

7 lesson 11

# Time Series Analysis

Python for Financial Analysis

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**elvtr**

# Syllabus Review

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Introduction to Python: Python in Finance

2

Python Basic Syntax: Importing Libraries

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Working with Pandas

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Pandas Underneath the Hood: Working with NumPy

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Data Wrangling and Visualization

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Extracting Financial Insights from Charts and Graphs

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Financial Calculations with Python: Part 1

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Financial Calculations with Python: Part 2

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CAPM and Portfolio Management

10

Linear Regression

11

**Time Series Analysis**

12

Algorithmic Trading



**Bonus Class:** Cryptocurrency Beyond the Basics with a Fintech Guest Speaker

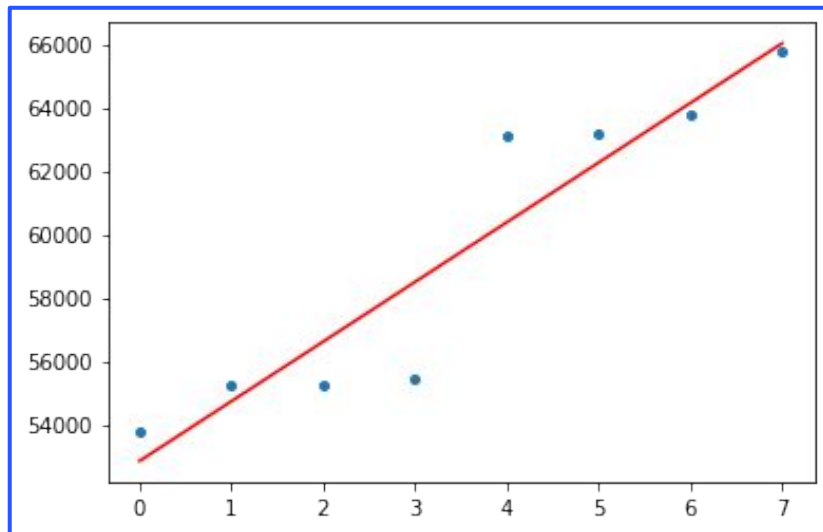
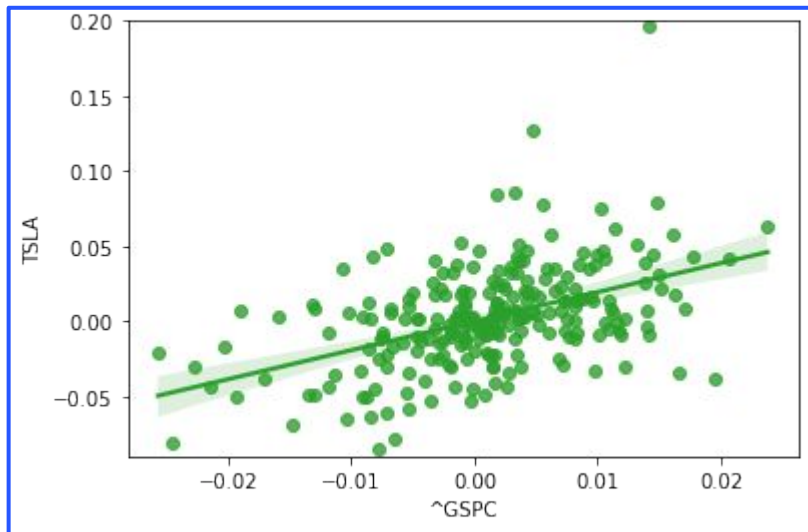
# Class agenda

- Differences between OLS and time series
- How Pandas can support time series
- Calculating SMA and EMA and defining trends
- Using statsmodels to find the trend and cycles
- ARIMA
- Graphing monthly prices with daily data
- Pythonic: Financial APIs, PyPi, and Financial libraries

# OLS vs. time series



- Time series always has (equally spaced) time on the x-axis
- Recall from chapter 10. SPX returns on x-axis (left). Years on x-axis (right)



## Differences between OLS and time series

- We'll look at USDA Milk Production
- Pandas
  - A. Simple Moving Average (SMA)
    - a. `df['6-month-SMA'] = df['price'].rolling(window=6).mean()`
  - B. Exponentially weighted Moving Average (EMA)
    - a. `df['EMA-12'] = df['price'].ewm(span=12).mean()`
    - b. Follows faster, fewer missing startups

