ESILV — A4 IF1

Machine Learning Project Report

Financial Resilience Analysis
Middle Eastern vs European Markets

Authors

Erian STANLEY YOGARAJ
Ouiam BOUSSAID BENCHAARA

Supervisor

Charly Alizadeh

Course

Machine Learning

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GitHub :
https://github.com/Erian15/Machine-Learning-Project/tree/main

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1 Introduction

Financial markets do not all behave the same way when uncertainty increases. Some react violently, with sharp drops and sudden spikes in volatility, while others adjust more gradually and seem to recover faster. This difference in behaviour is often described as market resilience, meaning the ability of a market to absorb shocks, limit losses, and stabilise more quickly.

In this project, we were interested in comparing the resilience of two equity markets that are often viewed as structurally different: the Saudi Arabian market, represented by the TASI index, and the European market, represented by the EURO STOXX 50. These two regions do not rely on the same economic fundamentals. The Middle Eastern market is strongly influenced by oil prices and tends to be more insulated from global financial flows, while European equities are usually more sensitive to international stress indicators, macroeconomic announcements, and changes in investor sentiment. These differences naturally raise an important question: does the TASI behave more resiliently than the EURO STOXX 50 during global shocks?

This question matters for both investors and portfolio managers, especially in periods of high volatility, when diversification and stability become crucial. Understanding which markets resist stress better can help in building more robust portfolios and anticipating risk transmission across regions.

To explore this, we analyse the two indices from several angles. We first study their behaviour through descriptive statistics such as returns, volatility, drawdowns, and correlations. We then investigate how each market reacts to global factors like the VIX and oil prices using simple econometric models. Because volatility is a key indicator of resilience, we also model its dynamics with a GARCH framework. Finally, we use machine learning models to test whether returns are more predictable in one market than the other, which can also reflect differences in structure and stability.

2 Dataset Description

Our analysis relies on four daily financial time series, each representing a different aspect of market behaviour or global uncertainty:

- **TASI**: Tadawul All Share Index, a major benchmark for the Saudi Arabian and Middle Eastern equity market.
- **EURO STOXX 50**: a key index for large-cap European equities.

- **VIX**: the CBOE Volatility Index, commonly interpreted as a measure of global risk sentiment.
- **Brent Crude Oil Futures**: a major economic driver in the Gulf region and a potential stabilising factor for TASI.

All datasets were downloaded from *Investing.com*. They include the usual market variables (Date, Price, Open, High, Low, Volume), along with daily percentage changes. Before starting the analysis, we cleaned and standardised the data: converting dates, handling missing values, aligning trading days, and computing log-returns to allow consistent statistical comparisons.

3 Data Exploration

We explored the behaviour of each series through price charts, return distributions, rolling volatility, correlations, and drawdown curves. This step helps us identify early differences between the Middle Eastern and European markets before moving into modelling.

