macro_mercati

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1 Macro-Financial variables and Returns

In this project, we investigate how major macro-financial variables influence the daily returns of the U.S. stock market. Using data collected through the yfinance API, we analyze a set of key economic indicators — Treasury yields, crude oil prices, the U.S. Dollar Index, and gold prices — together with the S&P 500 index, taken as the benchmark for the equity market.

The analysis covers the period from 2015 to 2025 and begins by computing daily log-returns for all assets in order to work with stationary, scale-independent series. We then estimate a multiple linear regression model where the S&P 500 log-return is the dependent variable, and the four macro-financial variables serve as regressors. The model is fitted using Ordinary Least Squares (OLS) to quantify the direction and magnitude of each variable's impact on stock market movements.

To better understand the structure of the data, we examine the correlation matrix among all variables and visualize it through a heatmap. We further assess model adequacy by inspecting the residuals versus fitted values plot, which helps identify potential violations of OLS assumptions. Finally, we compute the Variance Inflation Factors (VIF) to evaluate multicollinearity among regressors and verify the stability of coefficient estimates.

Overall, this work provides an empirical assessment of how daily changes in interest rates, commodity prices, and currency dynamics are associated with fluctuations in the U.S. equity market. The results offer useful insights into the macro-financial forces that contribute to short-term market behavior.

1.1 Import e download dei dati

This block imports all the necessary libraries for data collection, manipulation, visualization, and statistical modeling. We define a set of financial market tickers, including the S&P 500 index, Treasury yields, crude oil prices, the U.S. Dollar Index, and gold futures.

Using the yfinance API, we download daily historical price data for the period 2015–2025. The Close prices are then extracted from the downloaded dataset, forming the basis for the return calculations used in the regression analysis.

Finally, the first rows of the dataset are displayed to verify that the data has been downloaded correctly.

[1]:

```python
import yfinance as yf
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Symbols:
# ^GSPC = S&P500
# ^TNX  = 10yr Treasury Yield
# CL=F  = Crude Oil WTI
# DX-Y.NYB = Dollar Index (DXY)
# GC=F = Gold Futures

tickers = ["^GSPC", "^TNX", "CL=F", "DX-Y.NYB", "GC=F"]
data: pd.DataFrame | None = yf.download(
    tickers, start="2015-01-01", end="2025-01-01", progress=False
)

assert data is not None
close = data["Close"]
print(close.head())
```

```
/tmp/ipykernel_4282/1121848654.py:17: FutureWarning: YF.download() has changed
argument auto_adjust default to True
  data: pd.DataFrame | None = yf.download(

Ticker           CL=F   DX-Y.NYB        GC=F        ^GSPC   ^TNX
Date
2015-01-02  52.689999  91.080002  1186.000000  2058.199951  2.123
2015-01-05  50.040001  91.379997  1203.900024  2020.579956  2.039
2015-01-06  47.930000  91.500000  1219.300049  2002.609985  1.963
2015-01-07  48.650002  91.889999  1210.599976  2025.900024  1.954
2015-01-08  48.790001  92.370003  1208.400024  2062.139893  2.016
```

1.2 Pulizia dati e costruzione variabili

This block computes daily log-returns for all selected financial time series. We first calculate the ratio between each asset's closing price and its previous day value, and then apply the natural logarithm to obtain log-returns.

The resulting data is explicitly converted into a pandas DataFrame and cleaned by removing missing values. To improve readability, the columns are renamed according to the corresponding economic variables: oil prices, dollar index, gold prices, the S&P 500, and Treasury yields.

Finally, the first rows of the returns dataset are printed to confirm that the transformation was applied correctly.

[2]:

```
# log-returns giornalieri
ratio = close / close.shift(1)
log_ratio = np.log(ratio)
```

```
# Cast esplicito per Pylance
returns = pd.DataFrame(log_ratio).dropna()

# Rinomino le colonne con nomi più parlanti
# Ordine attuale: CL=F, DX-Y.NYB, GC=F, ^GSPC, ^TNX
returns.columns = ["Oil", "Dollar", "Gold", "SP500", "Yield"]

print(returns.head())
```

```
                 Oil    Dollar      Gold     SP500     Yield
Date
2015-01-05 -0.051603  0.003288  0.014980 -0.018447 -0.040371
2015-01-06 -0.043081  0.001312  0.012711 -0.008933 -0.037986
2015-01-07  0.014910  0.004253 -0.007161  0.011563 -0.004595
2015-01-08  0.002874  0.005210 -0.001819  0.017730  0.031237
2015-01-09 -0.008852 -0.004666  0.006270 -0.008439 -0.022574
```

```
/home/matteo/Documents/regression-timeseries/.venv/lib/python3.12/site-
packages/pandas/core/internals/blocks.py:395: RuntimeWarning: invalid value
encountered in log
  result = func(self.values, **kwargs)
```

1.3 Definizione della regressione

In this block, we set up and estimate the multiple linear regression model. The daily log-returns of the S&P 500 index are selected as the dependent variable.

