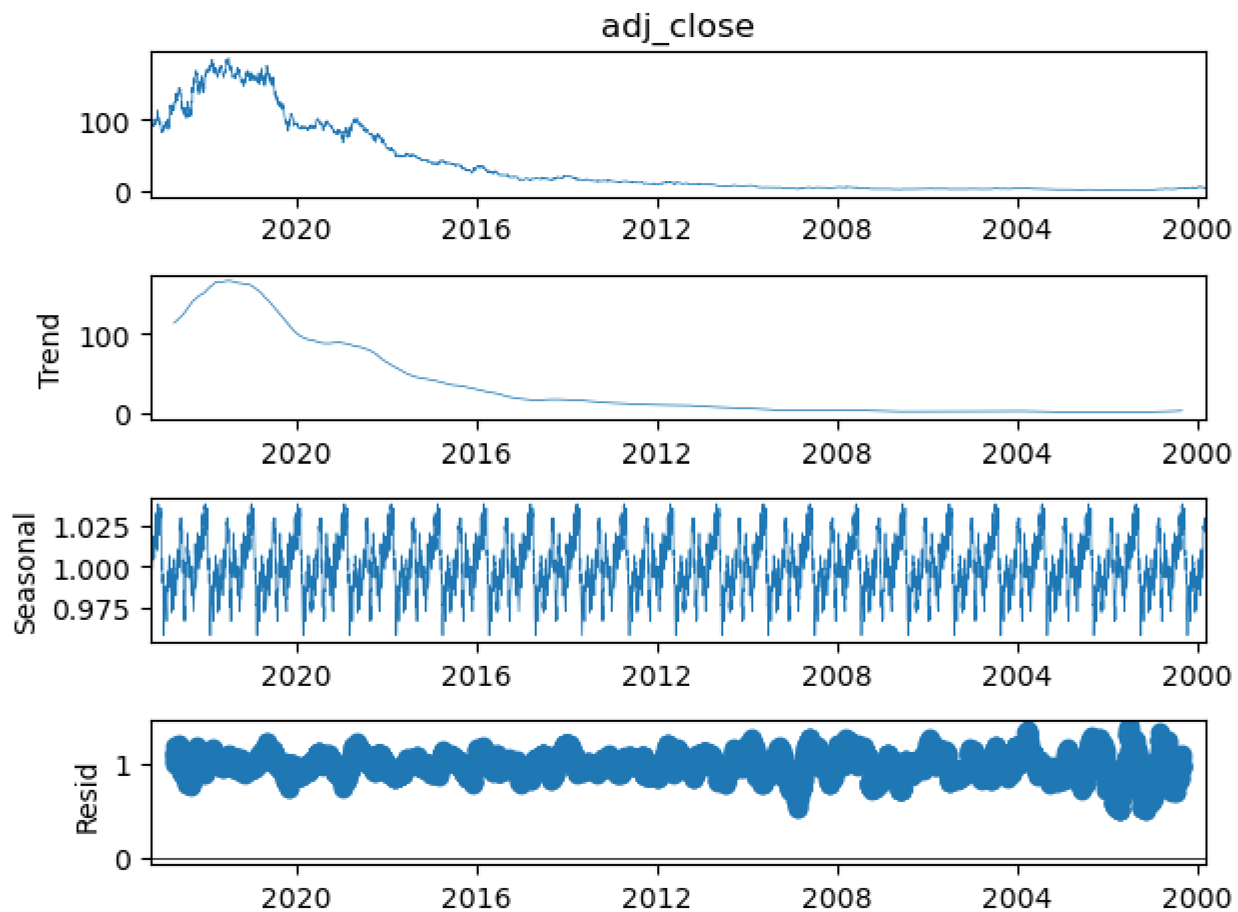
Out[14]:

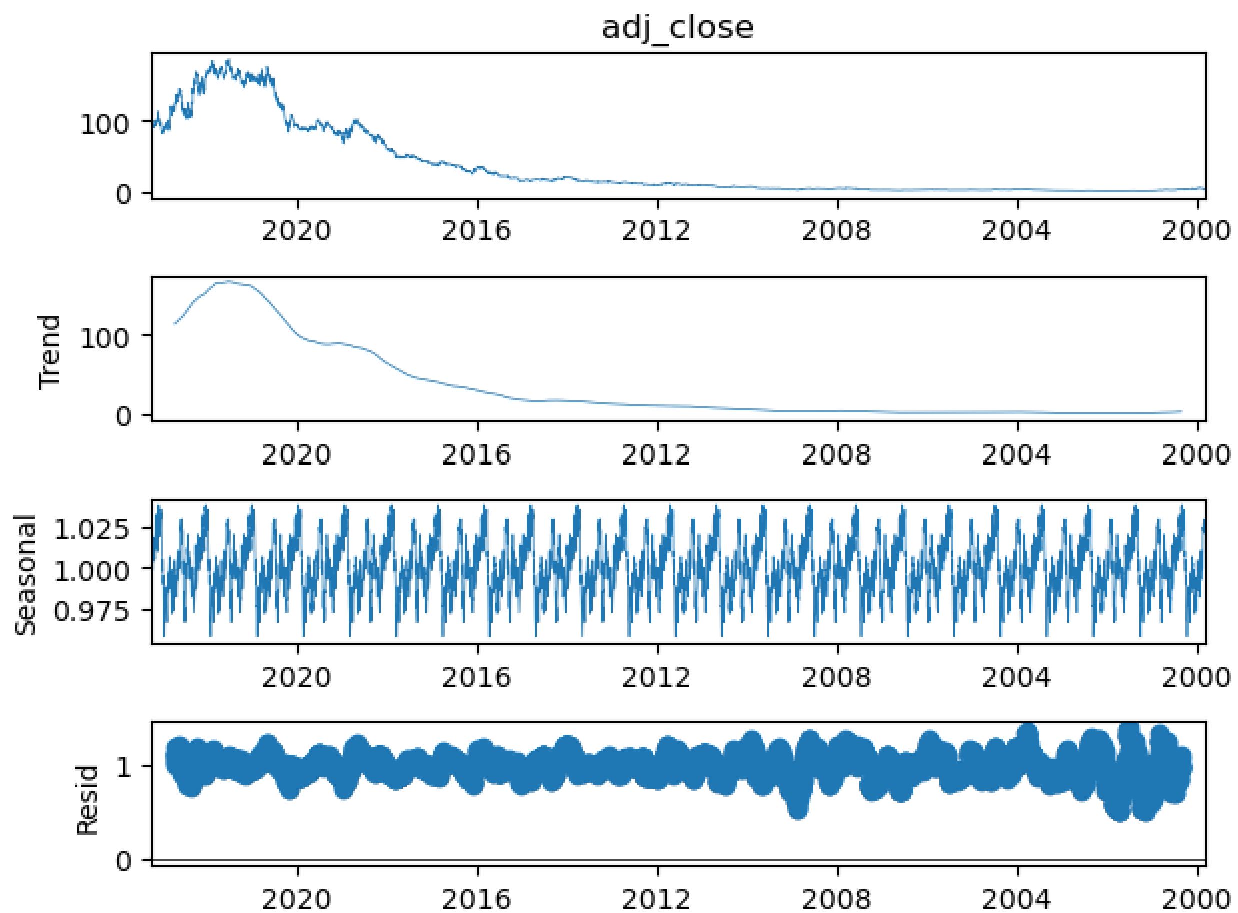
```
<AxesSubplot: title={'center': 'Annual Seasonality'}, xlabel='date'>
```



In [15]:
```
# Time Series Decomposition of stock_code (daily adjusted close values)
decompose.plot()
```

Out[15]:





Description of Time series

As expected from any stock price, there is a long term trend that corresponds to a general growth in the stock market. This will be true for any stock in general.

Stock prices are non-stationary and do not exhibit seasonality. As seen in our plots above, there are no seasonality patterns on weekly, monthly or annual basis. The weekly seasonality observed in prophet forecast showing a high on the weekends should be ignored because the stock price data is available only for business days (not weekends). Hence, the seasonal decomposition does not provide any meaningful insights.

Forecasting based on Quarterly Financial Data

Seth

Use data only till Sep-30-2022 to forecast for stock price on Dec-30-2022.

Install Packages

In [13]:

```
# Alpha Vantage API
!pip install -q alpha-vantage

# Yahoo! Finance APOI
!pip install -q yfinance

# SciKit Optimizer
# !pip install scikit-optimize

# Install Tensorflow and Keras
# !pip install tensorflow keras

# Keras Tuner
!pip install -q keras-tuner

# SciKeras --> to use Keras/TensorFlow with sklearn
# !pip install scikeras[tensorflow]

# Bayesian Optimizer
# !pip install pip install bayesian-optimization
```

Load Packages

In [14]:

```python
# Now, Let's import relevant python libraries

## Data Processing Libraries!
import numpy as np
import pandas as pd

# Importing pprint for better print displays of hyperparameters
from pprint import pprint

# Additional Imports
import requests
from datetime import datetime, timedelta
import json
from pandas_datareader import data
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure

# Import Alpha Vantage
from alpha_vantage.timeseries import TimeSeries

# Import Yahoo Finance
import yfinance as yf

# SciKitLearn
import sklearn
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.model_selection import TimeSeriesSplit

# TensorFlow and Keras
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping
from kerastuner.tuners import BayesianOptimization
```

```
<ipython-input-14-5fdc1bf011af>:37: DeprecationWarning:

`import kerastuner` is deprecated, please use `import keras_tuner`.
```

Data Preparation

Setup the API variables and desired Stock Ticker

In [15]:
```python
# Define API variables
api_key = "KBBHKE0UHFRYF83S" # Seth's key
base_url = "https://www.alphavantage.co/query"

# Prompt User for a Ticker
ticker = stock_code
```

Pull some KPIs from the Income Statement via Alpha Vantage API

In [16]:
```python
# Set the function parameters for the "Income Statement" endpoint of the Alpha Vantage API request
income_statement_params = {
    "function": "INCOME_STATEMENT",
    "symbol": ticker,
    "apikey": api_key,
    "period": "quarterly"
}

# Make a GET request to the Alpha Vantage API with the function parameters
income_statement_response = requests.get(base_url, params=income_statement_params)

# Convert the response content to a data frame using pandas
income_statement_data = pd.DataFrame(income_statement_response.json()["quarterlyReports"])
```

In [17]:
```python
# Extract the financial metrics from the data frame
comprehensive_income_net_of_tax = income_statement_data["comprehensiveIncomeNetOfTax"] # Amount after tax of increase (decrease) in equity from transactions and other events and ci
cost_of_revenue = income_statement_data["costOfRevenue"] # The aggregate cost of goods produced and sold and services rendered during the reporting period.
COGS = income_statement_data["costofGoodsAndServicesSold"] # The aggregate costs related to goods produced and sold and services rendered by an entity during the reporting period.
# depreciation_amortization = income_statement_data["decpreciationAndAmortization"] # The current period expense charged against earnings on long-lived, physical assets not used in
depreciation = income_statement_data["depreciation"] # The amount of expense recognized in the current period that reflects the allocation of the cost of tangible assets over the a
ebit = income_statement_data["ebit"] # The portion of profit or loss for the period, before income taxes and interest expenses, which is attributable to the parent.
ebitda = income_statement_data["ebitda"] # The portion of profit or loss for the period, before income taxes, interest expenses and depreciation and amortization, which is attribut
gross_profit = income_statement_data["grossProfit"] # Aggregate revenue less cost of goods and services sold or operating expenses directly attributable to the revenue generation a
income_before_tax = income_statement_data["incomeBeforeTax"] # The portion of profit or loss for the period, before income taxes, which is attributable to the parent.
income_tax_expense = income_statement_data["incomeTaxExpense"] # Amount of current income tax expense (benefit) and deferred income tax expense (benefit) pertaining to continuing o
interest_and_debt_expense = income_statement_data["interestAndDebtExpense"] # Interest and debt related expenses associated with nonoperating financing activities of the entity.
interest_expense = income_statement_data["interestExpense"] # Amount of the cost of borrowed funds accounted for as interest expense.
interest_income = income_statement_data["interestIncome"] # The amount of interest income.
net_investment_income = income_statement_data["investmentIncomeNet"] # Amount after accretion (amortization) of discount (premium), and investment expense, of interest income and d
net_income = income_statement_data["netIncome"] # The portion of profit or loss for the period, net of income taxes, which is attributable to the parent.
net_income_from_Ops = income_statement_data["netIncomeFromContinuingOperations"] # Amount after tax of income (loss) from continuing operations attributable to the parent.
net_interest_income = income_statement_data["netInterestIncome"] # The net amount of operating interest income (expense).
non_interest_income = income_statement_data["nonInterestIncome"] # The total amount of noninterest income which may be derived from: (1) fees and commissions; (2) premiums earned;
operating_expenses = income_statement_data["operatingExpenses"] # Generally recurring costs associated with normal operations except for the portion of these expenses which can be
operating_income = income_statement_data["operatingIncome"] # The net result for the period of deducting operating expenses from operating revenues.
other_non_operating_income = income_statement_data["otherNonOperatingIncome"] # Amount of income (expense) related to nonoperating activities, classified as other.
RnD = income_statement_data["researchAndDevelopment"] # The aggregate costs incurred (1) in a planned search or critical investigation aimed at discovery of new knowledge with the
COS = income_statement_data["sellingGeneralAndAdministrative"] # The aggregate total costs related to selling a firm's product and services, as well as all other general and admini
revenue = income_statement_data["totalRevenue"] # Amount of revenue recognized from goods sold, services rendered, insurance premiums, or other activities that constitute an earnin
```

