Project Title: *Market à la Mode: Comparative Analysis of Luxury Group Stocks (2015–2025)*
Author: Natthanicha Vongjarit
Tools Used: Python (Pandas), Tableau

Introduction

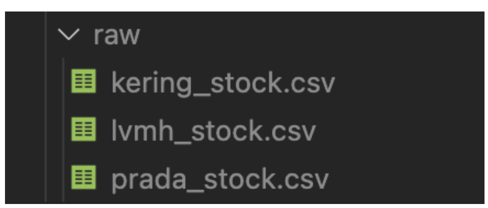
This project was inspired by my desire to merge my passion for fashion with my technical background in computer science, particularly in data analysis. The project investigates the market behavior of leading luxury conglomerates using a data-driven comparative framework.. Using Python (Pandas) for data cleaning and Tableau for visualization, I dedicated myself into hours of self study to learn and develop this project from scratch, overcoming several challenges along the way.

This project analyzes the stock performance of LVMH, Kering, and Prada Group between 2015 and 2025, focusing on how major luxury houses moved through economic cycles and post-pandemic recovery. The datasets were standardized and normalized to enable direct comparison of price evolution, yearly percentage returns, and price-movement intensity. The main goal was to identify whether these companies' stock prices move in sync and to observe how volatility and growth patterns reflect each brand's market strength.

By comparing normalized growth curves and yearly return heatmaps, the study aimed to uncover correlation trends and divergence points, revealing how LVMH maintained resilience, Kering displayed strong but uneven rebounds, and Prada showed slower, steadier recovery across the decade.

Data & Analysis

1. Raw data



    a. Prada Group: [Official Investor Relations]
    b. Kering: [Finance / Share Information]
    c. LVMH: [Investing.com – LVMH Historical Data]

2. Methodology

To compare performance across three luxury groups with different currencies, listing venues, and data granularities, the following methodological framework was applied:

Return and volatility calculation

Year-over-Year (YoY) % Return:

$$\Delta\% = \frac{P_t - P_{t-1}}{P_{t-1}} \times 100$$

Annualized Volatility

Volatility was derived from the standard deviation of period-to-period percentage changes, annualized using the square root of the number of periods per year:

$$\text{Volatility} = \sigma_r \times \sqrt{PPY}$$

where σ_r is the standard deviation of returns and PPY (Periods Per Year) is inferred from the data frequency (e.g., 12 for monthly data).

CAGR (Compounded Annual Growth Rate)

CAGR was calculated between the first and last valid price points within the analysis period (2015–2025). This metric represents the constant annual rate that would take the first price to the last price over the elapsed years.

$$\text{CAGR} = \left(P_{end} \,/\, P_{start}\right)^{1/Y} - 1$$

where Y is the total number of years between the start and end dates.

Normalization

Each company's price series was rebased to a **Base = 100** index at the starting point (2015) to visualize relative performance rather than absolute price levels.

Forecasting Model (Tableau)

A 5-year projection (2025–2030) was generated using Tableau's ETS (Exponential Smoothing) model, automatically estimating confidence intervals from historical patterns. Forecast bands visually represent uncertainty, showing expected range and directional bias (growth vs consolidation).

Note: The forecasted trends presented in Tableau were used as a reference point—not as the foundation of my written conclusions. My analysis was based primarily on historical data and visual trend interpretation; the Tableau forecast simply allowed me to validate whether my manual analysis aligned with the model's projection.

Visualization Design

The Tableau dashboard featured normalized growth curves, percentage-difference heatmaps, and forecast bands for interpretability. Each visualization emphasized trend relationships rather than absolute market values.

Note: I recognize that using static datasets instead of linking to a live, continuously updated database is not the optimal industry practice. However, this project was developed as a study-oriented exploration focused on understanding the luxury market in depth using freely available data sources. The objective was to strengthen both my technical data-analysis skills and my ability to interpret market behavior within the luxury industry context.

3. Data Cleaning & Preparation

After gathering the raw stock data from the official investor sources, all three datasets (LVMH, Kering, and Prada) were standardized using a custom Python cleaning pipeline built with **Pandas**. The goal was to unify column names, convert inconsistent date formats, standardize volume units, and prepare comparable price data for visualization.

To ensure scalability and reusability, the project was structured using a modular approach:

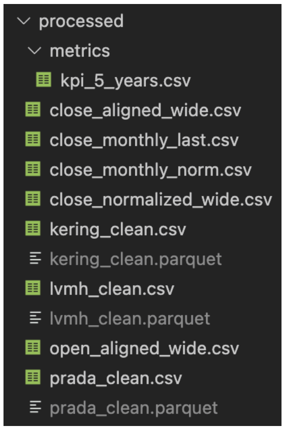
/src
└── ***pipeline/***
    └── ***cleaning.py***
/script
└── ***run_clean_all.py***

The script run_clean_all.py orchestrates the entire cleaning process — reading raw CSVs, applying cleaning functions, and exporting both cleaned and normalized versions of the data for analysis.