3.1 Price Evolution

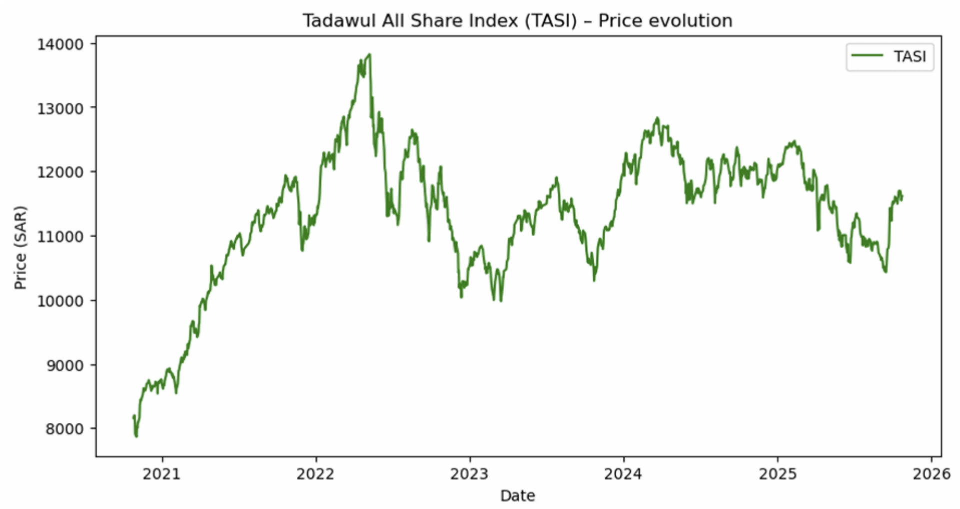

Figure 1: TASI Price Evolution

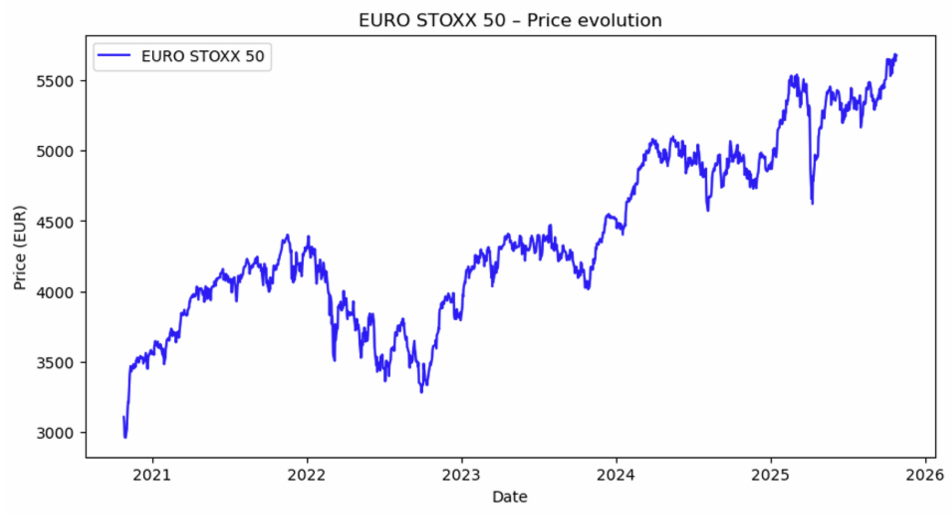

Figure 2: EURO STOXX 50 Price Evolution

TASI shows a relatively smoother upward trend with fewer abrupt shocks, while the EURO STOXX 50 exhibits more visible cycles and sharper downturns, particularly around periods of global tension. This already hints that the European market may be more sensitive to international events.

3.2 Return Distributions

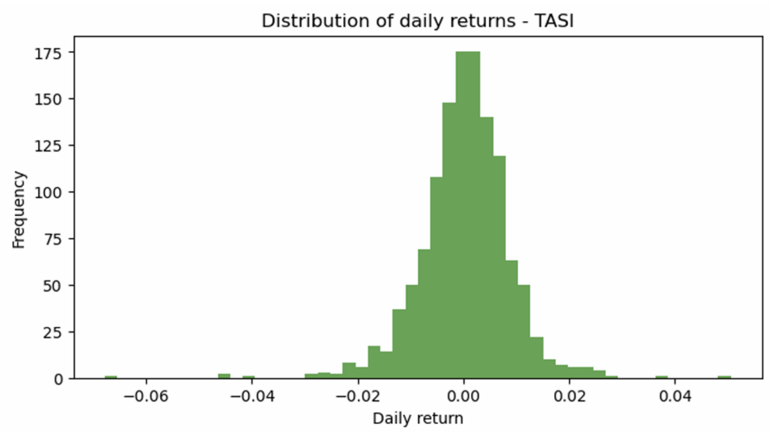

Figure 3: Distribution of Daily Returns (TASI)

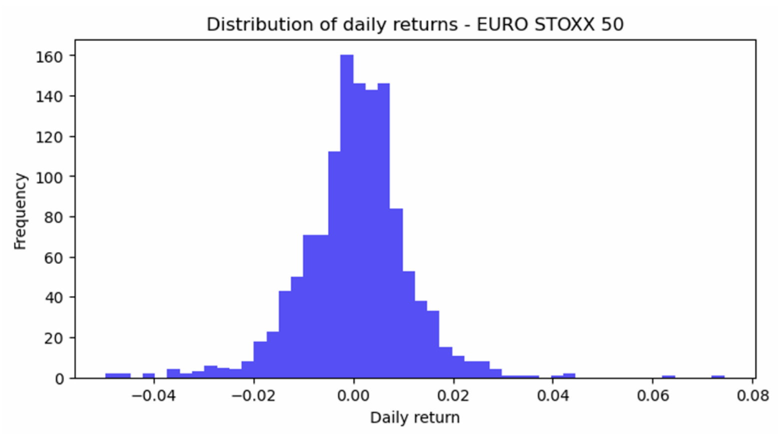

Figure 4: Distribution of Daily Returns (EURO STOXX 50)

Both distributions are centred around zero, but the EURO STOXX 50 shows heavier tails and more extreme values. TASI's distribution appears more concentrated, signalling fewer sudden movements. This supports the idea that Middle Eastern equity returns may be less volatile than their European counterparts.

