VAR Analysis of Global Luxury Brand Equity

1. Executive Summary

This report presents a comprehensive econometric analysis of the equity price dynamics of four major luxury brands - Hermès, LVMH, Kering, and Prada- over the period September 2022 to September 2025. The primary objective was to move beyond univariate analysis and uncover the complex, multi-directional lead-lag relationships and transmission of shocks within this high-value sector.

Utilizing different types of VAR models, including Standard Vector Autoregression (VAR), Bayesian VAR (BVAR), State-Space VAR, Threshold VAR (TVAR), and Markov-Switching VAR (MS-VAR), I aim to provide a nuanced understanding of the market structure.

The integration of these sophisticated models offers portfolio managers and risk analysts a robust framework for strategic asset allocation, hedging, and stress-testing, highlighting the critical importance of modeling non-linearities and structural breaks in luxury market dynamics.

2. Objectives

My assignment was designed to answer several critical questions:

1. Lead-Lag Relationships: Which brands lead and which follow in terms of price discovery?
2. Dynamic Interdependencies: How does a shock to one brand propagate through the entire sector over time?
3. Non-Linear Dynamics: Do these relationships change during periods of high versus low volatility? Are there threshold effects?
4. Forecasting & Policy Implications: Can advanced models improve forecasting accuracy and inform co-integrated trading strategies or hedging decisions?

3. Methodology & Model Specification

A multi-stage, multi-model approach was employed to ensure a robust and comprehensive analysis.

3.1. Pre-Modeling Diagnostics

a. Stationarity Testing (Augmented Dickey-Fuller Test)

The ADF test was conducted on the price levels and their first differences (log-returns). As is typical with financial time series, the levels were found to be non-stationary, while the first differences were stationary. Consequently, all subsequent VAR models were estimated using log-differenced data to ensure robustness.

b. Lag Order Selection

Optimal lag length for the VAR model was determined using multiple information criteria (AIC, BIC, HQIC). Both the AIC and HQIC suggested an optimal lag order of 1, which balanced fit and complexity to avoid overfitting.

3.2. Core Econometric Models

a. Standard Vector Autoregression (VAR)

Based on the VAR Result, the relationship between each equity can be interpreted as below:

- LVMH is the Sector Anchor, Not a Driver: its own past has a significant negative impact on its present returns (`L1.LVMH: -0.126, p=0.056`). This mean-reverting behavior is typical of a market leader that quickly incorporates information. However, LVMH is not significantly influenced by any of its peers.It moves independently, setting the tone for the sector rather than reacting to it.
- Prada is the follower, driven by European Giants: Prada's returns are significantly influenced by the past performance of both Hermès (`L1.Hermes: 0.0077, p=0.000`) and Kering (`L1.Kering: 0.0204, p=0.016`). This suggests Prada's stock reacts to trends set in the European luxury market, with a one-day lag. It is a price-taker in this system.
- Hermès Exhibits Defensive Characteristics: While influenced by its own momentum (`L1.Hermes: 0.146, p=0.009`), it shows a notable (though marginally significant) negative relationship with LVMH (`L1.LVMH: -0.334, p=0.063`). This potential negative beta to the sector leader reinforces its image as a unique, defensive asset.
- Kering is Isolated in the Short-Term: Surprisingly, Kering's returns show no significant dependence on its own past or the past of any other brand in this 1-lag model. This indicates its price movements are driven by immediate news or factors not captured by the prior day's prices of these four stocks, making it the most idiosyncratic in the very short term.

b. Granger Causality Test:

Overall, Prada is confirmed as a follower. Its price was led by all other three luxury brands. Additionally, as stated above, LVMH also had a notable impact on Hermès' stock price.