Pull some KPIs from the Cash Flow Statement via Alpha Vantage API

In [18]:
```python
# Set the function parameters for the "Cash Flow" endpoint of the Alpha Vantage API request
cash_flow_params = {
    "function": "CASH_FLOW",
    "symbol": ticker,
    "apikey": api_key,
    "period": "quarter"
}

# Make a GET request to the Alpha Vantage API with the function parameters
cash_flow_response = requests.get(base_url, params=cash_flow_params)

# Convert the response content to a data frame using pandas
cash_flow_data = pd.DataFrame(cash_flow_response.json()["quarterlyReports"])
```

In [19]:

```
# Extract the financial metrics from the data frame
cap_ex = cash_flow_data["capitalExpenditures"] # The cash outflow for purchases of and capital improvements on property, plant and equipment (capital expenditures), software, and o
# cash_and_cash_equivalents_at_carrying_value = cash_flow_data["cashAndCashEquivalentsAtCarryingValue"] # Amount of currency on hand as well as demand deposits with banks or financ
cash_flow_from_financing = cash_flow_data["cashflowFromFinancing"] # Amount of cash inflow (outflow) from financing activities, including discontinued operations. Financing activit
cash_flow_from_investment = cash_flow_data["cashflowFromInvestment"] # Amount of cash inflow (outflow) from investing activities, including discontinued operations. Investing activ
change_in_cash_and_cash_equivalents = cash_flow_data["changeInCashAndCashEquivalents"] # Amount of increase (decrease) in cash and cash equivalents. Cash and cash equivalents are t
change_in_exchange_rate = cash_flow_data["changeInExchangeRate"] # Amount of increase (decrease) from the effect of exchange rate changes on cash and cash equivalent balances held
change_in_inventory = cash_flow_data["changeInInventory"] # The increase (decrease) during the reporting period in the aggregate value of all inventory held by the reporting entity
change_in_Op_Ex = cash_flow_data["changeInOperatingAssets"] # The increase (decrease) during the reporting period in the aggregate amount of assets used to generate operating incom
change_in_Op_liabilities = cash_flow_data["changeInOperatingLiabilities"] # The increase (decrease) during the reporting period in the aggregate amount of liabilities that result f
change_in_receivables = cash_flow_data["changeInReceivables"] # The increase (decrease) during the reporting period in the total amount due within one year (or one operating cycle)
depreciation_depletion_amortization = cash_flow_data["depreciationDepletionAndAmortization"] # The aggregate expense recognized in the current period that allocates the cost of tan
dividend_payout_total = cash_flow_data["dividendPayout"] # Cash outflow in the form of capital distributions and dividends to common shareholders, preferred shareholders and noncon
dividend_payout_common_stock = cash_flow_data["dividendPayoutCommonStock"] # Amount of cash outflow in the form of ordinary dividends to common shareholders of the parent entity.
dividend_payout_preferred_stock = cash_flow_data["dividendPayoutPreferredStock"] # Amount of cash outflow in the form of ordinary dividends to preferred shareholders of the parent
net_income = cash_flow_data["netIncome"] # The portion of profit or loss for the period, net of income taxes, which is attributable to the parent.
operating_cashflow = cash_flow_data["operatingCashflow"] # A useful metric from the Cash Flow Statement.  Amount of cash inflow (outflow) from operating activities, including disco
payments_for_Op_activities = cash_flow_data["paymentsForOperatingActivities"] # Total amount of cash paid for operating activities during the current period.
stock_buybacks_common = cash_flow_data["paymentsForRepurchaseOfCommonStock"] # The cash outflow to reacquire common stock during the period.
stock_buybacks_all = cash_flow_data["paymentsForRepurchaseOfEquity"] # The cash outflow to reacquire common and preferred stock.
stock_buybacks_preferred = cash_flow_data["paymentsForRepurchaseOfPreferredStock"] # The cash outflow to reacquire preferred stock during the period.
stock_issuance = cash_flow_data["proceedsFromIssuanceOfCommonStock"] # The cash inflow from the additional capital contribution to the entity.
cash_raised_from_debt_and_equity = cash_flow_data["proceedsFromIssuanceOfLongTermDebtAndCapitalSecuritiesNet"] # The cash inflow associated with security instrument that either rep
cash_raised_preferred_stock = cash_flow_data["proceedsFromIssuanceOfPreferredStock"] # Proceeds from issuance of capital stock which provides for a specific dividend that is paid t
cash_raised_Op_activities = cash_flow_data["proceedsFromOperatingActivities"] # Total amount of cash received from operating activities during the current period.
cash_raised_from_short_term_debt = cash_flow_data["proceedsFromRepaymentsOfShortTermDebt"] # The net cash inflow or outflow for borrowing having initial term of repayment within on
net_cash_from_equity = cash_flow_data["proceedsFromRepurchaseOfEquity"] # The net cash inflow or outflow resulting from the entity's share transaction.
cash_raised_treasury_stock = cash_flow_data["proceedsFromSaleOfTreasuryStock"] # The cash inflow from the issuance of an equity stock that has been previously reacquired by the ent
profit_loss = cash_flow_data["profitLoss"] # The consolidated profit or loss for the period, net of income taxes, including the portion attributable to the noncontrolling interest.
```

Pull some KPIs from the Balance Sheet via Alpha Vantage API

In [20]:

```
# Set the function parameters for the "Balance Sheet" endpoint of the Alpha Vantage API request
balance_sheet_params = {
    "function": "BALANCE_SHEET",
    "symbol": ticker,
    "apikey": api_key,
    "period": "quarter"
}

# Make a GET request to the Alpha Vantage API with the function parameters
balance_sheet_response = requests.get(base_url, params=balance_sheet_params)

# Convert the response content to a data frame using pandas
balance_sheet_data = pd.DataFrame(balance_sheet_response.json()["quarterlyReports"])
```

In [21]:

```python
# Extract the financial metrics from the data frame
accumulated_depreciation_ammortization_PPE = balance_sheet_data["accumulatedDepreciationAmortizationPPE"] # Amount of accumulated depreciation, depletion and amortization for physi
capital_lease_obligations = balance_sheet_data["capitalLeaseObligations"] # Present value of lessee's discounted obligation for lease payments from finance lease, classified as non
cash_and_cash_equivalents_at_carrying_value = balance_sheet_data["cashAndCashEquivalentsAtCarryingValue"] # Amount of currency on hand as well as demand deposits with banks or fina
cash_and_short_term_investments = balance_sheet_data["cashAndShortTermInvestments"] # Cash includes currency on hand as well as demand deposits with banks or financial institutions
common_stock = balance_sheet_data["commonStock"] # Aggregate par or stated value of issued nonredeemable common stock (or common stock redeemable solely at the option of the issuer
outstanding_shares = balance_sheet_data["commonStockSharesOutstanding"] # Best estimate of Common Stock Shares Outstanding. If a company does not report a period end value the amou
current_accounts_payable = balance_sheet_data["currentAccountsPayable"] # Carrying value as of the balance sheet date of liabilities incurred (and for which invoices have typically
current_debt = balance_sheet_data["currentDebt"] # Amount of short-term debt and current maturity of long-term debt and capital lease obligations due within one year or the normal
current_long_term_debt = balance_sheet_data["currentLongTermDebt"] # Amount, after unamortized (discount) premium and debt issuance costs, of long-term debt, classified as current.
current_net_receivables = balance_sheet_data["currentNetReceivables"] # The total amount due to the entity within one year of the balance sheet date (or one operating cycle, if lon
# long_term_short_term_debt = balance_sheet_data["debtLongtermAndShorttermCombinedAmount"] # Represents the aggregate of total long-term debt, including current maturities and shor
deferred_revenue = balance_sheet_data["deferredRevenue"] # Amount of deferred income and obligation to transfer product and service to customer for which consideration has been rec
goodwill = balance_sheet_data["goodwill"] # Amount after accumulated impairment loss of an asset representing future economic benefits arising from other assets acquired in a busin
intangible_assets = balance_sheet_data["intangibleAssets"] # Carrying amount of finite-lived intangible assets, indefinite-lived intangible assets and goodwill. Goodwill is an asse
intangible_assets_excluding_goodwill = balance_sheet_data["intangibleAssetsExcludingGoodwill"] # Sum of the carrying amounts of all intangible assets, excluding goodwill, as of the
inventory = balance_sheet_data["inventory"] # Amount after valuation and LIFO reserves of inventory expected to be sold, or consumed within one year or operating cycle, if longer.
investments = balance_sheet_data["investments"] # Sum of the carrying amounts as of the balance sheet date of all investments.
long_term_debt = balance_sheet_data["longTermDebt"] # Amount, after unamortized (discount) premium and debt issuance costs, of long-term debt. Includes, but not limited to, notes p
long_term_debt_noncurrent = balance_sheet_data["longTermDebtNoncurrent"] # Amount after unamortized (discount) premium and debt issuance costs of long-term debt classified as noncu
long_term_investments = balance_sheet_data["longTermInvestments"] # The total amount of investments that are intended to be held for an extended period of time (longer than one ope
other_current_assets = balance_sheet_data["otherCurrentAssets"] #  Amount of current assets classified as other.
other_current_liabilities = balance_sheet_data["otherCurrentLiabilities"] # Amount of liabilities classified as other, due within one year or the normal operating cycle, if longer.
other_noncurrent_liabilities = balance_sheet_data["otherNonCurrentLiabilities"] # Amount of liabilities classified as other, due after one year or the normal operating cycle, if lo
# other_noncurrent_assets = balance_sheet_data["otherNonCurrrentAssets"] # Amount of noncurrent assets classified as other.
property_plant_equipment = balance_sheet_data["propertyPlantEquipment"] # Amount after accumulated depreciation, depletion and amortization of physical assets used in the normal co
retained_earnings = balance_sheet_data["retainedEarnings"] # The cumulative amount of the reporting entity's undistributed earnings or deficit.
short_term_debt = balance_sheet_data["shortTermDebt"] # Reflects the total carrying amount as of the balance sheet date of debt having initial terms less than one year or the norma
short_term_investments = balance_sheet_data["shortTermInvestments"] # Amount of investments including trading securities, available-for-sale securities, held-to-maturity securities
total_assets = balance_sheet_data["totalAssets"] # Sum of the carrying amounts as of the balance sheet date of all assets that are recognized. Assets are probable future economic b
current_assets = balance_sheet_data["totalCurrentAssets"] # Sum of the carrying amounts as of the balance sheet date of all assets that are expected to be realized in cash, sold, o
current_liabilities = balance_sheet_data["totalCurrentLiabilities"] # Total obligations incurred as part of normal operations that are expected to be paid during the following twel
total_liabilities = balance_sheet_data["totalLiabilities"] # Sum of the carrying amounts as of the balance sheet date of all liabilities that are recognized. Liabilities are probab
total_noncurrent_assets = balance_sheet_data["totalNonCurrentAssets"] # Sum of the carrying amounts as of the balance sheet date of all assets that are expected to be realized in c
total_noncurrent_liabilities = balance_sheet_data["totalNonCurrentLiabilities"] # Amount of obligation due after one year or beyond the normal operating cycle, if longer.
shareholder_equity = balance_sheet_data["totalShareholderEquity"] # Target Variable! Total of all stockholders' equity (deficit) items, net of receivables from officers, directors,
treasury_stock = balance_sheet_data["treasuryStock"] # The amount allocated to treasury stock. Treasury stock is common and preferred shares of an entity that were issued, repurcha
```