3.3 Rolling Volatility

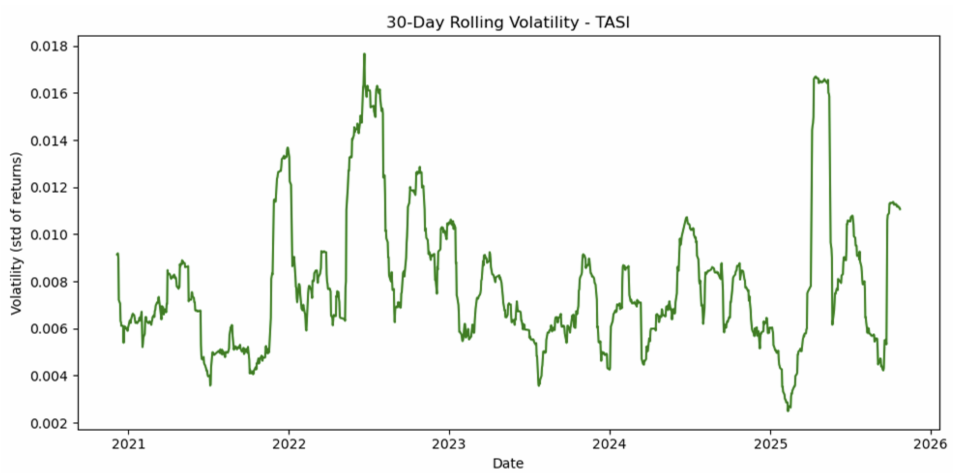

Figure 5: 30-day Rolling Volatility – TASI

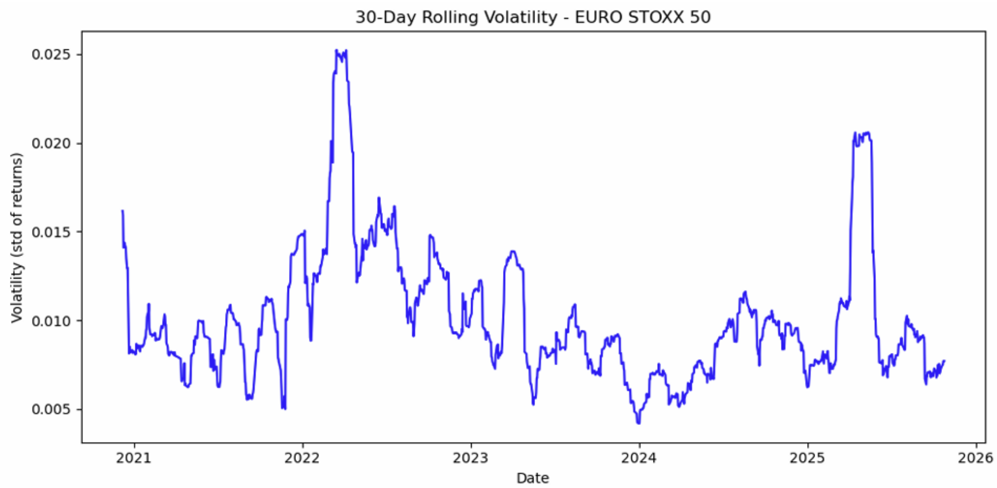

Figure 6: 30-day Rolling Volatility – EURO STOXX 50

Rolling volatility confirms the visual observation from price charts: EURO STOXX 50 volatility spikes more frequently and more sharply, while TASI remains comparatively stable. This is consistent with the hypothesis that structural factors (such as oil revenues and different investor bases) may cushion the Middle Eastern market.