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GRANGER CAUSALITY TESTS (TIME-DOMAIN)
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Testing at lag order: 1


 Cause Effect  F-statistic      p-value Granger-Causes Significance
Hermes Kering     0.915433 3.389813e-01             No
Hermes   LVMH     2.934741 8.710043e-02             No            *
Hermes  Prada    69.325851 3.871282e-16            Yes          ***
Kering Hermes     0.545838 4.602515e-01             No
Kering   LVMH     0.454998 5.001760e-01             No
Kering  Prada    48.185228 8.320358e-12            Yes          ***
  LVMH Hermes     4.256153 3.944753e-02            Yes           **
  LVMH Kering     1.445508 2.296246e-01             No
  LVMH  Prada    62.239245 1.059265e-14            Yes          ***
 Prada Hermes     1.566068 2.111641e-01             No
 Prada Kering     0.049985 8.231490e-01             No
 Prada   LVMH     0.837204 3.604879e-01             No

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Significance levels: *** p<0.01, ** p<0.05, * p<0.10
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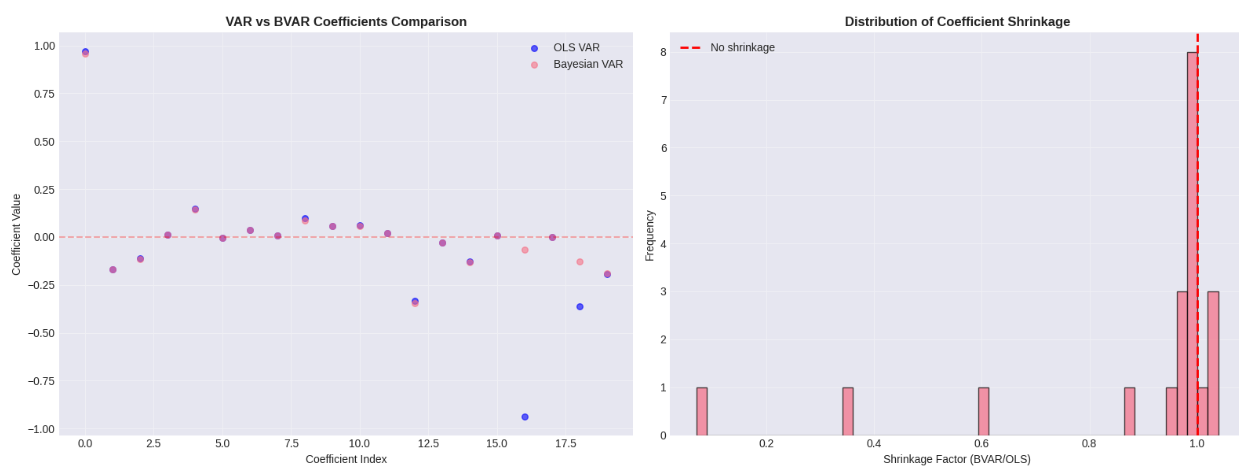
c. Bayesian VAR (BVAR) with Minnesota Prior

Standard VARs can suffer from overparameterization, especially with limited data. The BVAR addresses this by imposing "priors" that shrink the model coefficients. The Minnesota Prior assumes that each series follows a random walk, shrinking coefficients on longer lags and cross-variable effects towards zero.