Make the all-inclusive dataframe

In [22]:

```
# Create a data frame of the financial metrics
financial_metrics = pd.DataFrame({
    "Date": income_statement_data["fiscalDateEnding"],
    "Comprehensive_Income_Net_of_Tax": comprehensive_income_net_of_tax,
    "Cost_of_Revenue": cost_of_revenue,
    "COGS": COGS,
    "Depreciation": depreciation,
    "EBIT": ebit,
    "EBITDA": ebitda,
    "Gross_Profit": gross_profit,
    "Income_Before_Tax": income_before_tax,
    "Income_Tax_Expense": income_tax_expense,
    "Interest_and_Debt_Expense": interest_and_debt_expense,
    "Interest_Expense": interest_expense,
    "Interest_Income": interest_income,
    "Net_Investment_Income": net_investment_income,
    "Net_Income": net_income,
    "Net_Income_from_Ops": net_income_from_Ops,
    "Net_Interest_Income": net_interest_income,
    "Non_Interest_Income": non_interest_income,
    "Operating Expenses": operating_expenses,
    "Operating_Income": operating_income,
    "Other_Non_Operating_Income": other_non_operating_income,
    "RnD": RnD,
    "COS": COS,
    "Revenue": revenue,
    "Cap_Ex": cap_ex,
    "Cash_Flow_from_Financing": cash_flow_from_financing,
    "Cash_Flow_from_Investment": cash_flow_from_investment,
    "Change_in_Cash_and_Cash_Equivalents": change_in_cash_and_cash_equivalents,
    "Change_in_Exchange_Rate": change_in_exchange_rate,
    "Change_in_Inventory": change_in_inventory,
    "Change_in_Op_Ex": change_in_Op_Ex,
    "Change_in_Op_Liabilities": change_in_Op_liabilities,
    "Change_in_Receivables": change_in_receivables,
    "Depreciation_Depletion_Amortization": depreciation_depletion_amortization,
    "Dividend_Payout_Total": dividend_payout_total,
    "Dividend_Payout_Common_Stock": dividend_payout_common_stock,
    "Dividend_Payout_Preferred_Stock": dividend_payout_preferred_stock,
    "Net_Income": net_income,
    "Operating_Cashflow": operating_cashflow,
    "Payments_for_Op_Activities": payments_for_Op_activities,
    "Stock_Buybacks_Common": stock_buybacks_common,
    "Stock_Buybacks_All": stock_buybacks_all,
    "Stock_Buybacks_Preferred": stock_buybacks_preferred,
    "Stock_Issuance": stock_issuance,
    "Cash_Raised_from_Debt_and_Equity": cash_raised_from_debt_and_equity,
    "Cash_Raised_Preferred_Stock": cash_raised_preferred_stock,
    "Cash_Raised_Op_Activities": cash_raised_Op_activities,
    "Cash_Raised_from_Short_Term_Debt": cash_raised_from_short_term_debt,
    "Net_Cash_from_Equity": net_cash_from_equity,
    "Cash_Raised_Treasury_Stock": cash_raised_treasury_stock,
    "Profit_Loss": profit_loss,
    "Accumulated_Depreciation_Ammortization_PPE": accumulated_depreciation_ammortization_PPE,
    "Capital_Lease_Obligations": capital_lease_obligations,
    "Cash_and_Cash_Equivalents_at_Carrying_Value": cash_and_cash_equivalents_at_carrying_value,
    "Cash_and_Short_Term_Investments": cash_and_short_term_investments,
```

```
    "Common_Stock": common_stock,
    "Outstanding_Shares": outstanding_shares,
    "Current_AP": current_accounts_payable,
    "Current_Debt": current_debt,
    "Current_Long_Term_Debt": current_long_term_debt,
    "Current_net_receivables": current_net_receivables,
    "Deferred_Revenue": deferred_revenue,
    "Goodwill": goodwill,
    "Intangible_Assets": intangible_assets,
    "Intangible_Assets_Excluding_Goodwill": intangible_assets_excluding_goodwill,
    "Inventory": inventory,
    "Investments": investments,
    "Long_Term_Debt": long_term_debt,
    "Long_Term_Debt_Noncurrent": long_term_debt_noncurrent,
    "Long_Term_Investments": long_term_investments,
    "Other_Current_Assets": other_current_assets,
    "Other_Current_Liabilities": other_current_liabilities,
    "Other_Noncurrent_Liabilities": other_noncurrent_liabilities,
    "Property_Plant_Equipment": property_plant_equipment,
    "Retained_Earnings": retained_earnings,
    "Short_Term_Debt": short_term_debt,
    "Short_Term_Investments": short_term_investments,
    "Total_Assets": total_assets,
    "Current_Assets": current_assets,
    "Current_Liabilities": current_liabilities,
    "Total_Liabilities": total_liabilities,
    "Total_Noncurrent_Assets": total_noncurrent_assets,
    "Total_Noncurrent_Liabilities": total_noncurrent_liabilities,
    "Shareholder_Equity": shareholder_equity, # Target Variable, also known as Market Capitalization
    "Treasury_Stock": treasury_stock
})
```

In [23]:

```
# Print the financial metrics data frame
print(financial_metrics.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20 entries, 0 to 19
Data columns (total 84 columns):
 #   Column                                   Non-Null Count  Dtype 
---  ------                                   --------------  ----- 
 0   Date                                     20 non-null     object
 1   Comprehensive_Income_Net_of_Tax          20 non-null     object
 2   Cost_of_Revenue                          20 non-null     object
 3   COGS                                     20 non-null     object
 4   Depreciation                             20 non-null     object
 5   EBIT                                     20 non-null     object
 6   EBITDA                                   20 non-null     object
 7   Gross_Profit                             20 non-null     object
 8   Income_Before_Tax                        20 non-null     object
 9   Income_Tax_Expense                       20 non-null     object
 10  Interest_and_Debt_Expense                20 non-null     object
 11  Interest_Expense                         20 non-null     object
 12  Interest_Income                          20 non-null     object
 13  Net_Investment_Income                    20 non-null     object
 14  Net_Income                               20 non-null     object
 15  Net_Income_from_Ops                      20 non-null     object
 16  Net_Interest_Income                      20 non-null     object
 17  Non_Interest_Income                      20 non-null     object
 18  Operating Expenses                       20 non-null     object
 19  Operating_Income                         20 non-null     object
 20  Other_Non_Operating_Income               20 non-null     object
 21  RnD                                      20 non-null     object
 22  COS                                      20 non-null     object
 23  Revenue                                  20 non-null     object
 24  Cap_Ex                                   20 non-null     object
 25  Cash_Flow_from_Financing                 20 non-null     object
 26  Cash_Flow_from_Investment                20 non-null     object
 27  Change_in_Cash_and_Cash_Equivalents      20 non-null     object
 28  Change_in_Exchange_Rate                  20 non-null     object
 29  Change_in_Inventory                      20 non-null     object
 30  Change_in_Op_Ex                          20 non-null     object
 31  Change_in_Op_Liabilities                 20 non-null     object
 32  Change_in_Receivables                    20 non-null     object
 33  Depreciation_Depletion_Amortization      20 non-null     object
 34  Dividend_Payout_Total                    20 non-null     object
 35  Dividend_Payout_Common_Stock             20 non-null     object
 36  Dividend_Payout_Preferred_Stock          20 non-null     object
 37  Operating_Cashflow                       20 non-null     object
 38  Payments_for_Op_Activities               20 non-null     object
 39  Stock_Buybacks_Common                    20 non-null     object
 40  Stock_Buybacks_All                       20 non-null     object
 41  Stock_Buybacks_Preferred                 20 non-null     object
 42  Stock_Issuance                           20 non-null     object
 43  Cash_Raised_from_Debt_and_Equity         20 non-null     object
 44  Cash_Raised_Preferred_Stock              20 non-null     object
 45  Cash_Raised_Op_Activities                20 non-null     object
 46  Cash_Raised_from_Short_Term_Debt         20 non-null     object
 47  Net_Cash_from_Equity                     20 non-null     object
 48  Cash_Raised_Treasury_Stock               20 non-null     object
 49  Profit_Loss                              20 non-null     object
 50  Accumulated_Depreciation_Ammortization_PPE  20 non-null     object
 51  Capital_Lease_Obligations                20 non-null     object
```

```
 52  Cash_and_Cash_Equivalents_at_Carrying_Value  20 non-null     object
 53  Cash_and_Short_Term_Investments              20 non-null     object
 54  Common_Stock                                 20 non-null     object
 55  Outstanding_Shares                           20 non-null     object
 56  Current_AP                                   20 non-null     object
 57  Current_Debt                                 20 non-null     object
 58  Current_Long_Term_Debt                       20 non-null     object
 59  Current_net_receivables                      20 non-null     object
 60  Deferred_Revenue                             20 non-null     object
 61  Goodwill                                     20 non-null     object
 62  Intangible_Assets                            20 non-null     object
 63  Intangible_Assets_Excluding_Goodwill         20 non-null     object
 64  Inventory                                    20 non-null     object
 65  Investments                                  20 non-null     object
 66  Long_Term_Debt                               20 non-null     object
 67  Long_Term_Debt_Noncurrent                    20 non-null     object
 68  Long_Term_Investments                        20 non-null     object
 69  Other_Current_Assets                         20 non-null     object
 70  Other_Current_Liabilities                    20 non-null     object
 71  Other_Noncurrent_Liabilities                 20 non-null     object
 72  Property_Plant_Equipment                     20 non-null     object
 73  Retained_Earnings                            20 non-null     object
 74  Short_Term_Debt                              20 non-null     object
 75  Short_Term_Investments                       20 non-null     object
 76  Total_Assets                                 20 non-null     object
 77  Current_Assets                               20 non-null     object
 78  Current_Liabilities                          20 non-null     object
 79  Total_Liabilities                            20 non-null     object
 80  Total_Noncurrent_Assets                      20 non-null     object
 81  Total_Noncurrent_Liabilities                 20 non-null     object
 82  Shareholder_Equity                           20 non-null     object
 83  Treasury_Stock                               20 non-null     object
dtypes: object(84)
memory usage: 13.2+ KB
None
```

The data type of all these variables is 'object' - which needs to be converted into numeric format for further processing.