The independent variables include changes in Treasury yields, oil prices, the U.S. Dollar Index, and gold prices, representing key macro-financial factors.

An intercept term is added to the design matrix, and the model is fitted using Ordinary Least Squares (OLS) via the statsmodels library. The regression summary is printed to provide coefficient estimates, significance levels, and overall model diagnostics.

$$R_{\text{SP500},t} = \beta_0 + \beta_1 \Delta\text{Yield}_t + \beta_2 \Delta\text{Oil}_t + \beta_3 \Delta\text{Dollar}_t + \beta_4 \Delta\text{Gold}_t + u_t$$

[3]:

```
# variabile dipendente: rendimento S&P500
y = returns["SP500"]

# regressori: tasso, petrolio, dollar index, oro
X = returns[["Yield", "Oil", "Dollar", "Gold"]]

# aggiungo l'intercetta
X = sm.add_constant(X)

model = sm.OLS(y, X).fit()
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  SP500   R-squared:                       0.147
Model:                            OLS   Adj. R-squared:                  0.145
Method:                 Least Squares   F-statistic:                     107.4
Date:                Mon, 17 Nov 2025   Prob (F-statistic):           1.49e-84
Time:                        22:52:28   Log-Likelihood:                 7886.5
No. Observations:                2506   AIC:                        -1.576e+04
Df Residuals:                    2501   BIC:                        -1.573e+04
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.0004      0.000      1.873      0.061   -1.82e-05       0.001
Yield          0.1072      0.007     14.824      0.000       0.093       0.121
Oil            0.0709      0.007      9.668      0.000       0.056       0.085
Dollar        -0.3585      0.052     -6.855      0.000      -0.461      -0.256
Gold           0.0501      0.025      1.978      0.048       0.000       0.100
==============================================================================
Omnibus:                      542.820   Durbin-Watson:                   2.198
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            12871.178
Skew:                          -0.424   Prob(JB):                         0.00
Kurtosis:                      14.070   Cond. No.                         256.
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
```

1.4 Heatmap delle correlazioni

This block computes and visualizes the correlation matrix of all log-return series. The corr() function is used to quantify linear relationships between the S&P 500 returns and the selected macro-financial variables.

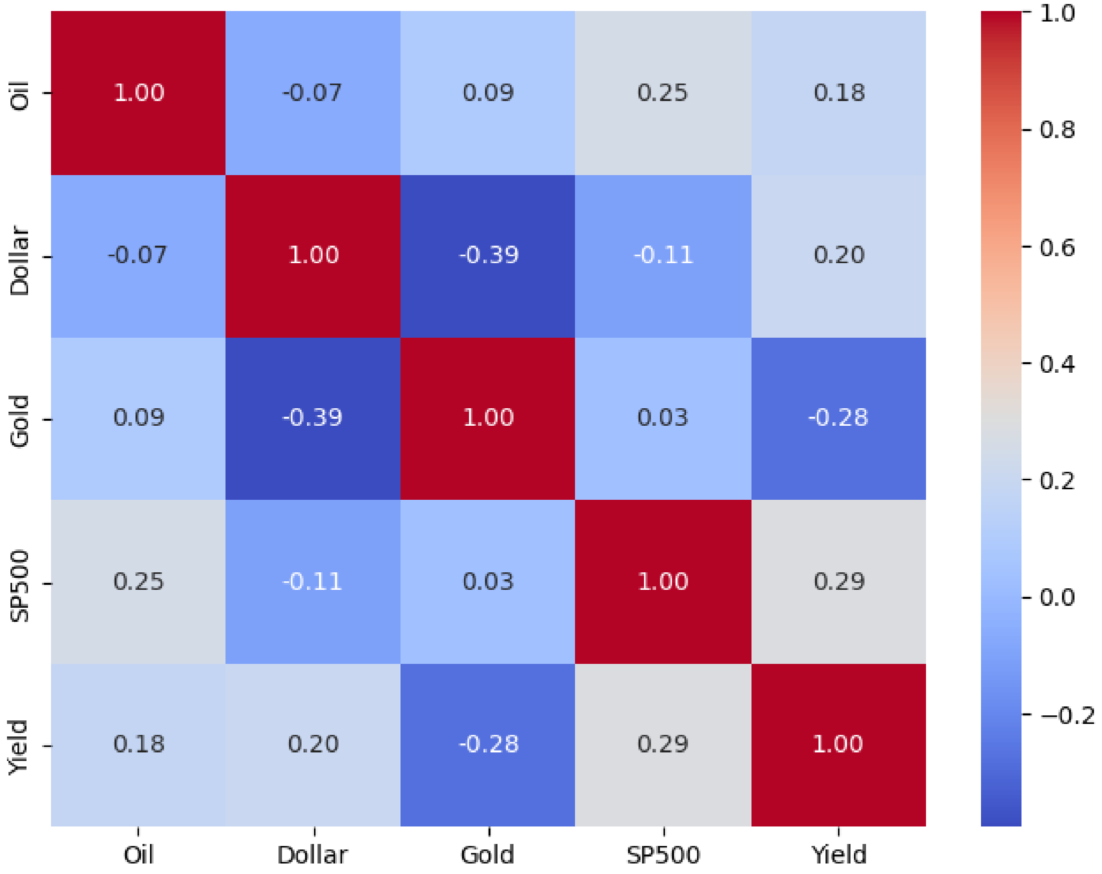
A heatmap is then generated using Seaborn to provide a clear and intuitive graphical representation of the correlation structure.

