HOW DOES THE EVOLUTION OF KERING'S STOCK PRICE REFLECT THE CHALLENGES FACED BY THE LUXURY INDUSTRY?

KERING

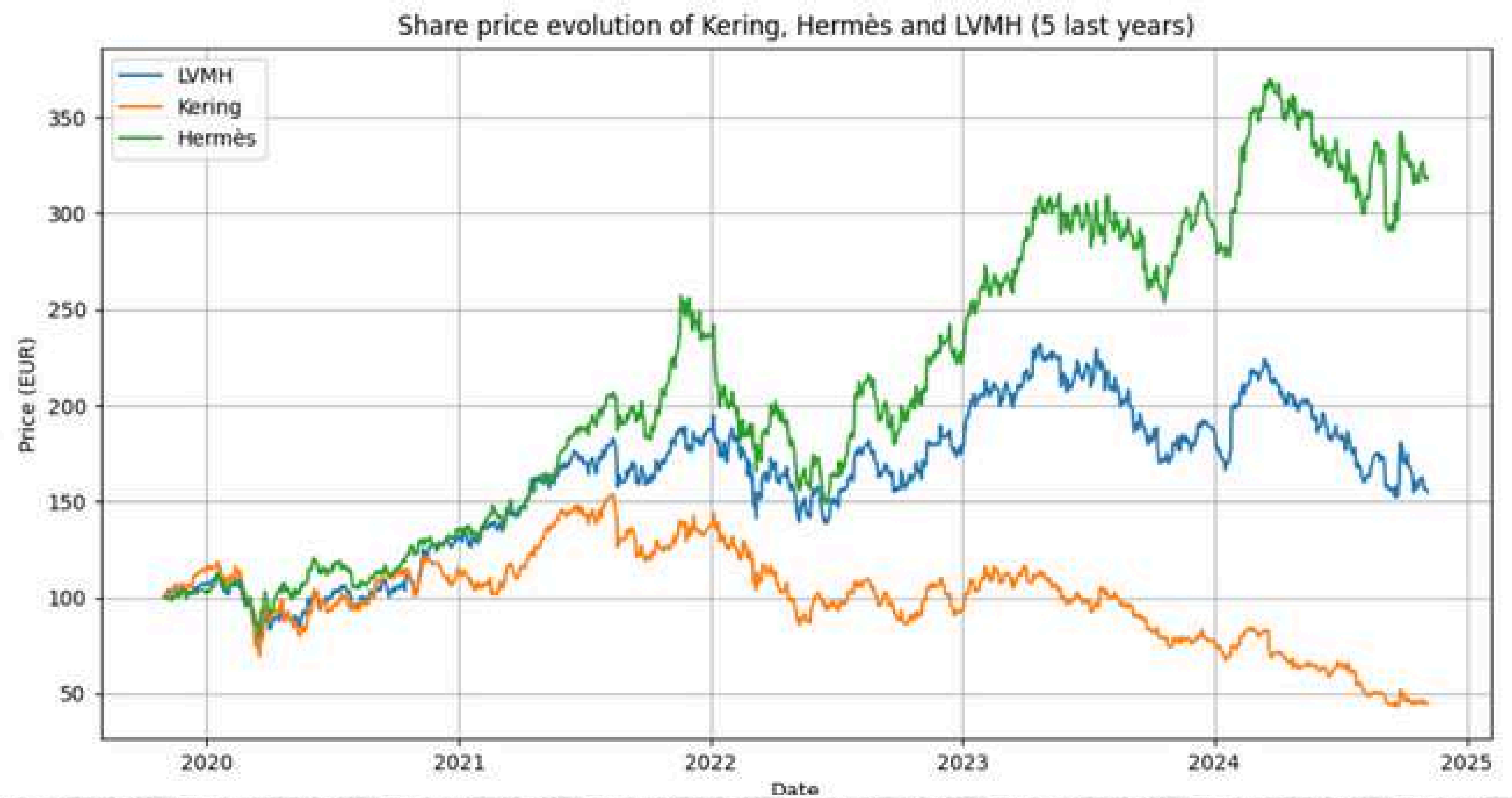
OVERVIEW

We have decided to work on a data-driven business challenge report. We will use the public data provided by Kering, a French luxury listed company, to draw patterns between the stock price evolution and the challenges faced by Kering, reflected by financial figures' evolution (sales, net income, etc). Our model will enable us to compare Kering's performance on the market to its peers' and recommend Kering a new strategy to remain attractive to investors.