In [24]:

```python
# Convert Any occurence of "None" to 0.  This will stave off later errors occurring in converting.
financial_metrics = financial_metrics.replace("None", 0)

# Date Column
financial_metrics.Date = pd.to_datetime(financial_metrics.Date) # ISO Formant

# Columns with Numbers;
financial_metrics.loc[:, financial_metrics.columns != "Date"] = financial_metrics.loc[:, financial_metrics.columns != "Date"].astype('int64')

# Check!
print(financial_metrics.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20 entries, 0 to 19
Data columns (total 84 columns):
 #   Column                                     Non-Null Count  Dtype
---  ------                                     --------------  -----
 0   Date                                       20 non-null     datetime64[ns]
 1   Comprehensive_Income_Net_of_Tax            20 non-null     int64
 2   Cost_of_Revenue                            20 non-null     int64
 3   COGS                                       20 non-null     int64
 4   Depreciation                               20 non-null     int64
 5   EBIT                                       20 non-null     int64
 6   EBITDA                                     20 non-null     int64
 7   Gross_Profit                               20 non-null     int64
 8   Income_Before_Tax                          20 non-null     int64
 9   Income_Tax_Expense                         20 non-null     int64
 10  Interest_and_Debt_Expense                  20 non-null     int64
 11  Interest_Expense                           20 non-null     int64
 12  Interest_Income                            20 non-null     int64
 13  Net_Investment_Income                      20 non-null     int64
 14  Net_Income                                 20 non-null     int64
 15  Net_Income_from_Ops                        20 non-null     int64
 16  Net_Interest_Income                        20 non-null     int64
 17  Non_Interest_Income                        20 non-null     int64
 18  Operating Expenses                         20 non-null     int64
 19  Operating_Income                           20 non-null     int64
 20  Other_Non_Operating_Income                 20 non-null     int64
 21  RnD                                        20 non-null     int64
 22  COS                                        20 non-null     int64
 23  Revenue                                    20 non-null     int64
 24  Cap_Ex                                     20 non-null     int64
 25  Cash_Flow_from_Financing                   20 non-null     int64
 26  Cash_Flow_from_Investment                  20 non-null     int64
 27  Change_in_Cash_and_Cash_Equivalents        20 non-null     int64
 28  Change_in_Exchange_Rate                    20 non-null     int64
 29  Change_in_Inventory                        20 non-null     int64
 30  Change_in_Op_Ex                            20 non-null     int64
 31  Change_in_Op_Liabilities                   20 non-null     int64
 32  Change_in_Receivables                      20 non-null     int64
 33  Depreciation_Depletion_Amortization        20 non-null     int64
 34  Dividend_Payout_Total                      20 non-null     int64
 35  Dividend_Payout_Common_Stock               20 non-null     int64
 36  Dividend_Payout_Preferred_Stock            20 non-null     int64
 37  Operating_Cashflow                         20 non-null     int64
 38  Payments_for_Op_Activities                 20 non-null     int64
 39  Stock_Buybacks_Common                      20 non-null     int64
 40  Stock_Buybacks_All                         20 non-null     int64
 41  Stock_Buybacks_Preferred                   20 non-null     int64
 42  Stock_Issuance                             20 non-null     int64
 43  Cash_Raised_from_Debt_and_Equity           20 non-null     int64
 44  Cash_Raised_Preferred_Stock                20 non-null     int64
 45  Cash_Raised_Op_Activities                  20 non-null     int64
 46  Cash_Raised_from_Short_Term_Debt           20 non-null     int64
 47  Net_Cash_from_Equity                       20 non-null     int64
 48  Cash_Raised_Treasury_Stock                 20 non-null     int64
 49  Profit_Loss                                20 non-null     int64
 50  Accumulated_Depreciation_Ammortization_PPE 20 non-null     int64
 51  Capital_Lease_Obligations                  20 non-null     int64
```

```
 52  Cash_and_Cash_Equivalents_at_Carrying_Value  20 non-null     int64
 53  Cash_and_Short_Term_Investments              20 non-null     int64
 54  Common_Stock                                 20 non-null     int64
 55  Outstanding_Shares                           20 non-null     int64
 56  Current_AP                                   20 non-null     int64
 57  Current_Debt                                 20 non-null     int64
 58  Current_Long_Term_Debt                       20 non-null     int64
 59  Current_net_receivables                      20 non-null     int64
 60  Deferred_Revenue                             20 non-null     int64
 61  Goodwill                                     20 non-null     int64
 62  Intangible_Assets                            20 non-null     int64
 63  Intangible_Assets_Excluding_Goodwill         20 non-null     int64
 64  Inventory                                    20 non-null     int64
 65  Investments                                  20 non-null     int64
 66  Long_Term_Debt                               20 non-null     int64
 67  Long_Term_Debt_Noncurrent                    20 non-null     int64
 68  Long_Term_Investments                        20 non-null     int64
 69  Other_Current_Assets                         20 non-null     int64
 70  Other_Current_Liabilities                    20 non-null     int64
 71  Other_Noncurrent_Liabilities                 20 non-null     int64
 72  Property_Plant_Equipment                     20 non-null     int64
 73  Retained_Earnings                            20 non-null     int64
 74  Short_Term_Debt                              20 non-null     int64
 75  Short_Term_Investments                       20 non-null     int64
 76  Total_Assets                                 20 non-null     int64
 77  Current_Assets                               20 non-null     int64
 78  Current_Liabilities                          20 non-null     int64
 79  Total_Liabilities                            20 non-null     int64
 80  Total_Noncurrent_Assets                      20 non-null     int64
 81  Total_Noncurrent_Liabilities                 20 non-null     int64
 82  Shareholder_Equity                           20 non-null     int64
 83  Treasury_Stock                               20 non-null     int64
dtypes: datetime64[ns](1), int64(83)
memory usage: 13.2 KB
None
```

Feature Engineering

In [25]:

```
# Convert Any occurence of "None" to 0.  This will stave off later errors occurring in converting.
financial_metrics = financial_metrics.replace("None", 0)

# Format the Date Column
financial_metrics.Date = pd.to_datetime(financial_metrics.Date, format='%Y-%m-%d') # ISO Format

# Convert the numbers
financial_metrics.loc[:, financial_metrics.columns != "Date"] = financial_metrics.loc[:, financial_metrics.columns != "Date"].astype('int64')

#### Add Several Financial Metrics

# Gross Profit Margin
# Gross Profit Margin = (Revenue - Cost of Sales) / Revenue * 100
# This measures the percentage of revenue after subtracting the cost of goods sold (does not include overhead -- operating expenses, interest, or taxes)
financial_metrics["Gross_Profit_Margin"] = ((financial_metrics.Revenue - financial_metrics.COGS) / financial_metrics.Revenue)

# Net Profit Margin
# Net Profit Margin = Net Profit / Revenue * 100
# This measures the percentage of revenue and other incomei s left after subtracting all costs for the business, including COGs and overhead (OpEx, Interest, and Taxes)
financial_metrics["Net_Profit_Margin"] = ((financial_metrics.Profit_Loss / financial_metrics.Revenue) * 100)

# Working Capital
# Working Capital = Current Assets - Current Liabilities
# This measures the business’s available operating liquidity, which can be used to fund day-to-day operations.
financial_metrics["Working_Capital"] = (financial_metrics.Current_Assets - financial_metrics.Current_Liabilities)

# Current Ratio
# Current Ratio = Current Assets / Current Liabilities
# This is a liquidity ratio that helps understand whether the business can pay its short-term obligations—that is (liabilities due at or within 1 yr).
financial_metrics["Current_Ratio"] = financial_metrics.Current_Assets / financial_metrics.Current_Liabilities

# Quick Ratio (Acid Test Ratio)
# Quick Ratio = (Current Assets - Inventory) / Current Liabilities
# liquidity ratio that measures a business’s ability to handle short-term obligations. The quick ratio uses only highly liquid current assets, such as cash, marketable securities,
financial_metrics["Quick_Ratio"] = ((financial_metrics.Current_Assets - financial_metrics.Inventory) / financial_metrics.Current_Liabilities)

# Leverage Ratio ("Equity Multiplier")
# Leverage = Total Assets / Total Equity
# refers to the use of debt to buy assets. If all the assets are financed by equity, the multiplier is one. As debt increases, the multiplier increases from one, demonstrating the
financial_metrics["Leverage_Ratio"] = financial_metrics.Total_Assets / financial_metrics.Shareholder_Equity

# Debt-to-Equity Ratio
# Debt to Equity Ratio = Total Debt / Total Equity
# solvency ratio that measures how much a company finances itself using equity versus debt. This ratio provides insight into the solvency of the business by reflecting the ability
financial_metrics["Debt-to-Equity_Ratio"] = ((financial_metrics.Long_Term_Debt + financial_metrics.Short_Term_Debt) / financial_metrics.Shareholder_Equity)

# Earning per Share
# ROA = Net Profit / (Beginning Total Assets + Ending Total Assets) / 2
# another profitability ratio, similar to ROE, which is measured by dividing net profit by the company’s average assets. It’s an indicator of how well the company is managing its a
financial_metrics["EPS"] = (financial_metrics.Revenue / financial_metrics.Outstanding_Shares)

# These calculations product some columns with float64 values.  While they are decimals, they do not need to be as long as float64.  This creates problems later.
financial_metrics.Gross_Profit_Margin = financial_metrics.Gross_Profit_Margin.astype("float16")
financial_metrics.Net_Profit_Margin = financial_metrics.Net_Profit_Margin.astype("float16")
financial_metrics.Current_Ratio = financial_metrics.Current_Ratio.astype("float16")
financial_metrics.Quick_Ratio = financial_metrics.Quick_Ratio.astype("float16")
financial_metrics.Leverage_Ratio = financial_metrics.Leverage_Ratio.astype("float16")
```

```
financial_metrics["Debt-to-Equity_Ratio"] = financial_metrics["Debt-to-Equity_Ratio"].astype("float16")
financial_metrics["EPS"] = financial_metrics["EPS"].astype("float16")
```

In [26]:

```
# Check!
print(financial_metrics.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20 entries, 0 to 19
Data columns (total 92 columns):
 #   Column                                    Non-Null Count  Dtype
---  ------                                    --------------  -----
 0   Date                                      20 non-null     datetime64[ns]
 1   Comprehensive_Income_Net_of_Tax           20 non-null     int64
 2   Cost_of_Revenue                           20 non-null     int64
 3   COGS                                      20 non-null     int64
 4   Depreciation                              20 non-null     int64
 5   EBIT                                      20 non-null     int64
 6   EBITDA                                    20 non-null     int64
 7   Gross_Profit                              20 non-null     int64
 8   Income_Before_Tax                         20 non-null     int64
 9   Income_Tax_Expense                        20 non-null     int64
 10  Interest_and_Debt_Expense                 20 non-null     int64
 11  Interest_Expense                          20 non-null     int64
 12  Interest_Income                           20 non-null     int64
 13  Net_Investment_Income                     20 non-null     int64
 14  Net_Income                                20 non-null     int64
 15  Net_Income_from_Ops                       20 non-null     int64
 16  Net_Interest_Income                       20 non-null     int64
 17  Non_Interest_Income                       20 non-null     int64
 18  Operating Expenses                        20 non-null     int64
 19  Operating_Income                          20 non-null     int64
 20  Other_Non_Operating_Income                20 non-null     int64
 21  RnD                                       20 non-null     int64
 22  COS                                       20 non-null     int64
 23  Revenue                                   20 non-null     int64
 24  Cap_Ex                                    20 non-null     int64
 25  Cash_Flow_from_Financing                  20 non-null     int64
 26  Cash_Flow_from_Investment                 20 non-null     int64
 27  Change_in_Cash_and_Cash_Equivalents       20 non-null     int64
 28  Change_in_Exchange_Rate                   20 non-null     int64
 29  Change_in_Inventory                       20 non-null     int64
 30  Change_in_Op_Ex                           20 non-null     int64
 31  Change_in_Op_Liabilities                  20 non-null     int64
 32  Change_in_Receivables                     20 non-null     int64
 33  Depreciation_Depletion_Amortization       20 non-null     int64
 34  Dividend_Payout_Total                     20 non-null     int64
 35  Dividend_Payout_Common_Stock              20 non-null     int64
 36  Dividend_Payout_Preferred_Stock           20 non-null     int64
 37  Operating_Cashflow                        20 non-null     int64
 38  Payments_for_Op_Activities                20 non-null     int64
 39  Stock_Buybacks_Common                     20 non-null     int64
 40  Stock_Buybacks_All                        20 non-null     int64
 41  Stock_Buybacks_Preferred                  20 non-null     int64
 42  Stock_Issuance                            20 non-null     int64
 43  Cash_Raised_from_Debt_and_Equity          20 non-null     int64
 44  Cash_Raised_Preferred_Stock               20 non-null     int64
 45  Cash_Raised_Op_Activities                 20 non-null     int64
 46  Cash_Raised_from_Short_Term_Debt          20 non-null     int64
 47  Net_Cash_from_Equity                      20 non-null     int64
 48  Cash_Raised_Treasury_Stock                20 non-null     int64
 49  Profit_Loss                               20 non-null     int64
 50  Accumulated_Depreciation_Ammortization_PPE  20 non-null     int64
 51  Capital_Lease_Obligations                 20 non-null     int64
```

```
 52  Cash_and_Cash_Equivalents_at_Carrying_Value  20 non-null     int64
 53  Cash_and_Short_Term_Investments              20 non-null     int64
 54  Common_Stock                                 20 non-null     int64
 55  Outstanding_Shares                           20 non-null     int64
 56  Current_AP                                   20 non-null     int64
 57  Current_Debt                                 20 non-null     int64
 58  Current_Long_Term_Debt                       20 non-null     int64
 59  Current_net_receivables                      20 non-null     int64
 60  Deferred_Revenue                             20 non-null     int64
 61  Goodwill                                     20 non-null     int64
 62  Intangible_Assets                            20 non-null     int64
 63  Intangible_Assets_Excluding_Goodwill         20 non-null     int64
 64  Inventory                                    20 non-null     int64
 65  Investments                                  20 non-null     int64
 66  Long_Term_Debt                               20 non-null     int64
 67  Long_Term_Debt_Noncurrent                    20 non-null     int64
 68  Long_Term_Investments                        20 non-null     int64
 69  Other_Current_Assets                         20 non-null     int64
 70  Other_Current_Liabilities                    20 non-null     int64
 71  Other_Noncurrent_Liabilities                 20 non-null     int64
 72  Property_Plant_Equipment                     20 non-null     int64
 73  Retained_Earnings                            20 non-null     int64
 74  Short_Term_Debt                              20 non-null     int64
 75  Short_Term_Investments                       20 non-null     int64
 76  Total_Assets                                 20 non-null     int64
 77  Current_Assets                               20 non-null     int64
 78  Current_Liabilities                          20 non-null     int64
 79  Total_Liabilities                            20 non-null     int64
 80  Total_Noncurrent_Assets                      20 non-null     int64
 81  Total_Noncurrent_Liabilities                 20 non-null     int64
 82  Shareholder_Equity                           20 non-null     int64
 83  Treasury_Stock                               20 non-null     int64
 84  Gross_Profit_Margin                          20 non-null     float16
 85  Net_Profit_Margin                            20 non-null     float16
 86  Working_Capital                              20 non-null     int64
 87  Current_Ratio                                20 non-null     float16
 88  Quick_Ratio                                  20 non-null     float16
 89  Leverage_Ratio                               20 non-null     float16
 90  Debt-to-Equity_Ratio                         20 non-null     float16
 91  EPS                                          20 non-null     float16
dtypes: datetime64[ns](1), float16(7), int64(84)
memory usage: 13.7 KB
None
```