The helper function _parse_volume() converts shorthand units (e.g., “2.5M”, “145K”) into numeric form for accurate volume analysis.

Tabnine | Edit | Test | Explain | Document
```python
def clean_data(df: pd.DataFrame, start: str | None = None) -> pd.DataFrame:
    # to standardize columns:  Datetime (index), Open, High, Low, Close, Volume
    tmp = df.copy()

    # standardize columns' name
    tmp = tmp.rename(columns={"Vol.": "Volume", "Price": "Close"})

    # changing date to datetime type and set as index (and drop the old Date column)
    if "Datetime" in tmp.columns:
        tmp["Datetime"] = pd.to_datetime(tmp["Datetime"], errors="coerce")
    elif "Date" in tmp.columns:
        tmp["Datetime"] = pd.to_datetime(tmp["Date"], errors="coerce")

    tmp = tmp.drop(columns=["Date", "Change %"], errors="ignore").set_index("Datetime")
    tmp.index = pd.to_datetime(tmp.index)

    # standardize the volume value with the existed function
    if "Volume" in tmp.columns:
        tmp["Volume"] = _parse_volume(tmp["Volume"])

    tmp = tmp.sort_index()
    tmp = tmp[~tmp.index.duplicated(keep="last")] # delete duplicated date

    if start is not None:
        tmp = tmp.loc[str(start):]

    cols = [c for c in ["Open", "High", "Low", "Close", "Volume"] if c in tmp.columns]
    return tmp[cols]
```

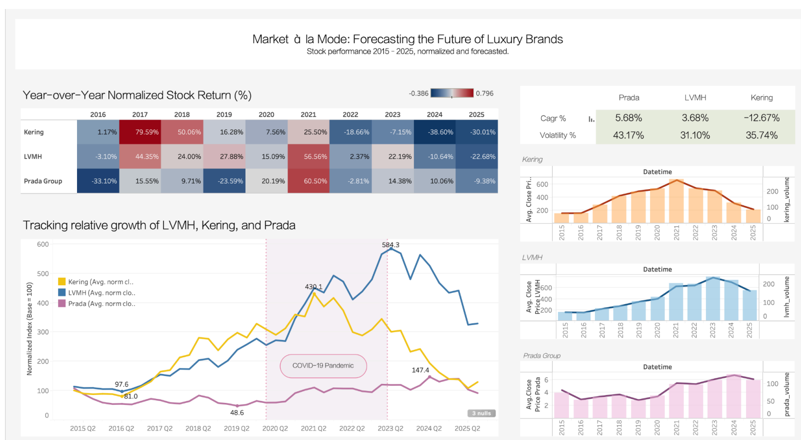
Core Cleaning Logic



Output Files: All processed files were exported to data/processed/ as both .csv and .parquet formats

4. Analysis & Visualization

After preparing the cleaned and standardized datasets, I moved to the analysis phase using Tableau to visualize and interpret the trends. The main objective was to understand how LVMH, Kering, and Prada's stock prices behaved over time, whether their movements were correlated, and how major market shifts affected each company differently.



Volume VS Price of each Brand, YoY% and tracking relative growth (norm price)

5. Insights & Interpretation

Big picture. Using a base-100 normalized index, all three names moved broadly together pre-2019. From 2017–2018 Kering outperformed (Gucci's hot streak), while Prada was not as intense but followed the same direction. During COVID-19, luxury behaved defensively versus most sectors: high-income clientele and strong cash generation helped sustain demand. The rebound was dramatic in 2021: Kering +25.5% YoY, LVMH +56.6%, Prada +60.5% (YoY on normalized closed prices).

Kering. After peaking around 2021, momentum faded. Kering's dependence on Gucci (≈50–60% of group revenue and a larger share of profit) or many expert called "One-trick pony" made it vulnerable to the “brand-fatigue” narrative as maximalism trends shift to quieter luxury style (Loewe, YSL, Prada, Bottega). In 2023 Sabato De Sarno took over at Gucci; markets are still assessing the reset. Net effect in the chart: steeper drawdowns post-2022 and choppier swings. This shows that Kering is better for short-term/speculative trades, riskier for buy-and-hold.

Prada Group. The sharp +60.5% YoY jump in 2021 aligns with a shift to DTC, controlled inventory and discount discipline with strong Asia (especially China) online demand. After a -23.6% dip in 2019, Prada’s trajectory turns steadier, suggesting a slower but more consistent compounding profile, credible long-term hold if execution sustains.