The color scale helps highlight positive and negative correlations, offering useful insights into the interdependencies among the variables before running more advanced diagnostics.

[4]:

```python
# Adesso il linter è felice
corr_matrix = returns.corr()

plt.figure(figsize=(8, 6))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="coolwarm")
plt.show()
```



The correlation matrix summarizes the linear relationships among all log-return series included in the analysis: oil, dollar index, gold, the S&P 500, and Treasury yields. The values range from –1 to +1, where positive values indicate direct relationships and negative values indicate inverse relationships.

1.4.1 1. Oil vs. S&P 500: moderately positive correlation (+0.25)

Oil returns show a modest positive correlation with S&P 500 returns. This suggests that days of rising oil prices are often associated with rising equity markets, reflecting broader growth-driven dynamics or risk-on sentiment.

1.4.2 2. Dollar Index vs. Gold: strong negative correlation (–0.39)

The strongest relationship in the matrix is the negative correlation between the Dollar and Gold. This aligns with economic intuition:

- A stronger dollar typically makes gold more expensive for non-U.S. buyers
- Investors often move from gold into dollars during risk-off episodes

This confirms typical market behavior.

1.4.3 3. Yields vs. S&P 500: positive but modest correlation (+0.29)

Stock returns and changes in yields display a weak-to-moderate positive correlation. This reflects the short-term nature of daily returns:

- On a daily basis, equity rallies often coincide with rising yields (growth optimism)
- Over longer horizons the relationship may turn negative (discount rate effect)

So this small positive correlation is consistent with high-frequency data.

1.4.4 4. Gold vs. Yields: moderate negative correlation (−0.28)

Gold returns are negatively correlated with yield changes, consistent with their traditional roles:

- Gold is a safe-haven asset
- Treasury yields rise during risk-on or tightening phases

This inverse relationship is economically meaningful.

1.4.5 5. S&P 500 vs. other macro variables: generally weak correlations

Except for Oil and Yields, correlations with the S&P 500 are small (between −0.10 and +0.10). This suggests that:

- the daily co-movement between stocks and macro variables is limited
- macro shocks often operate through nonlinear or lagged mechanisms
- daily data tends to produce weaker correlations than weekly or monthly

This justifies the need for regression analysis to extract marginal effects.

1.5 Fitted vs Residuals (diagnostica OLS)

This block performs a residual diagnostics check by plotting residuals against the fitted values of the regression model. The scatter plot helps assess whether the assumptions of linearity and homoscedasticity are reasonably satisfied.