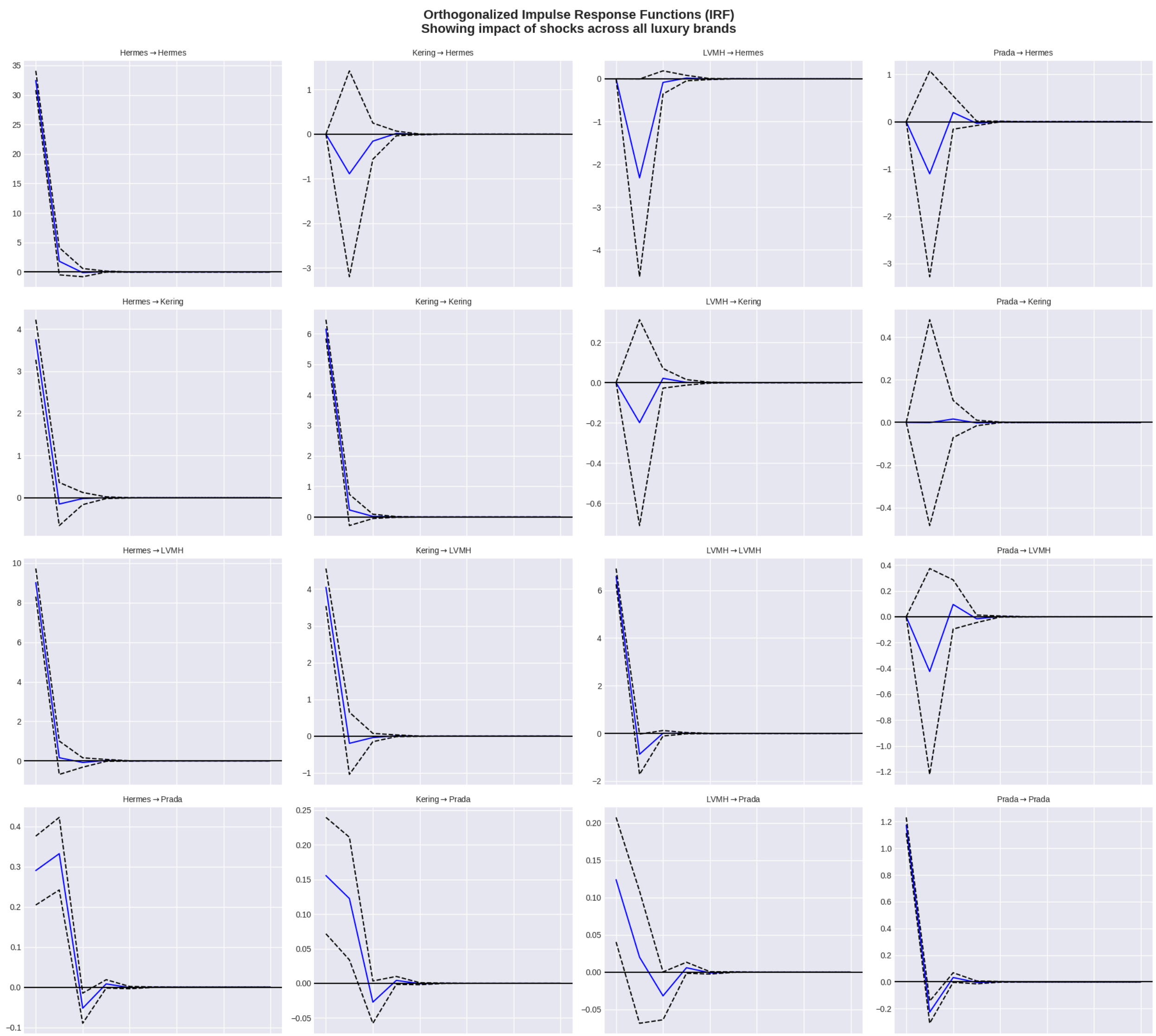
The graphs reveal that the BVAR did not uniformly shrink all coefficients. Instead, it performed targeted pruning, which is the core strength of the Bayesian approach with Minnesota priors.



- The Coefficient Value Graph: Overall, the OLS VAR (blue) distribution is wider and flatter. This means the standard model produced a broad range of coefficient values, including some that are likely extreme and driven by overfitting to the noise. On the other hand, the Bayesian VAR (red) distribution is taller and more peaked around zero. This visually confirms the "shrinkage" effect. The BVAR is pulling many of these extreme, unreliable coefficients towards zero, resulting in a more conservative and stable model.