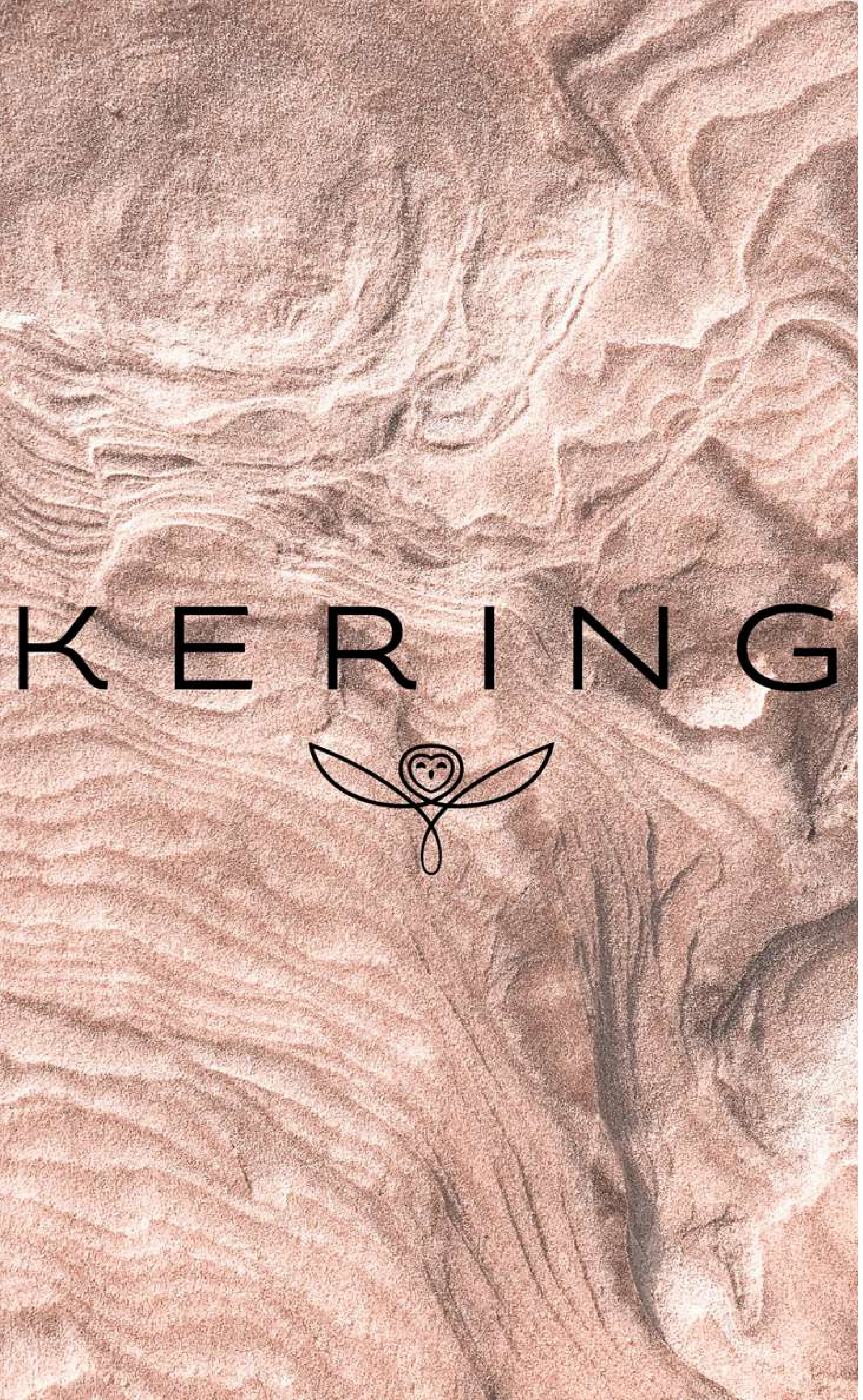
GOAL

- Understand the current challenges faced by the luxury industryand why Kering is the most affected player
- Show how stock price reflects the performance of a firm within its industry
- Apply machine learning to real case scenario and understand why as managers we need to adopt data-driven approach while making strategic decisions

THE LUXURY INDUSTRY: “A TURBULENT $387 BN MARKET” - BAIN & CO



Kering is the most affected by the current luxury downturn



ABOUT KERING

- **Company Overview**: Kering is a French multinational luxury goods conglomerate, founded in 1963.
- **Market Focus**: Operates primarily in the luxury consumer goods market (fashion, accessories, jewelry, and watches).
- **Key Brands**: Owns iconic luxury brands such as Gucci, Yves Saint Laurent, Balenciaga, and Boucheron.
- **Dependency on Gucci**: Financial success heavily reliant on Gucci's performance, which is currently facing challenges.
- **Recent Performance**: Sales declined by 16% in Q3 2024, marking the third consecutive quarter of decline.
- **Relevance of Analysis**: The ongoing struggles underscore the importance of examining Kering's current strategy and market position.