Data Cleaning

In [27]:
```
# Are there any null values in the dataframe?
financial_metrics.isnull().values.any()
```

Out[27]:
```
False
```

In [28]:
```
# Add up how many Null values there are
financial_metrics.isnull().sum().sum()
```
Out[28]:
```
0
```
In [29]:
```
# Check for any infinite values
financial_metrics.isin([np.inf, -np.inf]).any().any()
```
Out[29]:
```
False
```
In [30]:
```
# Print out the whole dataframe to look for infinitie or NAN values
# print(financial_metrics.to_markdown()) # uncomment if any of the above is true
```

Add the Target Variable (Stock Price)

With Alpha Vantage API, it is possible to pull the stock price on a daily, weekly, and monthly basis. However, these financial statements are only posted on a Quarterly basis. Therefore, deriving the stock price means pulling it from the dates the reports are filed and adding it to the report. Unfortunately, this is a premium feature in Alpha Vantage API, so we are going to use yfinance to download that data and add it to the dataframe.

In [31]:
```
# Note there may be a cap on how many requests the Yahoo Finance API may fill.
# If there are too many requests, the following error may be displayed.
```
In [32]:
```
# Assign the Variable
symbol = ticker

# Sample DataFrame with dates
data = {'Date': financial_metrics.Date.tolist()}
df = pd.DataFrame(data)

# Download historical closing prices for the stock
start_date = df['Date'].min()
end_date = df['Date'].max()
stock_data = yf.download(symbol, start=start_date, end=end_date)
stock_data = stock_data[['Close']]
```
```
[*********************100%***********************]  1 of 1 completed
```
In [33]:
```
# Add stock prices to the DataFrame based on the column of dates
def get_closing_price(date, stock_data):
    try:
        return stock_data.loc[date, 'Close']
    except KeyError:
        print(f'Error: No data found for {symbol} on {date}. Searching for the closest business day.')
        closest_date = stock_data.index.get_loc(date, method='nearest')
        return stock_data.iloc[closest_date]['Close']
```

In [34]:
```python
# Create a Dataframe from the pulled data
df['Date'] = pd.to_datetime(df['Date'])
```

In [35]:
```python
# Set the index to the date to make merging dataframes easier
df.set_index('Date', inplace=True)
```

In [36]:
```python
# Add the Closing Price data
df['Closing_Price'] = df.index.to_series().apply(get_closing_price, args=(stock_data,))
```

```
Error: No data found for AMZN on 2022-12-31 00:00:00. Searching for the closest business day.
Error: No data found for AMZN on 2019-06-30 00:00:00. Searching for the closest business day.
Error: No data found for AMZN on 2019-03-31 00:00:00. Searching for the closest business day.
Error: No data found for AMZN on 2018-09-30 00:00:00. Searching for the closest business day.
Error: No data found for AMZN on 2018-06-30 00:00:00. Searching for the closest business day.
Error: No data found for AMZN on 2018-03-31 00:00:00. Searching for the closest business day.

<ipython-input-33-5c18c6a2391e>:7: FutureWarning:

Passing method to DatetimeIndex.get_loc is deprecated and will raise in a future version. Use index.get_indexer([item], method=...) instead.
```

In [37]:
```python
# Check if the function worked
print(df)
```

```
            Closing_Price
Date
2022-12-31      84.000000
2022-09-30     113.000000
2022-06-30     106.209999
2022-03-31     162.997498
2021-12-31     166.716995
2021-09-30     164.251999
2021-06-30     172.007996
2021-03-31     154.703995
2020-12-31     162.846497
2020-09-30     157.436493
2020-06-30     137.940994
2020-03-31      97.486000
2019-12-31      92.391998
2019-09-30      86.795502
2019-06-30      96.109497
2019-03-31      90.709503
2018-12-31      75.098503
2018-09-30     100.218002
2018-06-30      84.989998
2018-03-31      68.599503
```

In [38]:

```python
# Set the Date Column as the Index for the financial_metrics dataframe
financial_metrics.set_index("Date", inplace=True)

# Merge the stock price DataFrame with the Financial Statements DataFrame
financial_metrics = financial_metrics.join(df, how="inner")

# Check the DF
print(financial_metrics.info())
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 20 entries, 2022-12-31 to 2018-03-31
Data columns (total 92 columns):
 #   Column                                     Non-Null Count  Dtype
---  ------                                     --------------  -----
 0   Comprehensive_Income_Net_of_Tax            20 non-null     int64
 1   Cost_of_Revenue                            20 non-null     int64
 2   COGS                                       20 non-null     int64
 3   Depreciation                               20 non-null     int64
 4   EBIT                                       20 non-null     int64
 5   EBITDA                                     20 non-null     int64
 6   Gross_Profit                               20 non-null     int64
 7   Income_Before_Tax                          20 non-null     int64
 8   Income_Tax_Expense                         20 non-null     int64
 9   Interest_and_Debt_Expense                  20 non-null     int64
 10  Interest_Expense                           20 non-null     int64
 11  Interest_Income                            20 non-null     int64
 12  Net_Investment_Income                      20 non-null     int64
 13  Net_Income                                 20 non-null     int64
 14  Net_Income_from_Ops                        20 non-null     int64
 15  Net_Interest_Income                        20 non-null     int64
 16  Non_Interest_Income                        20 non-null     int64
 17  Operating Expenses                         20 non-null     int64
 18  Operating_Income                           20 non-null     int64
 19  Other_Non_Operating_Income                 20 non-null     int64
 20  RnD                                        20 non-null     int64
 21  COS                                        20 non-null     int64
 22  Revenue                                    20 non-null     int64
 23  Cap_Ex                                     20 non-null     int64
 24  Cash_Flow_from_Financing                   20 non-null     int64
 25  Cash_Flow_from_Investment                  20 non-null     int64
 26  Change_in_Cash_and_Cash_Equivalents        20 non-null     int64
 27  Change_in_Exchange_Rate                    20 non-null     int64
 28  Change_in_Inventory                        20 non-null     int64
 29  Change_in_Op_Ex                            20 non-null     int64
 30  Change_in_Op_Liabilities                   20 non-null     int64
 31  Change_in_Receivables                      20 non-null     int64
 32  Depreciation_Depletion_Amortization        20 non-null     int64
 33  Dividend_Payout_Total                      20 non-null     int64
 34  Dividend_Payout_Common_Stock               20 non-null     int64
 35  Dividend_Payout_Preferred_Stock            20 non-null     int64
 36  Operating_Cashflow                         20 non-null     int64
 37  Payments_for_Op_Activities                 20 non-null     int64
 38  Stock_Buybacks_Common                      20 non-null     int64
 39  Stock_Buybacks_All                         20 non-null     int64
 40  Stock_Buybacks_Preferred                   20 non-null     int64
 41  Stock_Issuance                             20 non-null     int64
 42  Cash_Raised_from_Debt_and_Equity           20 non-null     int64
 43  Cash_Raised_Preferred_Stock                20 non-null     int64
 44  Cash_Raised_Op_Activities                  20 non-null     int64
 45  Cash_Raised_from_Short_Term_Debt           20 non-null     int64
 46  Net_Cash_from_Equity                       20 non-null     int64
 47  Cash_Raised_Treasury_Stock                 20 non-null     int64
 48  Profit_Loss                                20 non-null     int64
 49  Accumulated_Depreciation_Ammortization_PPE  20 non-null    int64
 50  Capital_Lease_Obligations                  20 non-null     int64
 51  Cash_and_Cash_Equivalents_at_Carrying_Value  20 non-null   int64
```

```
 52  Cash_and_Short_Term_Investments            20 non-null     int64
 53  Common_Stock                               20 non-null     int64
 54  Outstanding_Shares                         20 non-null     int64
 55  Current_AP                                 20 non-null     int64
 56  Current_Debt                               20 non-null     int64
 57  Current_Long_Term_Debt                     20 non-null     int64
 58  Current_net_receivables                    20 non-null     int64
 59  Deferred_Revenue                           20 non-null     int64
 60  Goodwill                                   20 non-null     int64
 61  Intangible_Assets                          20 non-null     int64
 62  Intangible_Assets_Excluding_Goodwill       20 non-null     int64
 63  Inventory                                  20 non-null     int64
 64  Investments                                20 non-null     int64
 65  Long_Term_Debt                             20 non-null     int64
 66  Long_Term_Debt_Noncurrent                  20 non-null     int64
 67  Long_Term_Investments                      20 non-null     int64
 68  Other_Current_Assets                       20 non-null     int64
 69  Other_Current_Liabilities                  20 non-null     int64
 70  Other_Noncurrent_Liabilities               20 non-null     int64
 71  Property_Plant_Equipment                   20 non-null     int64
 72  Retained_Earnings                          20 non-null     int64
 73  Short_Term_Debt                            20 non-null     int64
 74  Short_Term_Investments                     20 non-null     int64
 75  Total_Assets                               20 non-null     int64
 76  Current_Assets                             20 non-null     int64
 77  Current_Liabilities                        20 non-null     int64
 78  Total_Liabilities                          20 non-null     int64
 79  Total_Noncurrent_Assets                    20 non-null     int64
 80  Total_Noncurrent_Liabilities               20 non-null     int64
 81  Shareholder_Equity                         20 non-null     int64
 82  Treasury_Stock                             20 non-null     int64
 83  Gross_Profit_Margin                        20 non-null     float16
 84  Net_Profit_Margin                          20 non-null     float16
 85  Working_Capital                            20 non-null     int64
 86  Current_Ratio                              20 non-null     float16
 87  Quick_Ratio                                20 non-null     float16
 88  Leverage_Ratio                             20 non-null     float16
 89  Debt-to-Equity_Ratio                       20 non-null     float16
 90  EPS                                        20 non-null     float16
 91  Closing_Price                              20 non-null     float64
dtypes: float16(7), float64(1), int64(84)
memory usage: 14.3 KB
None
```

In [39]:

```
# Print out the whole dataframe to look for infinitie or NAN values
# print(financial_metrics.to_markdown()) # uncomment if need to investigate
```

Remove the target row

In [40]:
```
# Preserve the row to predict
latest_quater_df = financial_metrics.iloc[[0]]

# Remove the first row from the original DataFrame
financial_metrics = financial_metrics.iloc[1:]

# Select the relevant data to calculate the stock price
target_stock_price = latest_quater_df.Closing_Price

# Print the Target Stock Price
print(target_stock_price)
```

```
Date
2022-12-31    84.0
Name: Closing_Price, dtype: float64
```

LSTM modeling

Setup the GPU

In [41]:
```
# Setup the GPU (Google Colab)
device_name = tf.test.gpu_device_name()
if device_name != "/device:GPU:0":
  raise SystemError("GPU device not found")
print(f"Found GPU at: {device_name}")
```

```
Found GPU at: /device:GPU:0
```

Clear directores if re-running the model

In [42]:
```python
# Run only when getting a tuner file error

# Import
import shutil

# Define variables
tuner_directory = "my_dir"
project_name = "multivariate_timeseries"

# Remove the previous tuner directory if it exists
shutil.rmtree(f"{tuner_directory}/{project_name}", ignore_errors=True)
```

Load, Scale, and Assign the Data

In [43]:
```python
# 1. Load the dataset
data = financial_metrics
```

In [44]:
```python
# 2. Set the target variable
target_var = 'Closing_Price'
```

In [45]:
```python
# 3. Scale the data
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(data)
```

In [46]:
```python
# 4. Split the dataset into train and test sets (use all data for training in this case)
X_train, y_train = scaled_data[:, 1:], scaled_data[:, 0]
```

Define the Model and Hyperparameter Tuner

In [47]:
```python
# 5. Use Bayesian optimization for hyperparameter tuning
def build_model(hp):
    model = Sequential()
    model.add(LSTM(units=hp.Int('units', min_value=32, max_value=512, step=32), activation='relu', input_shape=(X_train.shape[1], 1)))
    model.add(Dropout(hp.Float('dropout', min_value=0.0, max_value=0.5, step=0.1)))
    model.add(Dense(1))
    model.compile(optimizer='adam', loss='mse')
    return model
```

In [48]:
```
tuner = BayesianOptimization(
    build_model,
    objective='val_loss',
    max_trials=25,
    executions_per_trial=5,
    directory='bayesian_optimization',
    project_name='stock_price_prediction'
)
```

```
WARNING:tensorflow:Layer lstm will not use cuDNN kernels since it doesn't meet the criteria. It will use a generic GPU kernel as fallback when running on GPU.
```

Stop. It's Model Time.