3.4 Correlation Matrix of Returns

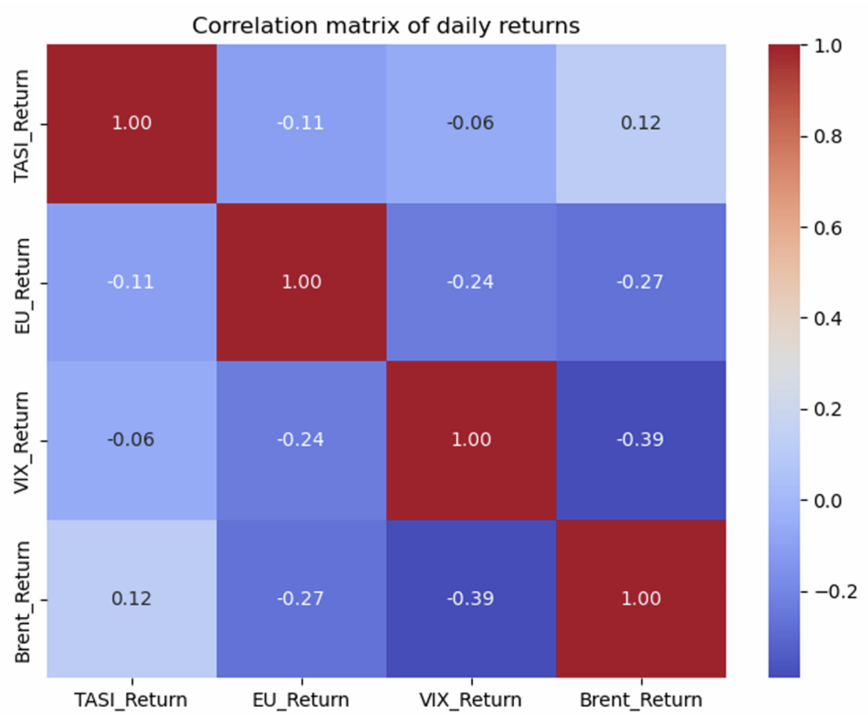

Figure 7: Correlation Matrix of Daily Returns

The correlation matrix illustrates clear differences across markets: TASI shows a weaker (and sometimes slightly negative) link with the European index and the VIX, whereas EURO STOXX 50 reacts more strongly to global risk sentiment. Brent oil behaves as expected: moderately correlated with TASI and negatively with the VIX.

3.5 Drawdown Analysis

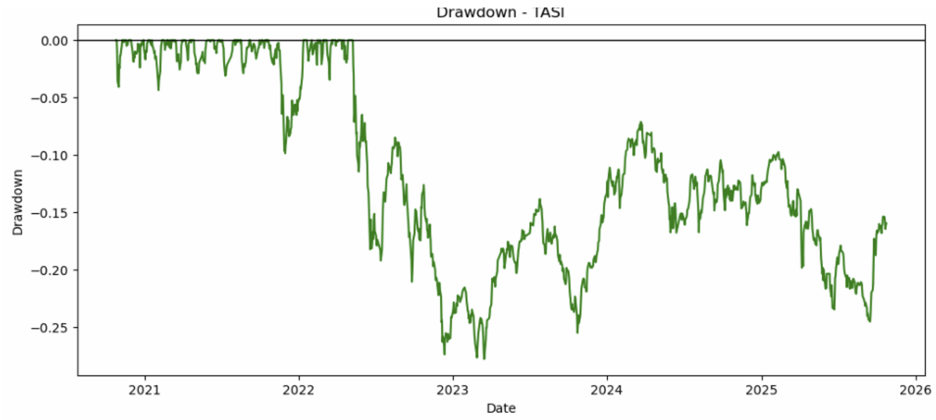

Figure 8: Drawdown Curve – TASI

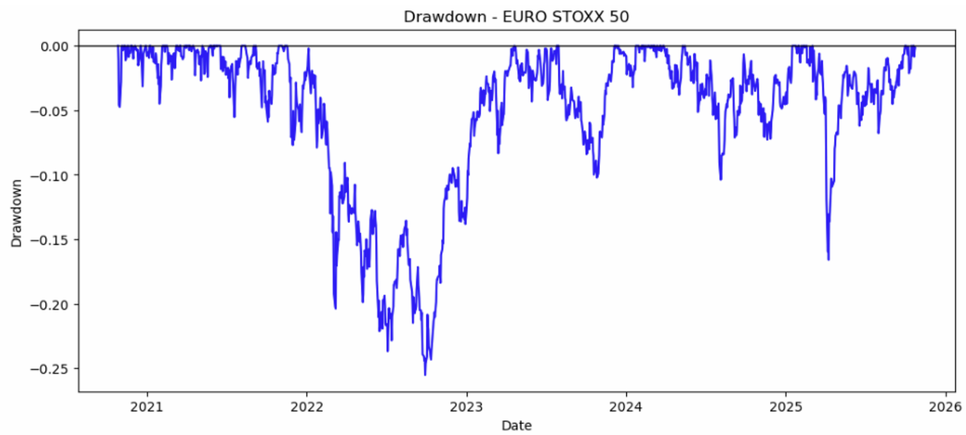

Figure 9: Drawdown Curve – EURO STOXX 50

Drawdowns provide a deeper look into how each market behaves in adverse conditions. TASI's drawdowns tend to be shallower and recover more quickly, while the EURO STOXX 50 experiences deeper and more persistent declines. This visual evidence strengthens the idea of higher resilience in the Middle Eastern market.

