

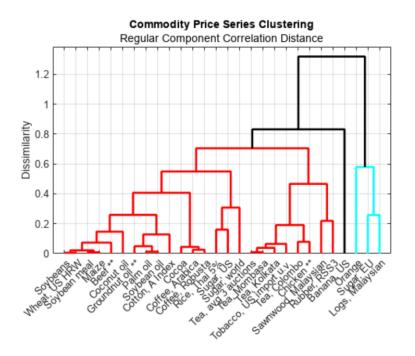
**Project:** Build a realistic volatility estimate for use in estimating loss on a portfolio of soft commodities.

https://github.com/malphons/QRM QuantitativeRiskMgt.git

In this project, a portfolio manager has handed you a set of weights which are equally weighted across a portfolio of soft commodity investments. The price series on these investments have been adjusted for inflation.

Soft commodities refer to agricultural products that are grown rather than mined or extracted. These commodities are typically perishable and have a shorter shelf life compared to hard commodities like metals or energy resources. Soft commodities are highly influenced by uncertainties arising from climate change-induced shifts in weather patterns, both in the short and the long term. With the growing magnitude of these uncertainties, volatility modeling is becoming increasingly crucial. Practitioners are actively seeking to enhance their ability to forecast market responses to climate change impacts, emphasizing the importance of volatility modeling for soft commodities.

The goal of this example is to provide insights into the patterns and dynamics of volatility in the soft commodities market and to improve the accuracy of volatility forecasts. With more accurate forecasts, market participants can make more informed decisions to effectively manage risk in the face of climate-related uncertainties.





## **Key Steps**

- Import the data from Excel (adjustedSoftCommodityPrices.xlsx) or the MAT file (InflationAdjustedCommodityPrices.mat)
- 1. Model #1 (Standard Deviation assume no correlation between the returns):

Calculate the long-term vol of the portfolio by calculating the individual volatilities of the securities and estimating the monthly volatility as follows.

Portfolio Volatility = 
$$\sqrt{\left(\frac{1}{n}\right)\sum_{i=1}^{n}\sigma_{i}^{2}}$$

n is the number of securities in the portfolio

 $\sigma_i$  is the volatility of security i

2. Model #2: (Standard Deviation – with correlation):

Calculate the long-term vol of the portfolio accounting for correlation.

$$ext{Portfolio Volatility} = \sqrt{\sum_{i=1}^n \sum_{j=1}^n w_i w_j \sigma_i \sigma_j 
ho_{ij}}$$

n is the number of securities in the portfolio

 $w_i$  is the weight of security i in the portfolio

 $\sigma_i$  is the volatility of security i

 $ho_{ij}$  is the correlation coefficient between securities i and j

3. Model #3: Estimate a non-parametric volatility (EWMA with lambda = 0.94)

$$y_1 = r_1^2$$
,  $y_n = \lambda y_{n-1} + (1 - \lambda)r_n^2$ ,  $\lambda \in [0, 1]$ ,  $n \ge 2$ 

For each security calculate a non-parametric volatility and then combine them assuming no correlation between the securities. (Similar to step #1)

4. **Model #4:** Estimate an AR model for each timeseries and create a portfolio volatility estimate. For this model use different time frames for the estimate.

2010-2012: Adverse weather event (droughts in the US & Russia) resulting in volatility spikes

2015-2016: El Nino resulted in erratic weather conditions globally

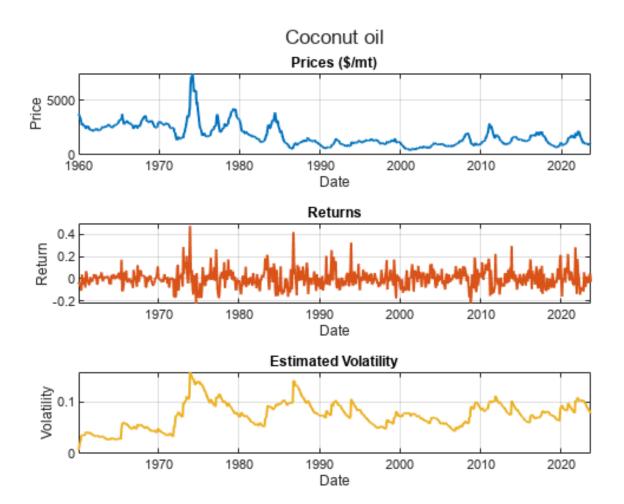
2010-2012: Weather-related concerns, trade tensions, and the COVID-19 pandemic.