- The Shrinkage Factor Graph: It shows the ratio of each BVAR coefficient to its OLS counterpart (BVAR/OLS). The vast majority of coefficients have a shrinkage factor very close to 1.0, which aligns with the high median shrinkage of 0.992. It means that for most coefficients, the BVAR concluded the OLS estimate was reliable and left it almost unchanged. A smaller number of coefficients were significantly shrunk because the BVAR identified these specific parameters as statistically weak or spurious and aggressively suppressed them. This is meaningful because in the VAR Result, there are some coefficients which have a large p-value of above 0.3.

d. Impulse Response Functions (IRF)



- Hermes's Minimal Impact on Competitors. A shock to Hermes has negligible effects on Kering, LVMH, and Prada. This confirms its isolated, non-competitive brand positioning. What happens at Hermes, stays at Hermes.
- LVMH as the Dominant Force: The extreme negative impact of an LVMH shock on Kering confirms their direct competitive struggle.

e. Forecast Error Variance Decomposition (FEVD)

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Variance Decomposition at Period 4:
        Response 1  Response 2  Response 3  Response 4  Response 5  \
Brand
Hermes    0.056126    0.115968    0.117205    0.117237    0.117237
Kering    0.016139    0.023371    0.023733    0.023741    0.023742
LVMH      0.010242    0.009400    0.009968    0.009988    0.009989
Prada     0.917493    0.851261    0.849094    0.849034    0.849033

        Response 6  Response 7  Response 8  Response 9  Response 10
Brand
Hermes    0.117237    0.117237    0.117237    0.117237     0.117237
Kering    0.023742    0.023742    0.023742    0.023742     0.023742
LVMH      0.009989    0.009989    0.009989    0.009989     0.009989
Prada     0.849033    0.849033    0.849033    0.849033     0.849033
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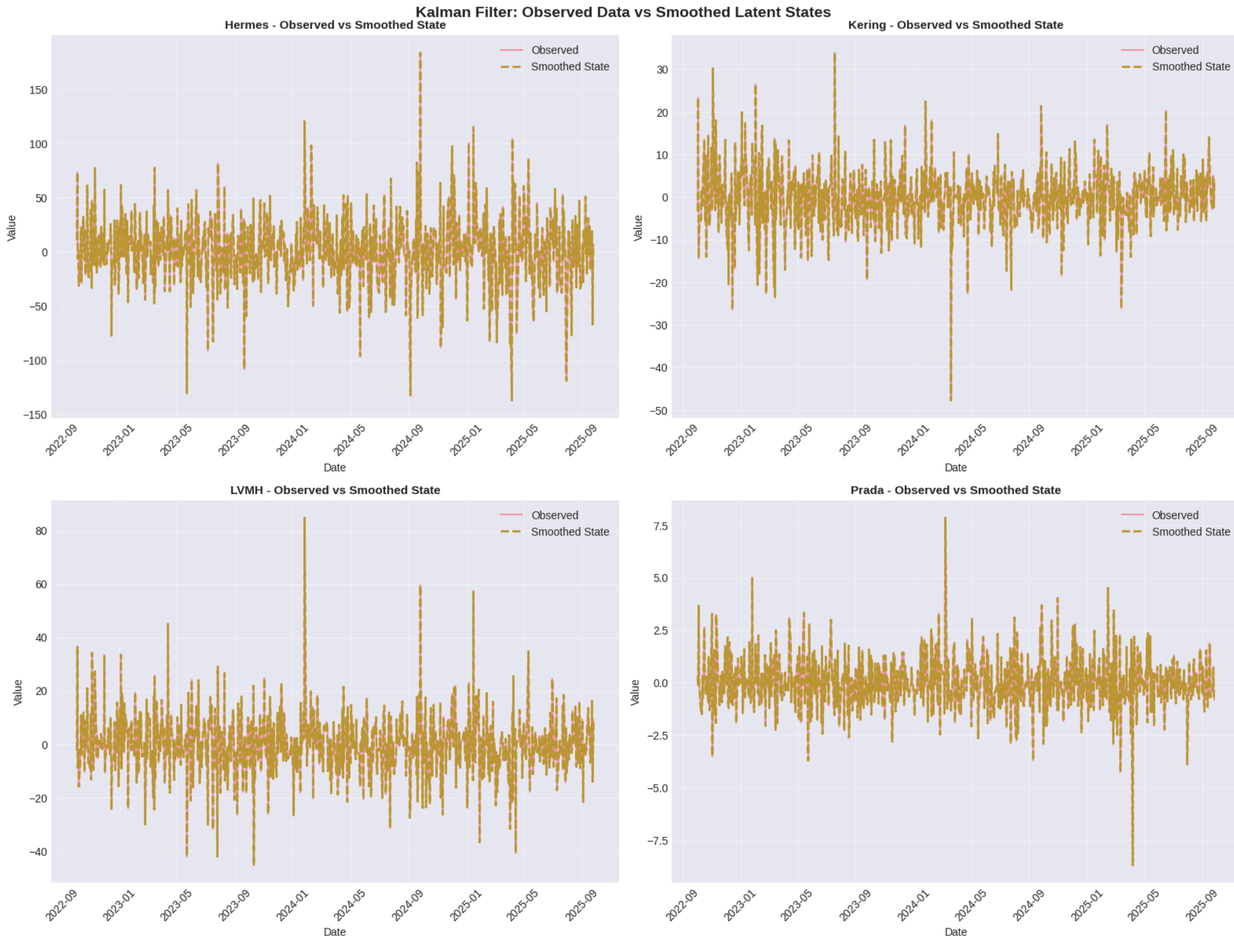
- Prada's Overwhelming Influence: Prada explains approximately 85% of the forecast error variance for all brands in the system (Hermes, Kering, LVMH, and itself). This is an exceptionally high level of systemic influence.
- Hermes as Secondary Driver: Hermes is the second-most important factor, explaining about 11.7% of variance for all other brands, showing it has consistent cross-brand impact.