3.6 Rolling Correlation with Global Factors

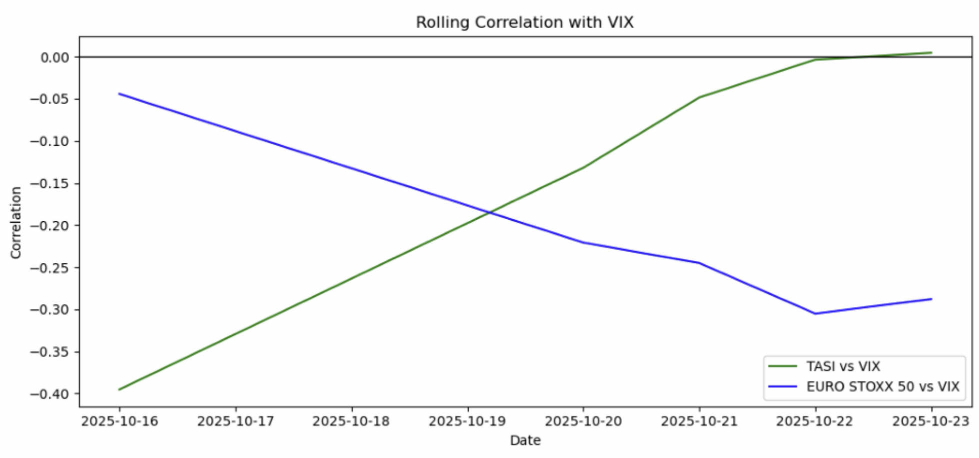

Figure 10: Rolling Correlation with VIX

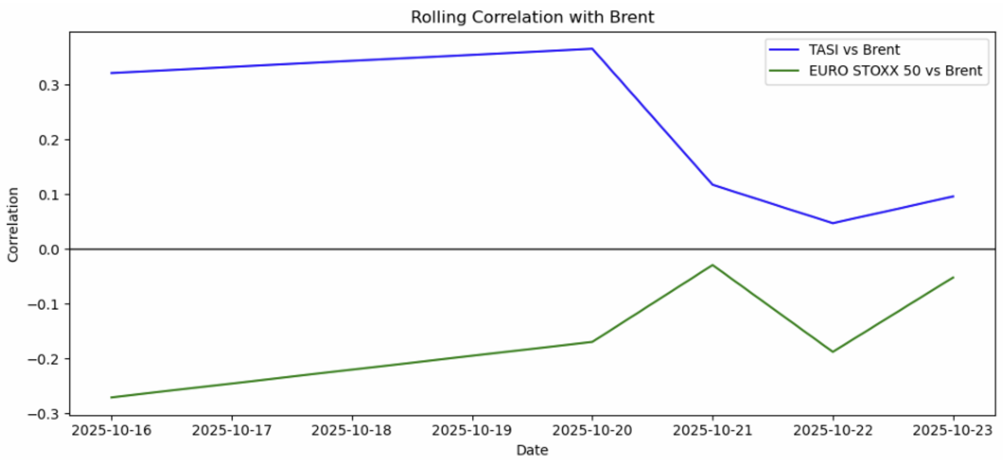

Figure 11: Rolling Correlation with Brent Oil

The rolling correlation plots provide dynamic insight:

- TASI's correlation with the VIX remains weaker and fluctuates less, meaning it is less driven by global fear indicators.
- The European index shows a stronger negative correlation with the VIX, reflecting its immediate reaction to risk-off periods.
- Brent oil maintains a stable and positive influence on TASI, as expected for an oil-dependent region.

Summary of EDA Findings

The exploratory analysis highlights several consistent patterns:

- EURO STOXX 50 is more volatile, more cyclical, and more sensitive to global financial stress.
- TASI displays smoother price dynamics, fewer extreme returns, and faster recovery from downturns.
- Correlations indicate that Europe is tightly connected to international risk factors, while TASI behaves more independently.
- Brent oil appears to stabilise the Middle Eastern market, whereas the VIX destabilises the European one.

These observations align well with the main hypothesis of the project: **TASI shows early signs of being structurally more resilient than the European market.**

4 Risk and Resilience Metrics

In order to understand how each market behaves under stress, we computed a set of classical risk metrics. Even though these indicators do not capture all dimensions of resilience, they give a first quantitative view of the stability of each index.

4.1 Volatility and Extreme Movements

Daily return volatility is one of the simplest ways to compare market behaviour. TASI shows a lower overall volatility than the EURO STOXX 50, which is consistent with what we observed in the exploratory section. The European index experiences more abrupt movements, especially during periods of global uncertainty.

We also looked at the distribution of extreme returns. EURO STOXX 50 exhibits more negative outliers, while TASI remains more concentrated around moderate variations. This suggests that severe daily shocks are more common in Europe.

4.2 Sharpe Ratio

The Sharpe ratio measures the return earned per unit of volatility. A higher Sharpe ratio indicates better risk_adjusted performance, meaning the market compensates investors more efficiently for the risk taken.

Here ,the Sharpe ratio confirms this difference: TASI achieves a slightly better return-to-risk profile over the full sample, meaning it compensates its volatility more effectively. While neither market delivers exceptional risk-adjusted performance, TASI benefits from its lower variability.

4.3 Value-at-Risk and Expected Shortfall

VaR estimates the maximum expected loss under normal market conditions for a given confidence level and Expected Shortfall measures the average loss beyond the VaR threshold. We computed 95% Value-at-Risk (VaR) and Expected Shortfall (ES) using historical simulation. EURO STOXX 50 systematically shows more severe tail-risk measures.