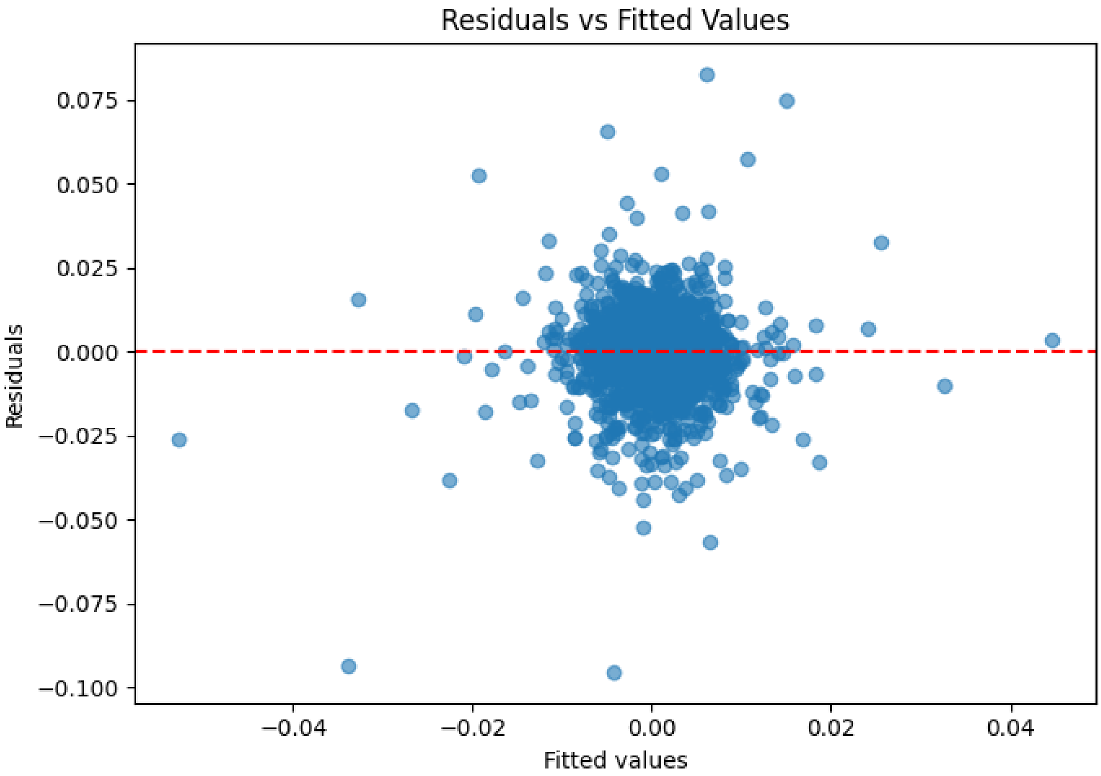
A horizontal reference line at zero residuals is added to highlight potential patterns or deviations. If the residuals appear randomly scattered around the zero line without clear structure, it indicates that the linear model is appropriately specified.

This visualization is a standard tool for evaluating the quality of the regression fit.

[5]:

```
fitted = model.fittedvalues
residuals = model.resid

plt.figure(figsize=(7, 5))
plt.scatter(fitted, residuals, alpha=0.6)
plt.axhline(0, color="red", linestyle="--")
plt.xlabel("Fitted values")
plt.ylabel("Residuals")
plt.title("Residuals vs Fitted Values")
plt.tight_layout()
plt.show()
```



The residuals–versus–fitted plot is a key diagnostic tool for evaluating whether the assumptions of the linear regression model are reasonably satisfied.

1.5.1 1. Random cloud around zero → the linear model is appropriate

In the plot, the residuals appear as a dense, symmetric cloud centered around the horizontal zero line. This is what we expect when the linear model is correctly specified:

- no systematic curvature
- no visible patterns
- no directional trend

This suggests that the relationship between the macro variables and S&P 500 returns can be reasonably approximated by a linear model.

1.5.2 2. No signs of heteroscedasticity

Heteroscedasticity occurs when the spread of residuals changes with the fitted values (e.g., funnel shape).

In the plot the spread is uniform in all directions, meaning:

- variance of residuals is roughly constant
- homoscedasticity assumption is not violated

This is good: it means the model errors have stable volatility.

1.5.3 3. No visible clusters or structure

If the plot showed clusters or diagonally aligned points, it would suggest missing variables or non-linearity. Instead, your points form a radial, isotropic cloud, which supports the idea that the included regressors capture the main linear dynamics.

This also indicates no major issues with serial correlation (which would show as arcs or waves).

1.5.4 4. Outliers exist but are rare

The few isolated points far from the central cloud correspond to days of large market shocks (e.g., high volatility events). This is totally normal in financial return data.

Outliers are expected and do not compromise the overall validity of the model.

1.6 Computo del Variance Inflation Factor (VIF)

This block computes the Variance Inflation Factor (VIF) for each explanatory variable in the regression model. The design matrix X is cast to a pandas DataFrame to ensure compatibility with downstream operations.

The VIF measures how strongly each variable is linearly related to the others, providing a diagnostic for multicollinearity.

A VIF value substantially greater than 10 typically indicates problematic collinearity that may distort coefficient estimates. The resulting table lists all regressors alongside their corresponding VIF values, helping evaluate the stability of the model.

[6]:

```
vif_df = pd.DataFrame()

# Cast esplicito per Pylance (evita warning)
X = pd.DataFrame(X)

vif_df["variable"] = X.columns
vif_df["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.
 ↪shape[1])]
vif_df
```

[6]:

```
  variable       VIF
0    const  1.002645
1    Yield  1.150311
2      Oil  1.060680
3   Dollar  1.200340
4     Gold  1.264135
```