5. Model #6: Build a custom model that makes sense to you to estimate the portfolio volatility.



# Fill out this table

| Mode | Model         | Number of     | Score    | Rational for the model |
|------|---------------|---------------|----------|------------------------|
| I #  |               | parameters in | (User    |                        |
|      |               | the model     | defined) |                        |
|      |               | that you use. |          |                        |
| 1    | Std Vol       |               |          |                        |
| 2    | Std Vol (With |               |          |                        |
|      | correlation)  |               |          |                        |
| 3    | EWMA          |               |          |                        |
|      | AR Model      |               |          |                        |
| 4a   | 2010-2012     |               |          |                        |
| 4b   | 2015-2016     |               |          |                        |
| 4c   | 2019-2020     |               |          |                        |
| 5    | Custom        |               |          |                        |





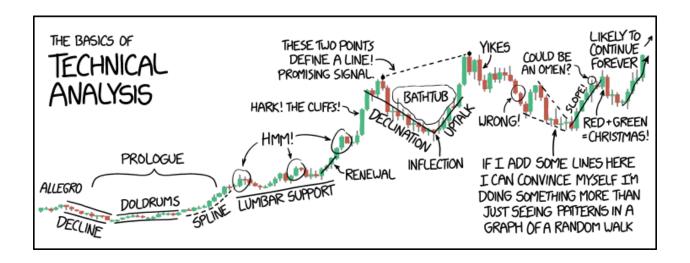
### Questions to answer -

#### **Important Note:**

- \* Please include any assumptions around the answers.
- \* My portfolio is worth \$100 Million in equity
  - 1. What monthly portfolio volatility forecast would you recommend to the risk manager?
  - 2. What would be my potential 1-month worst loss estimate?
  - 3. What are the minimum and maximum losses on the portfolio that we should plan for?
  - 4. In simple language, explain to Chief Investment Officer and the Chief Risk Officer, what loss we should plan for and what is the rational for the recommendation. Do not use technical jargon in the explanation.

## Things to remember

The current state of the art in volatility forecasting leans heavily on humans understanding the nature of the market. In this exercise you are selecting amongst a series of pre-defined models. As you get more experience in the field, you will learn to blend models and intuition into more coherent estimates of future volatility.





### Appendix A

Volatility spikes in the soft commodities market can occur due to various factors, including weather events, geopolitical tensions, supply chain disruptions, changes in demand, and macroeconomic conditions. Here are a few notable periods of volatility spikes in recent years and the macro conditions that may have contributed to them:

- 1. **2010-2012:** This period saw significant volatility spikes in soft commodities such as wheat, corn, and soybeans. One of the primary drivers was adverse weather conditions, including droughts in key agricultural regions such as the United States and Russia. These weather events led to concerns about crop yields and supply shortages, contributing to heightened price volatility. Additionally, macroeconomic factors such as increased demand from emerging economies and the weakening of the US dollar also played a role.
- 2. **2015-2016:** Soft commodities experienced volatility spikes during this period due to a combination of factors. El Niño weather patterns led to erratic weather conditions in various parts of the world, affecting crop production. In addition, currency fluctuations, particularly the strengthening of the US dollar, impacted commodity prices. Economic slowdowns in China and other emerging markets also influenced demand dynamics.
- 3. 2019-2020: Volatility in the soft commodities market surged again, driven by weather-related concerns, trade tensions, and the COVID-19 pandemic. Adverse weather conditions, such as floods and droughts in key agricultural regions, affected crop yields and supply chains. Trade disputes between major economies, particularly the US-China trade tensions, added uncertainty to commodity markets. The COVID-19 pandemic further disrupted supply chains, labor availability, and demand patterns, contributing to heightened volatility.

Macro conditions to be aware of during periods of volatility spikes in the soft commodities market include:



- Weather Patterns: Keep an eye on weather forecasts and patterns, as adverse weather events such as droughts, floods, hurricanes, and frosts can significantly impact crop yields and supply dynamics.
- Global Economic Conditions: Changes in global economic conditions, including economic growth rates, inflation, interest rates, and currency movements, can influence demand for soft commodities and affect prices.
- Trade Policies and Geopolitical Tensions: Trade policies, tariffs, and geopolitical tensions between major trading partners can disrupt supply chains, affect export/import dynamics, and lead to uncertainty in commodity markets.
- Crop Reports and Production Estimates: Pay attention to crop reports, production estimates, and planting intentions released by government agencies and industry organizations, as they provide insights into supply and demand fundamentals.
- Government Policies and Subsidies: Government policies related to agricultural subsidies, export/import regulations, biofuel mandates, and food security initiatives can have significant implications for soft commodity markets.

By monitoring these macro conditions and factors, market participants can better understand and anticipate volatility spikes in the soft commodities market and adjust their strategies accordingly.