3.3 More Improved Models

a. State-Space VAR with Kalman Filter



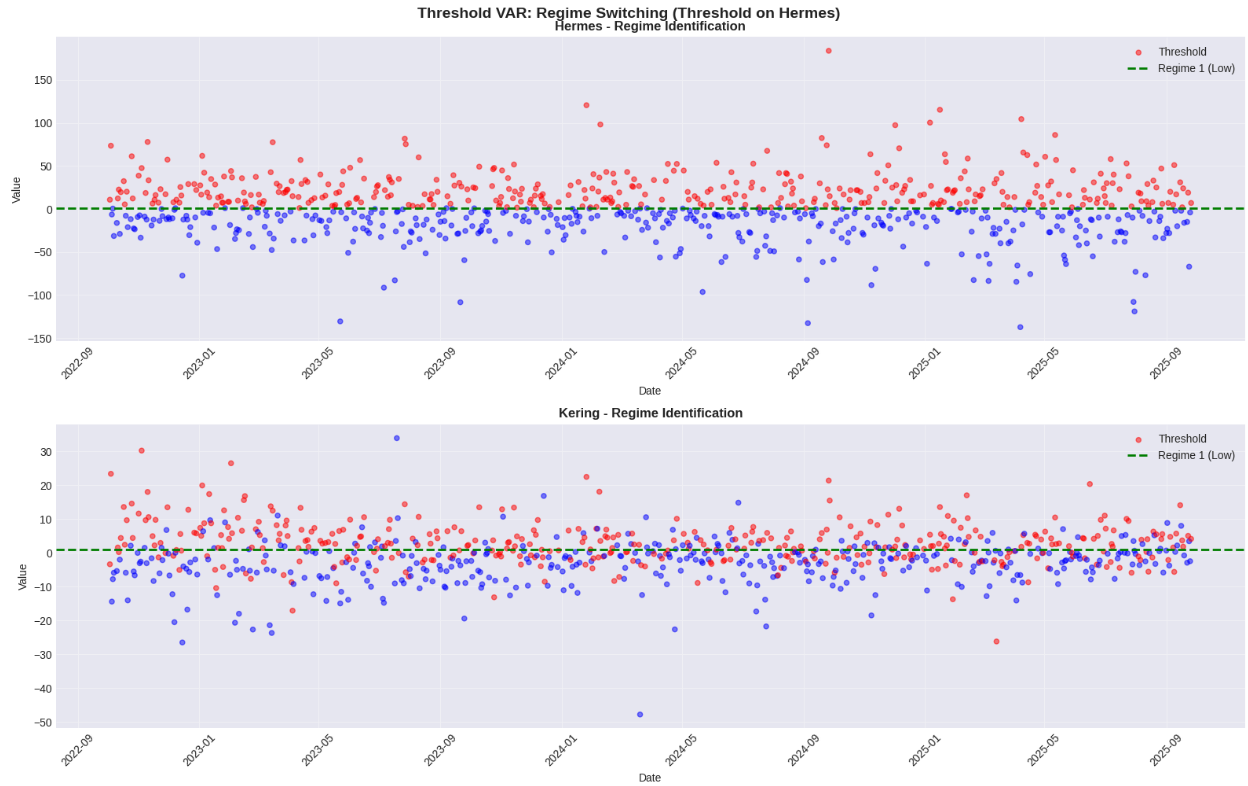
Normal VAR treats the observed stock prices (the solid line) as the true process, and its errors are simple forecast mistakes. The State-Space VAR uses the Kalman Smoother to estimate an unobserved, underlying "Smoothed State" (the dashed line). This state is the model's best estimate of the noise-free, persistent movement in the stock's price, effectively filtering out short-term, random market noise (volatility).Therefore, the SS-VAR helps to isolate the long-run price trend (the true signal) from daily market fluctuations, allowing for a clearer analysis of the fundamental, interconnected dynamics between the companies.