In [49]:
```
# Display the Tuner Search Space Summary
tuner.search_space_summary()
```

```
Search space summary
Default search space size: 2
units (Int)
{'default': None, 'conditions': [], 'min_value': 32, 'max_value': 512, 'step': 32, 'sampling': 'linear'}
dropout (Float)
{'default': 0.0, 'conditions': [], 'min_value': 0.0, 'max_value': 0.5, 'step': 0.1, 'sampling': 'linear'}
```

In [50]:
```
# 6. Train the model
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
```

In [51]:
```
# Search!
tuner.search(X_train, y_train, epochs=100, validation_split=0.2, verbose=1)
```

```
Trial 25 Complete [00h 02m 53s]
val_loss: 0.0004355630953796208

Best val_loss So Far: 0.0003295243484899402
Total elapsed time: 01h 03m 52s
```

In [52]:
```
# Retrieve the best hyperparameters
best_hps = tuner.get_best_hyperparameters(num_trials=1)[0]
```

In [53]:
```
# Display the Best Hyperparameters determined:
print(f"Best hyperparameters: {best_hps}")
```

```
Best hyperparameters: <keras_tuner.engine.hyperparameters.hyperparameters.HyperParameters object at 0x7f8ea01d6a30>
```

In [54]:
```python
# Define the model with the bet hyperparameters
model = tuner.hypermodel.build(best_hps)
```

```
WARNING:tensorflow:Layer lstm_1 will not use cuDNN kernels since it doesn't meet the criteria. It will use a generic GPU kernel as fallback when running on GPU.
```

In [55]:
```python
# Build the model using the best hyperparamters
model.fit(X_train, y_train, epochs=100, verbose=1)
```

```
Epoch 1/100
1/1 [==============================] - 2s 2s/step - loss: 0.2541
Epoch 2/100
1/1 [==============================] - 0s 131ms/step - loss: 0.2033
Epoch 3/100
1/1 [==============================] - 0s 132ms/step - loss: 0.1581
Epoch 4/100
1/1 [==============================] - 0s 150ms/step - loss: 0.1140
Epoch 5/100
1/1 [==============================] - 0s 141ms/step - loss: 0.0678
Epoch 6/100
1/1 [==============================] - 0s 134ms/step - loss: 0.0697
Epoch 7/100
1/1 [==============================] - 0s 128ms/step - loss: 0.0445
Epoch 8/100
1/1 [==============================] - 0s 129ms/step - loss: 0.0435
Epoch 9/100
1/1 [==============================] - 0s 132ms/step - loss: 0.0455
Epoch 10/100
```

Predict the Future

In [56]:
```python
# 7. Predict the next value for "Closing_Price"
next_value_input = X_train[-1]  # Use the last sequence of the training data as input
```

In [57]:
```python
next_value_input = next_value_input.reshape((1, next_value_input.shape[0], 1))
```

In [58]:
```python
predicted_scaled_value = model.predict(next_value_input)
```

```
1/1 [==============================] - 0s 173ms/step
```

What is the Forecast?

In [59]:
```python
# 8. Unscale the output
predicted_value = scaler.inverse_transform(np.hstack((predicted_scaled_value, np.zeros((1, 91)))))[0, 0]
```

In [60]:
```python
print(f"Next predicted 'Closing_Price': {predicted_value}")
```

```
Next predicted 'Closing_Price': 1744552924.901247
```

In [61]:
```python
print(f"Next scaled predicted 'Closing_Price': {predicted_scaled_value}")
```

```
Next scaled predicted 'Closing_Price': [[0.34884927]]
```

The LSTM model does not seem to capture the price trends even in the training dataset.

Forecasting using ARIMA

Costas

Use data only till Sep-30-2022 to forecast for stock price on Dec-30-2022.

Data import

We are using the same df_prices dataframe created earlier in the data plot section.

In [17]:
```python
# Inputs
# Pick range and quantity to model
dt_from = '2020-01-01'      # Set to 0 to start from the first date
dt_to = '2022-12-30'        # Set to -1 to go till last available date
test_size = 90              # Use these many days to test going backwards from dt_to, rest to train
q_modeled = 'close'         # Quantity to model
transform = 'log'           # 'log'/'linear' transformation prior to fitting the model
```

Define data transformation

In [18]:
```python
if transform=='linear':
    transf = lambda x: x
    inv_transf = lambda x: x
elif transform=='log':
    transf = lambda x: np.log10(x)
    inv_transf = lambda x: 10**x
else:
    raise RuntimeError('Invalid transform')
```

Training

In [19]:
```
# Extract the part of the data to use in modeling
if dt_to==0:
    dt_from = df_prices.date[-1].strftime('%Y-%m-%d')
if dt_to==-1:
    dt_to = df_prices.date[0].strftime('%Y-%m-%d')
df_modelled = df_prices.loc[ (df_prices.date  >= dt_from) & (df_prices.date <= dt_to), ['date',q_modeled] ]
df_modelled.rename(columns={q_modeled:'price'},inplace=True)

df_train, df_test = model_selection.train_test_split(df_modelled, test_size=test_size)
modl = pm.auto_arima(transf(df_train['price'].values), start_p=1, start_q=1,
                     max_p=5, max_q=5, seasonal=False,
                     stepwise=True, suppress_warnings=True,
                     error_action='ignore')
```

Prediction

In [20]:
```
# Create predictions for the future, evaluate on test
preds_price, conf_int = modl.predict(n_periods=df_test.shape[0], return_conf_int=True)
preds_price = inv_transf(preds_price)
conf_int = inv_transf(conf_int)

df_preds = pd.DataFrame({'date':df_test['date'], 'price':preds_price,
                         'ci_lower':conf_int[:,0], 'ci_upper':conf_int[:,1]})

df_preds
```

Out[20]:

	date	price	ci_lower	ci_upper
151	2022-08-24	133.62	127.501535	140.032074
150	2022-08-25	133.62	125.049992	142.777334
149	2022-08-26	133.62	123.200866	144.920283
148	2022-08-29	133.62	121.663240	146.751841
147	2022-08-30	133.62	120.324473	148.384647
...	...	...	...	...
66	2022-12-23	133.62	86.516173	206.369559
65	2022-12-27	133.62	86.298440	206.890233
64	2022-12-28	133.62	86.082499	207.409225
63	2022-12-29	133.62	85.868317	207.926568
62	2022-12-30	133.62	85.655863	208.442292

90 rows × 4 columns

Evaluation

In [21]:
```
# Print the error:
print("Test RMSE: %.3f" % np.sqrt(mean_squared_error(df_test['price'], df_preds['price'])))
```

```
Test RMSE: 31.451
```

Plot Forecast

In [22]:
```
def plot_fit(df_train,df_test,df_preds,title='ARIMA' + str(modl.order), log_plot=False):
    """
        df_train, df_test : dataframes with columns date and price holding train and test data
        df_preds : dataframe with columns date, price, ci_upper, ci_lower holding the price
            predictions and upper and lower CIs
        title: string to show as plot title
        log_plot: set to True to make y-axis logarithmic
    """
    fig = go.Figure()
    fig.add_trace(go.Scatter(x=df_train.date, y=df_train['price'], name="train",
                        line_shape='linear'))
    fig.add_trace(go.Scatter(x=df_test.date, y=df_test['price'], name="test",
                        line_shape='linear'))
    fig.add_trace(go.Scatter(x=df_preds.date, y=df_preds['price'], name="predictions",
                        line_shape='linear'))

    fig.add_trace(go.Scatter(x=df_preds.date, y=df_preds['ci_lower'],
        fill=None,
        mode='lines',
        line_color='indigo',
        name="CI-lower"
        ))
    fig.add_trace(go.Scatter(
        x=df_preds.date, y=df_preds['ci_upper'],
        fill='tonexty',
        fillcolor='rgba(0, 0, 255, 0.1)',
        mode='lines', line_color='indigo', name="CI-upper"))

    fig.update_traces(hoverinfo='text+name')
    fig.update_layout(legend=dict(y=0.5, traceorder='reversed', font_size=16),
                    yaxis_title= stock_code + ' Stock (Adjusted for splits)',
                    title = title,
        autosize=True,
        width=1024,
        height=600)
    fig.update_yaxes(type=("log" if log_plot else "linear"))

    fig.show()

plot_fit(df_train,df_test,df_preds,log_plot=False)
```

Forecasting using Prophet

Shubham

Use data only till Sep-30-2022 to forecast for stock price on Dec-30-2022.

Data import

In [68]:

```
!pip install -q alpha-vantage
!pip install -q prophet
```

In [23]:

```python
# package imports

import pandas as pd
#pd.set_option('display.precision', 2)
from alpha_vantage.timeseries import TimeSeries
from prophet import Prophet
#print('Prophet %s' % prophet.__version__)
from plotly import graph_objs as go
from prophet.plot import plot_plotly
#from datetime import datetime
```

In [70]:

```python
"""# fetching the data
VANTAGE_KEY = 'C62Q8YVLLD1R9LO5' # Shubham's key
#stock_code = 'AMZN' # input from user

ts = TimeSeries(key=VANTAGE_KEY, output_format='pandas', indexing_type='date')
df_main, meta_data = ts.get_daily_adjusted(stock_code,outputsize='full')
df_main.rename(columns={
    '1. open':'open',
    '2. high':'high',
    '3. low':'low',
    '4. close':'close',
    '5. adjusted close':'adj_close',
    '6. volume':'volume',
    '7. dividend amount':'dividend',
    '8. split coefficient':'split'
}, inplace=True)
"""
```

Out[70]:

```
"# fetching the data\nVANTAGE_KEY = 'C62Q8YVLLD1R9LO5' # Shubham's key\n#stock_code = 'AMZN' # input from user\n\nts = TimeSeries(key=VANTAGE_KEY, output_format='pandas', indexing
_type='date')\ndf_main, meta_data = ts.get_daily_adjusted(stock_code,outputsize='full')\ndf_main.rename(columns={\n    '1. open':'open',\n    '2. high':'high',\n    '3. low':'lo
w',\n    '4. close':'close',\n    '5. adjusted close':'adj_close',\n    '6. volume':'volume',\n    '7. dividend amount':'dividend',\n    '8. split coefficient':'split'\n}, inplace
=True)\n"
```

In [24]:

```python
# Using the same df_main dataframe that was produced in the plotting section
df_main.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 5892 entries, 2023-03-31 to 1999-11-01
Data columns (total 8 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   open       5892 non-null   float64
 1   high       5892 non-null   float64
 2   low        5892 non-null   float64
 3   close      5892 non-null   float64
 4   adj_close  5892 non-null   float64
 5   volume     5892 non-null   float64
 6   dividend   5892 non-null   float64
 7   split      5892 non-null   float64
dtypes: float64(8)
memory usage: 414.3 KB
```