4.4 Drawdown-Based Resilience

Maximum drawdown and drawdown duration provide insight into how each market behaves in adverse conditions. TASI tends to experience shallower drawdowns and faster recoveries. In contrast, drawdowns in EURO STOXX 50 are both deeper and more persistent.

This difference reinforces the intuition that resilience is not only about volatility, but also about how quickly a market normalises after a shock.

Summary

These metrics show a consistent pattern:

- EURO STOXX 50 is more exposed to severe downside risk,
- TASI absorbs shocks in a less disruptive way,
- drawdown behaviour indicates faster recovery in the Middle Eastern market.

5 Econometric Analysis

To better understand how each index reacts to global factors, we estimated simple OLS regressions of daily returns on the VIX and Brent oil prices:

$$\text{Return}_t = \alpha + \beta_1 \cdot \text{VIX}_t + \beta_2 \cdot \text{Brent}_t + \varepsilon_t.$$

The goal of this model is not to predict returns, but rather to measure how sensitive each market is to these two external drivers.

5.1 Sensitivity to the VIX

For the EURO STOXX 50, the coefficient associated with the VIX is negative and statistically significant. This means that European returns tend to decrease when global financial stress rises, which is consistent with the idea that Europe is deeply integrated into global risk cycles.

On the other hand, TASI's reaction to the VIX is much weaker and far less significant. Although the sign is still negative, the magnitude is much smaller. This suggests that global risk perception affects the Middle Eastern market, but to a lesser extent than Europe.

5.2 Impact of Brent Oil Prices

Brent has a positive and significant effect on TASI returns, which makes sense for a market heavily influenced by the energy sector. When oil prices improve, the region tends to benefit from increased revenues and investment.

For the EURO STOXX 50, the Brent coefficient is small and often not significant. This confirms that oil prices do not directly influence European equities in a substantial way, at least on a daily basis.

5.3 Interpretation

The differences between the two regressions highlight an important structural divergence:

- EURO STOXX 50 is strongly driven by global risk sentiment (VIX),
- TASI is more closely linked to regional fundamentals (oil),
- the Middle Eastern market seems less exposed to international stress.

6 Predictive Modeling

Daily financial returns are notoriously difficult to predict, but machine learning can still help assess the relative stability of each market. We tested four regression models:

- Linear Regression
- Ridge Regression
- Support Vector Regression (SVR)
- Random Forest Regressor

Models were evaluated using time-series cross-validation to avoid information leakage.

6.1 Results

As expected for equity returns, predictive performance is low for all models. R-squared values are negative or close to zero, which is typical in this type of dataset.

However, an interesting pattern emerges: **across all models, TASI systematically produces less negative scores than EURO STOXX 50**. This means that its returns contain slightly more structure and are less noisy.

Even though the differences are small, they consistently favour TASI.

6.2 Interpretation

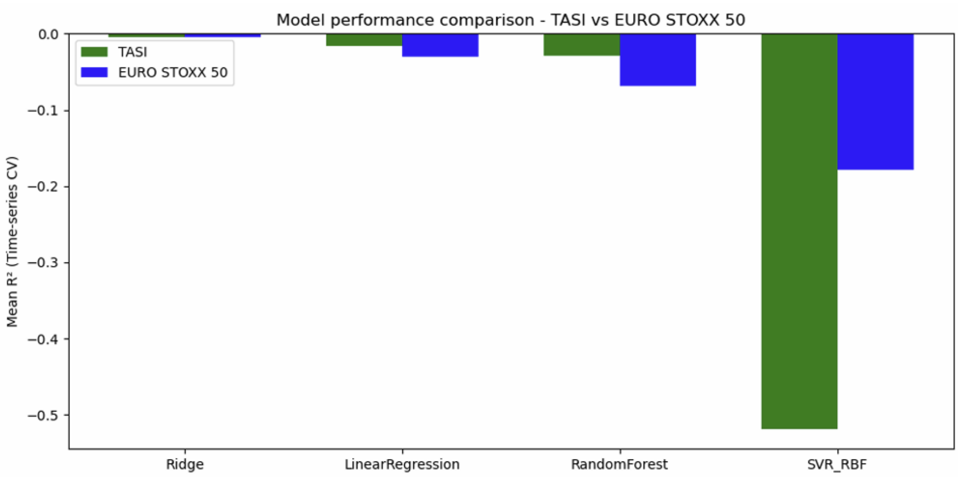

Figure 12: Rolling Correlation with VIX

The machine learning results should not be interpreted as evidence that either index is predictable. Instead, they indicate:

- TASI returns are slightly easier to approximate,
- EURO STOXX 50 behaves in a more erratic and unstable manner,
- this reinforces the notion of structural resilience in the Middle Eastern market.