LVMH. Diversification across fashion, jewelry, wines & spirits, beauty, and hospitality dampened drawdowns and extended the up-cycle into a 2023 peak. LVMH’s resilience through shocks (pandemic, macro jitters) reflects multi-brand balance and geographic breadth (Europe/US/Asia). The Tiffany & Co. integration strengthened US exposure. In the lines, LVMH never revisits early-period levels—signal of higher floor and brand-portfolio durability.

Why Luxury outperformed in 2020-2023

- Resilient top-decile consumers (“the rich got richer” effect).
- Self-reward / revenge-spending after lockdowns.
- Category scarcity and price discipline protecting margins.

Investor takeaway.

- *LVMH*: core defensive compounder.
- *Prada:* improving quality; long-term skew.
- *Kering:* turnaround optionality with higher volatility; timing matters.

6. Forecasting & Future Outlook

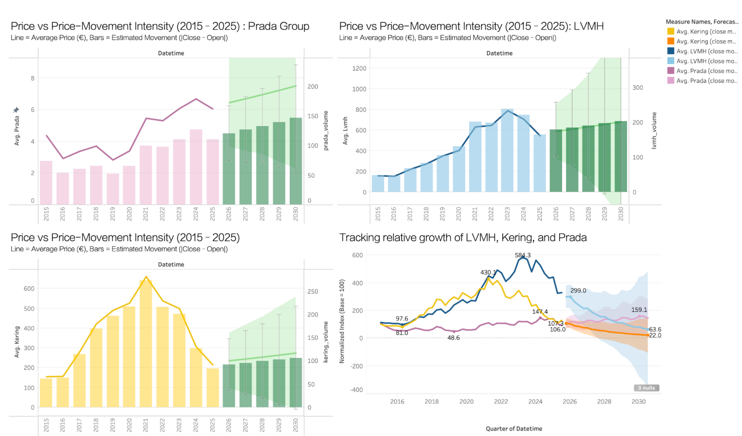


Tableau forecasting 5 years from a decade before (2015 - 2025)

Prada Group

- Tableau forecast projects a gradual upward trajectory through 2030 (base 100 → 159)
- Volatility range remains broad but stable, no sharp deviations indicate market confidence.
- Statistical profile (CAGR ≈ 5.7%, Volatility ≈ 43.2%): high-variance but positive-drift asset

  Interpretation: Prada's innovation pipeline and Asia-Pacific expansion sustain long-term compounding potential. From a quantitative standpoint, a steady CAGR compounded over five years implies a potential ~80–100 % price increase under base-case conditions.

  Investment Outlook: Positive. Strong long-term growth exposure for investors comfortable with moderate volatility; upside supported by innovation-driven resilience.

Kering

- Kering's trajectory displays persistent volatility with wide forecast bands and no clear upward drift, implying limited directional momentum.
- Following its strong rally between 2017–2021, Kering enters a corrective consolidation phase, with forecasts suggesting continued sideways movement and partial recovery attempts.
- Statistical profile (CAGR ≈ **–12.7%**, Volatility ≈ **35.7%**): minimal drift, trading-oriented dynamics.

  Interpretation: Quantitatively, high amplitude of yearly returns (±40 %) and weak mean drift favor short-term tactical trading rather than compounding. With Gucci's creative rebranding initiatives and portfolio diversification efforts underway, a successful turnaround could trigger outsized recovery momentum.

  Investment Outlook: Cautious / Short-term Tactical. Best suited for short-term traders seeking to capitalize on volatility while awaiting stronger confirmation of recovery momentum. Depressed valuations provide an attractive entry point for long-horizon investors anticipating cyclical recovery.

LVMH

- LVMH retains the most stable and positive long-term projection, maintaining a gradual increase from 100 to approximately 299 by 2030.
- Its forecast confidence band is relatively narrow, demonstrating lower perceived risk and sustained growth momentum.
- 5-year CAGR ≈ 3.7%, Volatility ≈ 31.1%; even during crises (COVID-19 2020–2021) trend resilience persisted.

  Interpretation: Even under macroeconomic tightening, LVMH continues to exhibit strong defensive resilience, driven by diversified brand portfolios and robust demand elasticity in high-income markets.

Investment Outlook: Positive / Accumulate Gradually. A strategic buy opportunity for long-term investors — but timing matters. Short-term caution recommended before building full exposure.

Conclusion

This study demonstrates how data analytics can illuminate the financial dynamics behind the world's leading luxury groups. By comparing normalized price movements, volatility profiles, and compounding growth rates, the project highlights how brand diversification, creative strategy, and market positioning translate into measurable market resilience.

For brand management, financial planning, and investor relations teams within luxury conglomerates, understanding relative volatility and cross-brand correlation provides a factual foundation for strategic decisions, from pricing and inventory allocation to investor communication and long-term portfolio balancing. The insights derived from this analysis could support internal KPI dashboards or quarterly market briefings, enabling data-driven storytelling that connects financial performance with brand identity.