In [72]:
```
#df_main #.head()
```

Training

Date Range used for training: Jan-01-2020 to Sep-30-2022

Predict price for date: Dec-30-2022

In [25]:
```
# Filter training data
train_start = "2020-1-1" # input from user
train_end = "2022-9-30" # input from user
#today = pd.to_datetime("today").strftime("%Y-%m-%d")
predict_date = pd.to_datetime("2022-12-30").strftime("%Y-%m-%d") # input from user

df_training = df_main.loc[train_start:train_end]
df_training
```

```
C:\Users\vishu\AppData\Local\Temp\ipykernel_19856\3601398354.py:7: FutureWarning:

Value based partial slicing on non-monotonic DatetimeIndexes with non-existing keys is deprecated and will raise a KeyError in a future Version.
```

Out[25]:

date	open	high	low	close	adj_close	volume	dividend	split
2022-09-30	114.075	116.9200	112.8400	113.0000	113.0000	59479586.0	0.0	1.0
2022-09-29	115.600	116.0700	113.0600	114.8000	114.8000	58969714.0	0.0	1.0
2022-09-28	114.380	118.7000	113.8000	118.0100	118.0100	55763750.0	0.0	1.0
2022-09-27	117.195	118.3200	113.0500	114.4100	114.4100	60094693.0	0.0	1.0
2022-09-26	113.295	117.3400	113.1300	115.1500	115.1500	62723268.0	0.0	1.0
...	...	...	...	...	...	...	...	...
2020-01-08	94.902	95.5500	94.3220	94.5985	94.5985	3511966.0	0.0	1.0
2020-01-07	95.225	95.6945	94.6020	95.3430	95.3430	4134010.0	0.0	1.0
2020-01-06	93.000	95.1845	93.0000	95.1440	95.1440	4065698.0	0.0	1.0
2020-01-03	93.225	94.3100	93.2250	93.7485	93.7485	3766604.0	0.0	1.0
2020-01-02	93.750	94.9005	93.2075	94.9005	94.9005	4035910.0	0.0	1.0

693 rows × 8 columns

In [26]:

```
# prepare the dataframe for prophet
# adjusted close values are the 'y' and the date-time index is the 'ds'
df_training = df_training[['adj_close']]
df_training = df_training.reset_index()
df_training.columns = ['ds', 'y']
df_training
```

Out[26]:

	ds	y
0	2022-09-30	113.0000
1	2022-09-29	114.8000
2	2022-09-28	118.0100
3	2022-09-27	114.4100
4	2022-09-26	115.1500
...	...	...
688	2020-01-08	94.5985
689	2020-01-07	95.3430
690	2020-01-06	95.1440
691	2020-01-03	93.7485
692	2020-01-02	94.9005

693 rows × 2 columns

In [27]:

```
# verify the datatypes
df_training.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 693 entries, 0 to 692
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   ds      693 non-null    datetime64[ns]
 1   y       693 non-null    float64
dtypes: datetime64[ns](1), float64(1)
memory usage: 11.0 KB
```

In [28]:

```
# define the model
model = Prophet()

# fit the model
model.fit(df_training)
```

```
17:08:25 - cmdstanpy - INFO - Chain [1] start processing
17:08:25 - cmdstanpy - INFO - Chain [1] done processing
```

Out[28]:

```
<prophet.forecaster.Prophet at 0x212a9f5ceb0>
```

Prediction

In [29]:

```
from pandas.tseries.holiday import USFederalHolidayCalendar
from pandas.tseries.offsets import CustomBusinessDay

# define US federal holidays
us_bdays = CustomBusinessDay(calendar=USFederalHolidayCalendar())

# count business days between training end date and prediction date
delta = len(pd.bdate_range(train_end, predict_date, freq=us_bdays))-1

future = model.make_future_dataframe(periods=delta, freq=us_bdays)
future
```

Out[29]:

	ds
0	2020-01-02
1	2020-01-03
2	2020-01-06
3	2020-01-07
4	2020-01-08
...	...
749	2022-12-23
750	2022-12-27
751	2022-12-28
752	2022-12-29
753	2022-12-30

754 rows × 1 columns

In [30]:

```
# use the model to make a forecast
forecast = model.predict(future)

# summarize the forecast
print(forecast[['ds', 'yhat', 'yhat_lower', 'yhat_upper']].tail())
```

```
             ds       yhat  yhat_lower  yhat_upper
749 2022-12-23  96.836858   85.664535  106.742785
750 2022-12-27  97.461640   87.220037  108.085563
751 2022-12-28  97.715631   86.444584  108.114255
752 2022-12-29  97.484673   86.828412  108.490672
753 2022-12-30  97.089492   86.364462  107.841415
```

Evaluation

In [31]:

```
# Calculate the RMSE
#df_train = df_main.loc[train_start:train_end]
df_real = df_main.loc[train_end:predict_date, 'adj_close']
df_pred1 = forecast[['ds', 'yhat']].copy()
df_pred1 = df_pred1.set_index('ds')
df_pred1 = df_pred1.loc[train_end:predict_date, 'yhat']
df_rmse = pd.concat([df_real, df_pred1], axis=1, join='inner')

print("Test RMSE: %.3f" % np.sqrt(mean_squared_error(df_rmse['adj_close'], df_rmse['yhat'])))
```

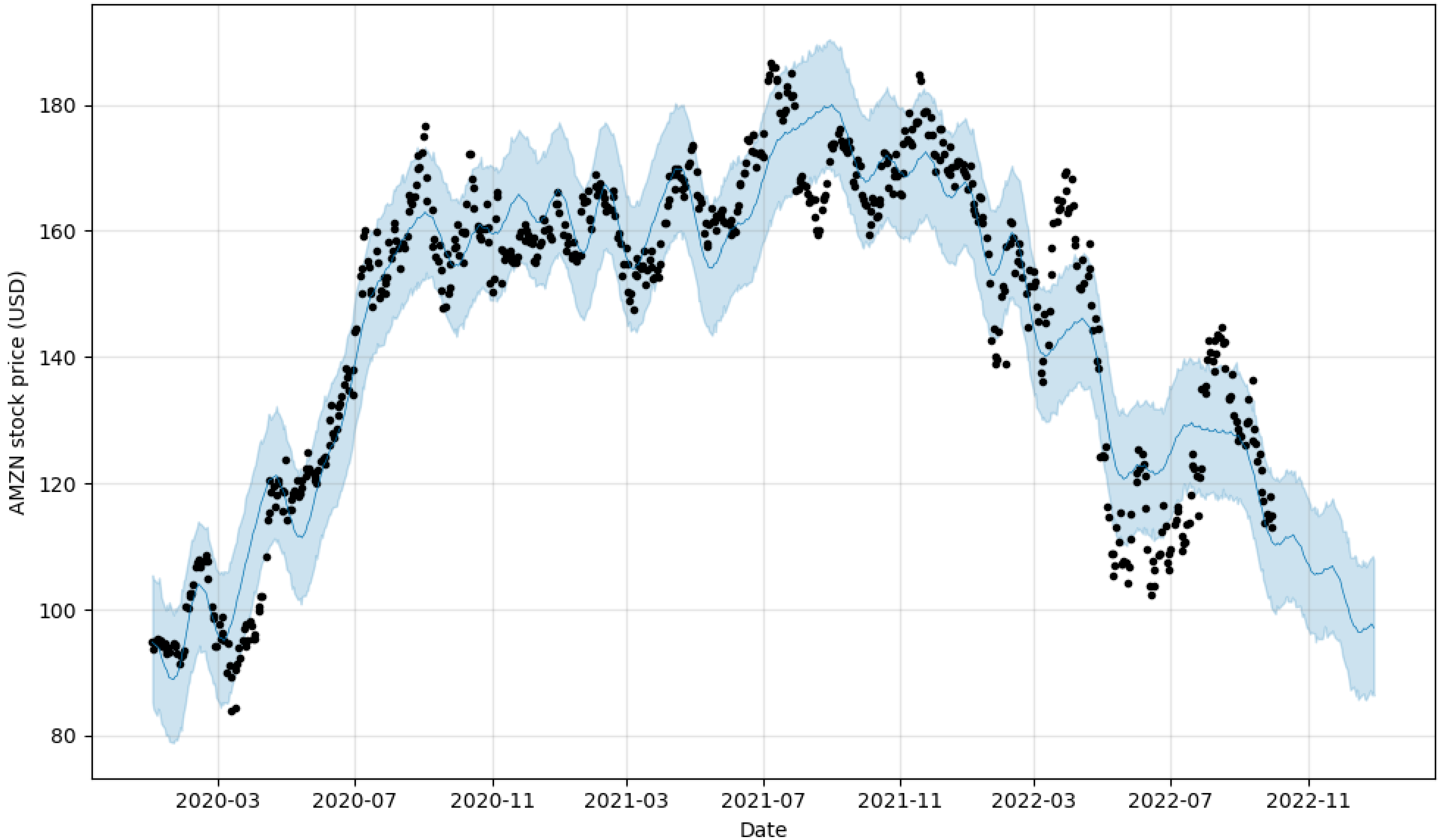
```
Test RMSE: 10.328
```

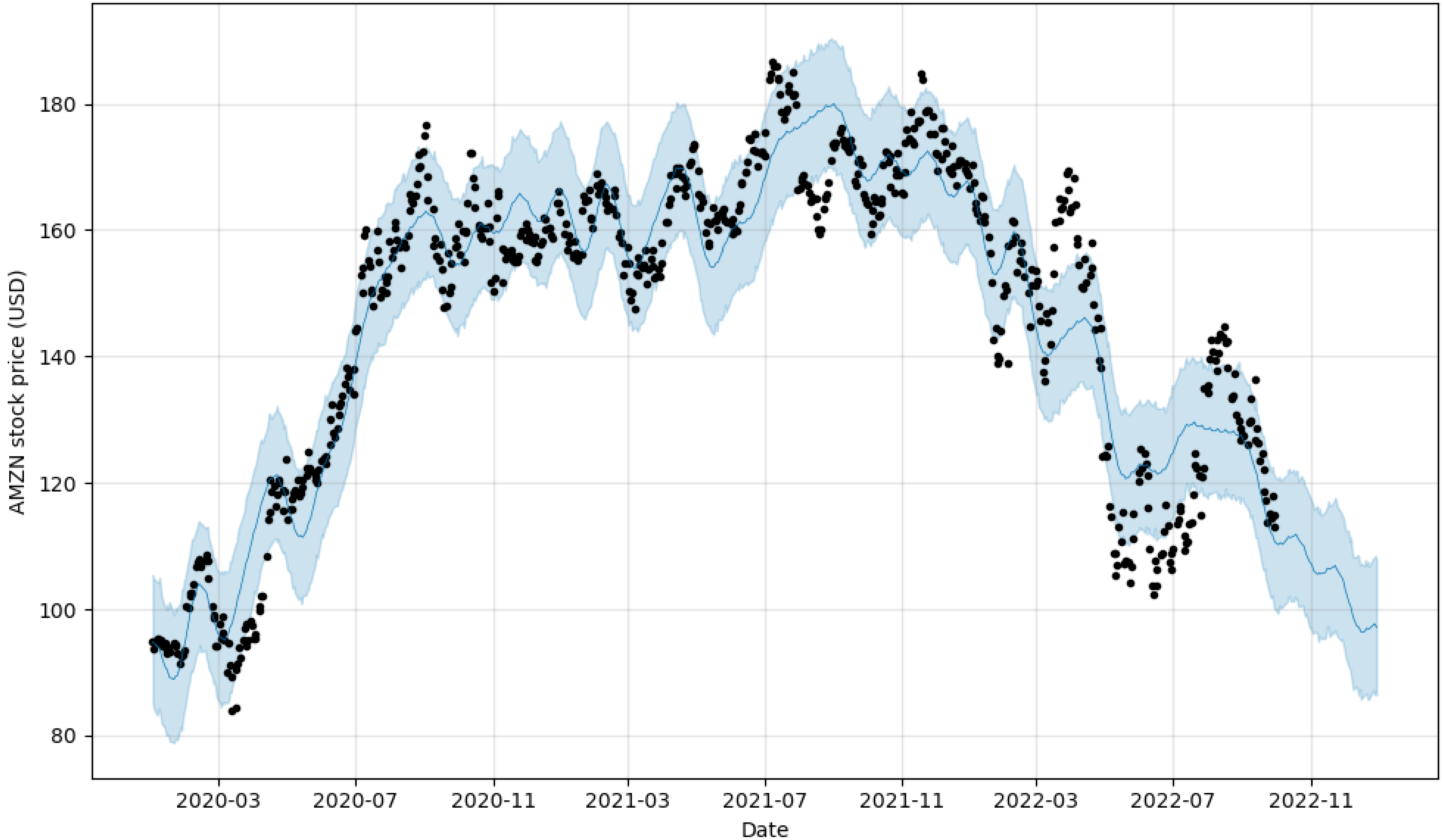
Plot Forecast

In [32]:

```
# plot forecast
model.plot(forecast, xlabel='Date', ylabel=stock_code+' stock price (USD)')
```