## Time series – statsmodels

- Statsmodels – we apply tools to extract several items
  - A. Hodrick–Prescott filter separates a timeseries into
    - a. Trend
    - b. Cycle
  - B. Will also look at an ETS model (Error – Trend – Seasonality)

# Calculating SMA and EMA and defining trends

- Simple Moving Average
  - A. For 14-day SMA, calculate average of last 14 days
  - B. Roll the 14-day frame forward with each subsequent day
  - C. Has a lag
  - D. Example: `milk_df['12-month-SMA'] = milk_df['milk_B_lbs'].rolling(window=12).mean()`
- Exponentially-weighted Moving Average
  - A. Last day more heavily weighted
  - B. No lag
  - C. Example: `milk_df['EMA-12'] = milk_df['milk_B_lbs'].ewm(span=12).mean()`

# Time series – ARIMA

- AutoRegressive Integrated Moving Average
  - think AR + I + MA
  - A. Non-seasonal ARIMA
  - B. Seasonal
- ARIMA, indicated by 3 non-negative integers (p, d, q)
  - A. AutoRegression – AR (p) – performs a regression on self (“auto”)
    - i. p = number of lag observations
  - B. Integrated – I (d) – takes differences to make the time series stationary
    - i. d = number of differences
  - C. Moving Average – MA(q) – tries to minimize residual error on a moving avg
    - i. q = size of MA window
  - D. Generally set AR (p) or MA (q), but not both



# Time series – ARIMA

- AutoCorrelations
  - A. Autocorrelation (ACF) – Better at identifying MA models
    - a. How much does it autocorrelate when lagged by  $p$  units?
    - b. Gradual decline
    - c. Sharp drop-off
  - B. Partial Autocorrelation (PACF) – Better at identifying AR models
    - a. Takes into account partial correlation between RHS variables
    - b. Gradual decline suggests MA
    - c. Sharp drop after lag “ $k$ ” means use an AR with  $p=k$
- More about stationary = constant mean and variance
  - A. Detrend to get a constant mean
  - B. ADF (Augmented Dickey-Fuller) test helps us
  - C. If not stationary, we transform it with the  $p, d, q$

## What ARIMA is used for (and what it's not)

- Used for macroeconomic variables
- Used for many of the climate change models
- Not great for stocks and securities
  - A. Time is not the only driver.
  - B. Market (=trader's) sentiment exogenous to time

## Adjusting your time windows

- Can turn hourly into daily data, daily into monthly, quarterly, or annual
- See references (or module) for resample
- Can interpolate on smaller periods

# Financial APIs, PyPi, and Financial libraries

- Financial APIs
  - A. These are for getting data off a server and into Python
  - B. We have used tiingo for this
  - C. Top 7 Best Stock Market APIs (for Developers):  
<https://rapidapi.com/blog/best-stock-api/>
- PyPi
  - A. Everything Python, good and bad
  - B. Try “candlestick” or “stock API”
  - C. I have used edgar 5.4.1 for accessing the SEC Edgar database
  - D. Watch out for unloved packages!
- Financial libraries
  - A. Quick search for “best python financial libraries”
  - B. I have used backtrader to test trading systems



# Assignment #11

Download several stock prices, and plot the prices and a simple moving average.

Go Deeper: Install a financial library or API of your choice and test out some features that interest you.



# Resources

- Simple Moving Average (SMA)

Reference:

<https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.rolling.html>

- Exponentially weighted Moving Average (EMA)

Reference:

<https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.ewm.html>

Formula for EMA: <https://www.investopedia.com/terms/e/ema.asp>

- Statsmodels

Reference: <https://www.statsmodels.org/stable/index.html>

Hodrick-Prescott (HP) filter:

[https://www.statsmodels.org/stable/examples/notebooks/generated/statepace\\_cycles.html](https://www.statsmodels.org/stable/examples/notebooks/generated/statepace_cycles.html)

# Resources

- ARIMA

Reference:

<https://stats.stackexchange.com/questions/44992/what-are-the-values-p-d-q-in-arima>

- Time Series

<https://www.kaggle.com/prashant111/complete-guide-on-time-series-analysis-in-python>

<https://people.duke.edu/~rnau/4111696.htm>

- ACF and PACF interpretation

<https://people.duke.edu/~rnau/411arim3.htm>

<https://towardsdatascience.com/identifying-ar-and-ma-terms-using-acf-and-pacf-plots-in-time-series-forecasting-ccb9fd073db8>

- Resample

Reference:

<https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.resample.html>

<https://www.geeksforgeeks.org/python-pandas-dataframe-resample/>

Q&A