7 GARCH Modeling

To complement the risk metrics and econometric analysis, we estimated GARCH(1,1) models for both indices. This model is widely used to capture volatility clustering, a common characteristic of financial time series where periods of high volatility tend to follow each other.

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$$

For both TASI and the EURO STOXX 50, the persistence term $(\alpha + \beta)$ is high, close to 0.90–0.95, which is typical for equity markets. This means volatility takes time to decay after a shock, and neither market returns immediately to a calm regime.

However, despite similar persistence levels, the **scale of volatility is different**. The European index shows consistently larger estimated variances, meaning that shocks—when they occur—tend to be more intense. TASI, on the other hand, experiences milder fluctuations even when persistence remains elevated.

7.1 Model Estimation

To estimate the volatility dynamics of each index, we rely on the `arch_model` function from the *ARCH* package in Python. The following code fits a GARCH(1,1) model to the TASI returns:

```
garch_tasi = arch_model(tasi_ret, vol="Garch", p=1, q=1, dist="normal")
res_tasi = garch_tasi.fit(update_freq=0, disp="off")
```

This command performs three essential tasks. First, it specifies a GARCH(1,1) structure, where the parameter α captures the immediate impact of new market shocks (the

ARCH effect), while β measures the persistence of past volatility (the GARCH effect). This specification is widely used because it reproduces volatility clustering, a defining property of financial time series.

Second, the `fit()` method estimates the parameters using maximum likelihood, producing the volatility process that best explains the behaviour of the returns. The arguments `update_freq=0` and `disp="off"` simply suppress intermediate output to keep the estimation log concise.

Finally, the model summary provides estimates for ω, α, and β, which correspond respectively to the unconditional variance level, the sensitivity to new shocks, and the persistence of volatility. The key diagnostic quantity is the sum $(\alpha + \beta)$: in our results, it is close to one for both indices, confirming that volatility is highly persistent and shocks decay slowly over time.

These estimation results strengthen the conclusions drawn earlier: although both markets exhibit similar persistence, the EURO STOXX 50 displays a larger scale of conditional variance, while TASI shows smoother and less intense volatility regimes.

7.2 Interpretation

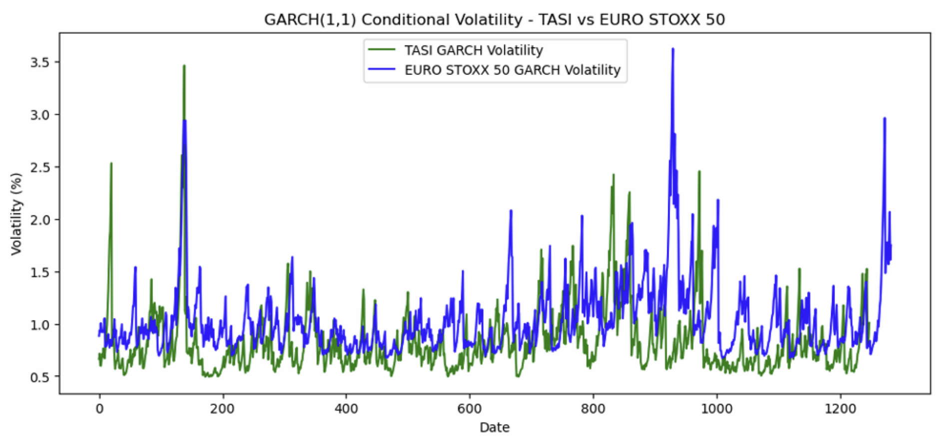

Figure 13: Rolling Correlation with VIX

The GARCH results confirm several observations from earlier sections:

- Volatility is persistent in both markets, meaning they both remember past turbulence.
- The European market experiences stronger shocks, amplifying instability during stressful periods.

- The Middle Eastern market reacts in a more contained manner, even when volatility increases.

8 Use of AI Assistance

We used AI tools such as ChatGPT only as a writing and clarification assistant throughout the project. The analyses, coding and modelling were done by us, but AI helped us in a few specific situations: mainly to restructure or rephrase technical explanations (for example GARCH, volatility concepts, or the ML models), to make our interpretations clearer, and to improve the readability of some sections of the notebook. It was also useful when we needed quick clarification on certain theoretical points before writing them in our own words. Overall, AI supported the communication of the project, while the data preparation, modelling choices, and interpretation remained entirely our own work.

9 Limitations of the Study

Our analysis provides useful insights into market resilience, but several limitations remain. First, we rely on daily price data, which simplifies the study but does not capture intraday movements or longer-term structural changes. The machine-learning models also use a restricted set of predictors (lagged returns and volatility), meaning that important macroeconomic drivers are not included.

The GARCH(1,1) model we use assumes symmetric reactions to shocks, while real markets often respond differently to bad news than to good news. More advanced volatility models could reflect this asymmetry.