Out[32]:



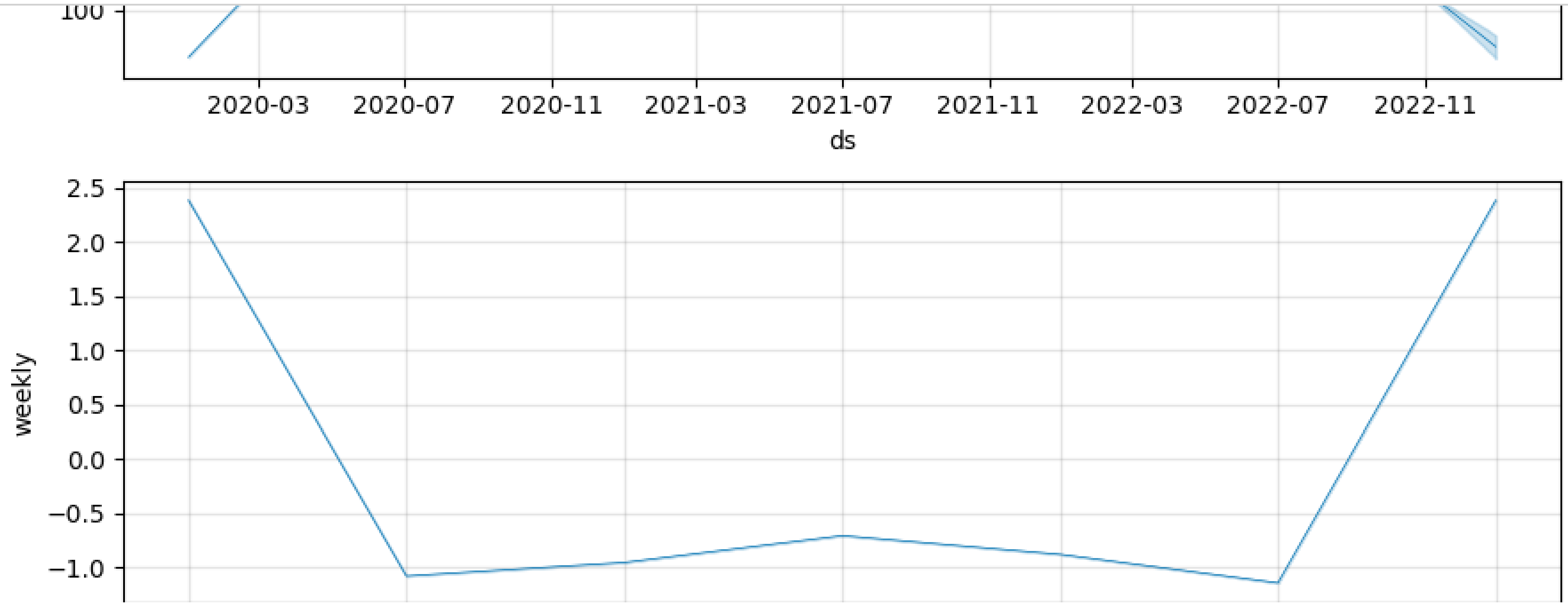


AMZN stock price (USD)
180
160
140
120
100
80
2020-03
2020-07
2020-11
2021-03
2021-07
2021-11
2022-03
2022-07
2022-11
Date

Plot Forecast Components

In [33]:

```
# Plot Forecast Components
model.plot_components(forecast)
```



Compare the results

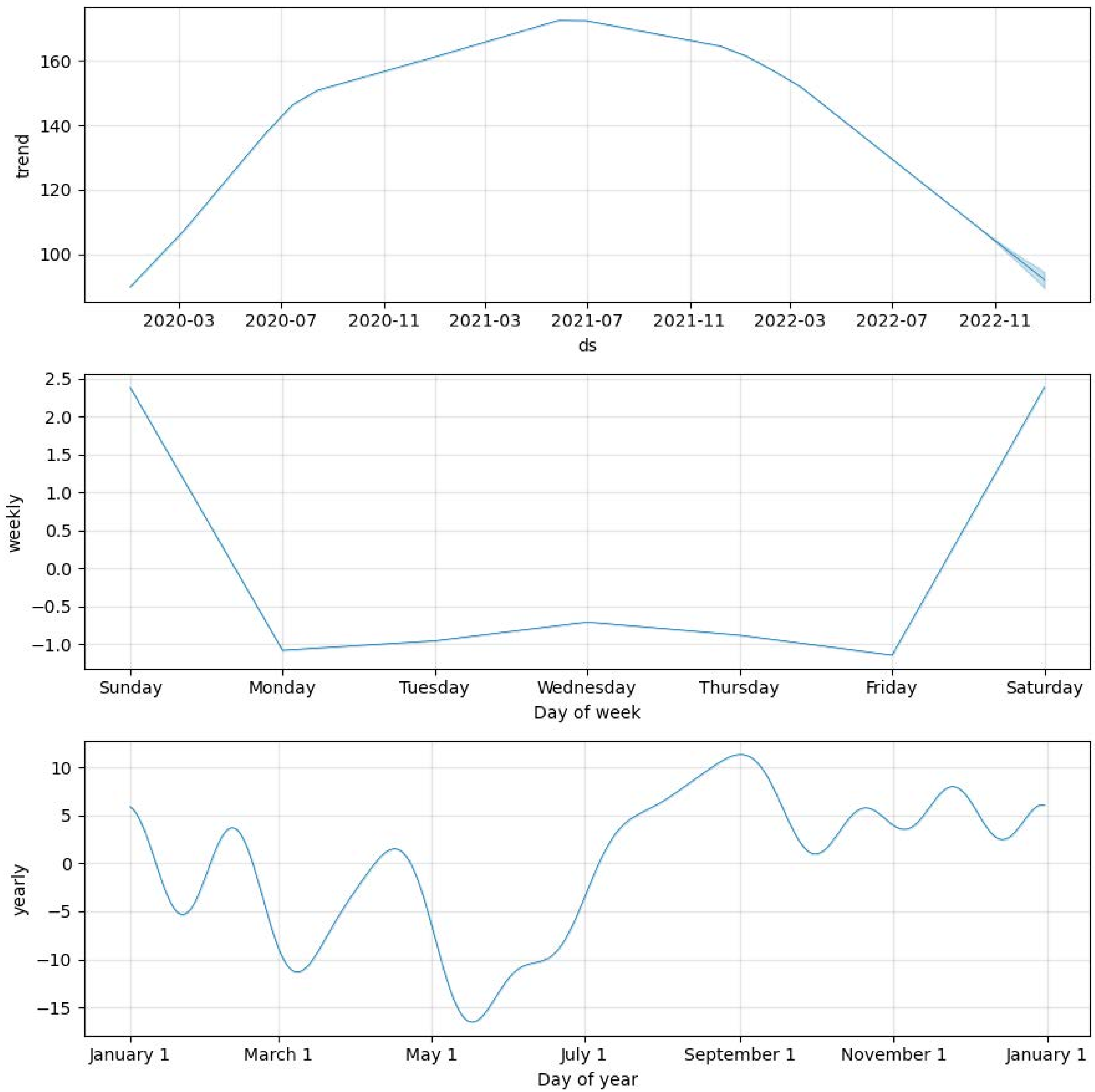
We will not use the prediction from LSTM model because the prediction is several orders of magnitude off any realistic value. Plotting it would mess up the scale of the graph.

In [34]:

```
# Create summary dataframe with dummy data for prophet, lstm
df_preds_summary = pd.DataFrame(columns=['price','ci_lower','ci_upper'])
df_preds_summary.loc['arima'] = df_preds.iloc[-1]
df_preds_summary.loc['prophet'] = [forecast.iloc[-1,:]['yhat'], forecast.iloc[-1,:]['yhat_lower'], forecast.iloc[-1,:]['yhat_upper']]
#df_preds_summary.loc['lstm'] = [120,70,160]

df_preds_summary
```

Out[34]:

	price	ci_lower	ci_upper
arima	133.62	85.655863	208.442292
prophet	97.089492	86.364462	107.841415



trend
160
140
120
100
2020-03
2020-07
2020-11
2021-03
2021-07
2021-11
2022-03
2022-07
2022-11
ds
weekly
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
−1.0
Sunday
Monday
Tuesday
Wednesday
Thursday
Friday
Saturday
Day of week
yearly
10
5
0
−5
−10
−15
January 1
March 1
May 1
July 1
September 1
November 1
January 1
Day of year

In [35]:

```python
def plot_model_comparison(df_train, df_test, df_preds_summary, title=None, log_plot=False):
    """
        df_train, df_test : dataframes with columns date and price holding train and test data
        df_preds : dataframe with columns date, price, ci_upper, ci_lower holding the price
            predictions and upper and lower CIs
        title: string to show as plot title
        log_plot: set to True to make y-axis logarithmic
    """
    fig = go.Figure()
    fig.add_trace(go.Scatter(x=df_train.date, y=df_train['price'], name="train",
                    line_shape='linear'))
    fig.add_trace(go.Scatter(x=df_test.date, y=df_test['price'], name="test",
                    line_shape='linear'))

    # Calculate the range for the horizontal line
    last_30_dates = df_test['date'].tail(30)

    def make_pred_trace(y_line, model, color, mode):
        # Add the horizontal line as a scatter trace to include it in the legend

        if mode=='pred':
            showlegend=True
            width=2
            dash=None
        else:
            showlegend=False
            width=1
            dash='dot'

        fig.add_trace(go.Scatter(
            #             x=pd.concat([last_30_dates.head(1), last_30_dates.tail(1)]),
            x=pd.concat([last_30_dates.tail(1)+timedelta(days=15),last_30_dates.tail(1)-timedelta(days=15)]),
            y=[y_line, y_line],
            name=model,
            mode='lines',
            line=dict(color=color, width=width, dash=dash),
            showlegend=showlegend
        ))

    colors = {'arima':'magenta','prophet':'green','lstm':'black'};
    for model_name, row in df_preds_summary.iterrows():
        make_pred_trace(row['price'], model_name,colors[model_name],'pred')
        make_pred_trace(row['ci_lower'], model_name,colors[model_name],'ci')
        make_pred_trace(row['ci_upper'], model_name,colors[model_name],'ci')

    # Add custom legend entries for pred/ci
    # Invisible entry for separation
    fig.add_trace(go.Scatter(
        x=[None],
        y=[None],
        mode='markers',
        name='',
        marker=dict(size=1, opacity=0)
    ))
    fig.add_trace(go.Scatter(
        x=[None],
        y=[None],
```

```
        mode='lines',
        name='Prediction',
        line=dict(color='gray', width=2),
    ))

    fig.add_trace(go.Scatter(
        x=[None],
        y=[None],
        mode='lines',
        name='CI limits',
        line=dict(color='gray', width=1, dash='dot'),
    ))

    fig.update_traces(hoverinfo='text+name')
    fig.update_layout(
                    yaxis_title= stock_code + ' Stock (Adjusted for splits)',
                    title = title,
        autosize=True,
        width=1024,
        height=600)
    fig.update_yaxes(type=("log" if log_plot else "linear"))
    fig.update_xaxes(range=['2022-1-1', '2022-12-31'])

    fig.show()

plot_model_comparison(df_train, df_test, df_preds_summary, title=None, log_plot=False)
```

Conclusion

Based on the plot above we can see that the actual value of the AMZN stock was USD 84 which was most accurately predicted by the Prophet model (USD 97). The ARIMA model's prediction came in second place at USD 134.

This is also consistent with the RMSEs obtained: 31.45 for the ARIMA model versus 10.33 for the Prophet model.

Based on these results, the Prophet model seems to be the better choice. The team will continue to repeat the experiments and decide upon a final model to be used for integrating with the user interface.

Team Contribution

- Costas
  - ARIMA modeling and prediction
- Seth
  - LSTM modeling and prediction
- Shubham
  - Prophet modeling and prediction

- Teamwork
  - Time Series Decomposition
  - Description of Time series
  - Time Series Visualizations
  - Compare and discuss the models