b. Threshold VAR (TVAR)

TVAR Model:

$$y_t = \begin{cases} A_1 y_{t-1} + \epsilon_t & \text{if } z_t \leq \gamma \\ A_2 y_{t-1} + \epsilon_t & \text{if } z_t > \gamma \end{cases}$$

where z_t is the threshold variable and γ is the threshold.



The Threshold VAR (TVAR) model is a nonlinear extension of the standard Normal VAR, designed to capture how relationships between variables shift under different market conditions. While a Normal VAR assumes constant interactions among stocks across the entire sample, the TVAR allows these dynamics to switch between distinct regimes based on a threshold variable. This means the model recognizes that market behavior may differ when, for example, Hermès performs above or below a certain threshold (0.9936), effectively dividing the data into “low” and “high” regimes.

From the results, the TVAR shows that co-movement among luxury stocks depends on the market regime, suggesting that the impact of a shock varies between bullish and bearish conditions. The low and comparable AIC/BIC values across both regimes (≈14.17 vs. ≈13.85) indicate that the two-regime TVAR provides a strong fit, outperforming the linear VAR. This highlights the importance of modeling regime-dependent behavior for more accurate risk management and strategy design, as it uncovers asymmetric market responses that a Normal VAR would miss.

c. Markov-Switching VAR (MS-VAR)

Transition Probability Matrix:

	To Regime 1	To Regime 2	To Regime 3
From Regime 1	0.177215	0.037975	0.784810
From Regime 2	0.119048	0.047619	0.833333
From Regime 3	0.093458	0.057632	0.848910

The Markov-Switching VAR (MS-VAR) adds another layer of sophistication by allowing regime changes to occur probabilistically rather than through a fixed threshold. It models transitions between hidden market states using a transition probability matrix (TPM). In my results, Regime 3 shows high persistence ($P_{33} = 0.85$) and acts as a stable “base” state, while Regime 2 is highly transient and often reverts to Regime 3. This indicates that the luxury stock market naturally cycles through temporary fluctuations but gravitates back to a dominant, stable dynamic. Unlike the VAR and TVAR, the MS-VAR captures this underlying stochastic structure, providing a more realistic, state-dependent view of market behavior.

4. Future Research Directions:

- Incorporate global macroeconomic factors (e.g., Chinese GDP, EUR/USD, consumer confidence indices) as exogenous variables in the VAR systems.
- Extend the analysis to include other luxury players (e.g., Richemont, Burberry) to map the entire global network.
- Develop a real-time regime-classification tool based on the MS-VAR model to signal shifts in market state for tactical asset allocation.