Finally, our results describe patterns and co-movements based on prices alone. Structural factors such as liquidity, investor behaviour, or regulation are not captured, and correlations should not be interpreted as causal relationships.

Despite these limits, the findings remain consistent and provide a solid first exploration of resilience across the two markets.

10 Difficulties Encountered

Several challenges arose throughout the project. First, implementing and tuning the GARCH model required careful handling: the model is sensitive to data cleaning, parameter initialization, and stationarity assumptions, which sometimes led to convergence issues or unexpected volatility patterns. Interpreting the GARCH outputs (especially persistence and shock reactions) also demanded additional attention to ensure we were drawing the right conclusions.

For the machine-learning models, the main difficulty was adapting standard techniques to a time-series context. We had to avoid data leakage, build lag-based features, and use time-series cross-validation instead of random splits, which made the workflow more complex. The limited predictive power of the models also required careful interpretation, as low R^2 values are common in financial return prediction.

Another difficulty was the interpretation of all results, linking statistical outputs, econometric findings, and volatility measures back to the economic question of market resilience. Ensuring that the technical analysis remained meaningful and coherent from a financial perspective required several iterations.

Finally, we used AI assistance mostly for restructuring explanations, clarifying technical concepts, and improving the readability of certain interpretations. The methodology, code, and analysis were done manually, but AI helped us rephrase and organise our ideas more effectively.

11 Conclusion

The goal of this project was to compare how two very different equity markets, TASI and the EURO STOXX 50, react to periods of uncertainty. Across all the analyses we performed, from descriptive statistics to GARCH modelling and machine learning, the same idea kept coming back.

TASI shows a smoother behaviour overall, with fewer extreme daily movements, smaller drawdowns, and a more moderate reaction to global stress indicators such as the VIX. On the other hand, the European index reacts more sharply to market tension and displays heavier tails and stronger volatility spikes.

The econometric results also point in the same direction: while Europe is strongly influenced by global risk sentiment, TASI is more closely tied to regional factors, especially oil prices. Even though neither index is easy to predict, the machine learning models suggest that TASI behaves in a slightly more structured and stable way.

Taken together, these elements suggest that, over our sample period, **TASI appears more resilient than the EURO STOXX 50**. It does not avoid shocks, but it tends to absorb them with less intensity. This makes it an interesting market to consider in diversification or in periods of global stress.

References and Glossary

External Data Sources

All market data used in this project were downloaded from:

- **Investing.com** — historical daily prices for the Tadawul All Share Index (TASI), EURO STOXX 50, CBOE VIX Index, and Brent Oil Futures.

These datasets were manually collected (2020 - 2025) and processed before the analysis.

Glossary of Key Terms

This glossary provides short and practical definitions of the financial and technical terms used throughout the report.

Volatility A measure of how much asset returns fluctuate over time. Higher volatility indicates stronger price movements.

Rolling Window / Rolling Statistics A computation technique where metrics (mean, volatility, correlation) are recalculated over a moving time window (e.g., 30 days), allowing us to observe how behaviour evolves over time.

Drawdown The percentage decline from a market peak to the next trough. It reflects the severity of losses during downturns.

Maximum Drawdown The deepest historical drawdown observed over the entire period. A key indicator of market resilience.

Sharpe Ratio A risk-adjusted performance measure defined as the mean return divided by return volatility. A higher Sharpe Ratio indicates a better return per unit of risk.

Value-at-Risk (VaR) An estimate of the worst expected loss over a given period at a specific confidence level (e.g., 95%). It captures tail-risk in financial returns.

Expected Shortfall (ES) The average loss conditional on exceeding the VaR threshold. ES provides a deeper understanding of extreme downside risk.

Volatility Persistence In GARCH models, persistence refers to how long volatility remains elevated after a shock. High persistence means volatility decreases slowly over time.

Volatility Clustering A common market phenomenon where high-volatility periods tend to group together, as do low-volatility periods. GARCH models are designed to capture this effect.

Stationarity A property of a time series whose statistical characteristics (mean, variance) remain constant through time. Returns typically exhibit stationarity, unlike price levels.

GARCH(1,1) Model A volatility forecasting model where current volatility depends on a constant term, the previous period's shock (alpha), and the previous period's volatility (beta).

Ordinary Least Squares (OLS) A regression technique estimating how a dependent variable reacts to explanatory factors by minimizing the sum of squared errors.

Data Leakage A modelling issue where future information unintentionally enters the training data, leading to unrealistically high performance. Time-series modelling requires strict chronological separation to avoid leakage.

Overfitting A situation where a model captures noise rather than meaningful patterns, causing good performance on training data but poor generalization to new data.

Predictability in Financial Markets Due to market efficiency, financial returns are inherently difficult to forecast. Low R^2 values are normal and reflect realistic predictive limitations.