OUR DATASET

- **Financial markets data**

Kering stock price
LVMH stock price
Hermès stock price

- **Macroeconomic indicators**

Indexes, exchange and treasury rates, commodities

- **Financial figures of Kering and its brands**

Revenues, CAPEX, stores openings of Kering, Gucci, YSL, Bottega and Other Houses

OUR MODELS

Our approach followed a “funnel” methodology with a top-down analysis.

1 - Global Macroeconomic view:
-Linear regressions

2 - Microeconomic view:
-Decision trees

3 - Brand Specific:
-Clusterings
-Monte-Carlo Simulations

1 - GLOBAL MACROECONOMIC VIEW: LINEAR REGRESSIONS

KERING

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.959
Model:	OLS	**Adj. R-squared:**	0.958
Method:	Least Squares	**F-statistic:**	982.1
Date:	Wed, 20 Nov 2024	**Prob (F-statistic):**	7.35e-229
Time:	23:11:56	**Log-Likelihood:**	-1646.9
No. Observations:	347	**AIC:**	3312.
Df Residuals:	338	**BIC:**	3346.
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	164.1129	39.970	4.106	0.000	85.491	242.735
Q("000300.SS")	0.1285	0.012	10.586	0.000	0.105	0.152
Q("^STOXX50E")	0.3154	0.021	14.842	0.000	0.274	0.357
Q("^N225")	-0.0162	0.001	-15.376	0.000	-0.018	-0.014
Q("GC=F")	-0.1858	0.018	-10.588	0.000	-0.220	-0.151
Q("^HSI")	-0.0129	0.002	-6.910	0.000	-0.017	-0.009
Q("^KS11")	0.1295	0.013	9.720	0.000	0.103	0.156
Q("^NSEI")	-0.0090	0.002	-4.450	0.000	-0.013	-0.005
Q("FTSEMIB.MI")	-0.0203	0.003	-6.743	0.000	-0.026	-0.014

Omnibus:	4.295	**Durbin-Watson:**	2.002
Prob(Omnibus):	0.117	**Jarque-Bera (JB):**	4.383
Skew:	-0.259	**Prob(JB):**	0.112
Kurtosis:	2.813	**Cond. No.**	1.34e+06

HERMES

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.950
Model:	OLS	**Adj. R-squared:**	0.949
Method:	Least Squares	**F-statistic:**	803.0
Date:	Wed, 20 Nov 2024	**Prob (F-statistic):**	1.20e-215
Time:	23:11:59	**Log-Likelihood:**	-2058.4
No. Observations:	349	**AIC:**	4135.
Df Residuals:	340	**BIC:**	4170.
Df Model:	8		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	-543.9845	125.767	-4.325	0.000	-791.363	-296.606
Q("000300.SS")	0.1778	0.037	4.858	0.000	0.106	0.250
Q("^STOXX50E")	1.2814	0.065	19.649	0.000	1.153	1.410
Q("^N225")	0.0096	0.003	2.807	0.005	0.003	0.016
Q("GC=F")	-0.0345	0.053	-0.656	0.512	-0.138	0.069
Q("^HSI")	-0.0581	0.006	-9.944	0.000	-0.070	-0.047
Q("^KS11")	-0.4289	0.043	-9.946	0.000	-0.514	-0.344
Q("^NSEI")	-0.0336	0.006	-5.284	0.000	-0.046	-0.021
Q("FTSEMIB.MI")	-0.0446	0.009	-4.879	0.000	-0.063	-0.027

Omnibus:	4.967	**Durbin-Watson:**	1.974
Prob(Omnibus):	0.083	**Jarque-Bera (JB):**	3.335
Skew:	-0.049	**Prob(JB):**	0.189
Kurtosis:	2.531	**Cond. No.**	1.34e+06

LVMH

OLS Regression Results

Dep. Variable:	Price	**R-squared:**	0.816
Model:	OLS	**Adj. R-squared:**	0.811
Method:	Least Squares	**F-statistic:**	184.4
Date:	Wed, 20 Nov 2024	**Prob (F-statistic):**	2.02e-117
Time:	23:11:59	**Log-Likelihood:**	-1710.8
No. Observations:	342	**AIC:**	3440.
Df Residuals:	333	**BIC:**	3474.
Df Model:	8		
Covariance Type:	nonrobust		

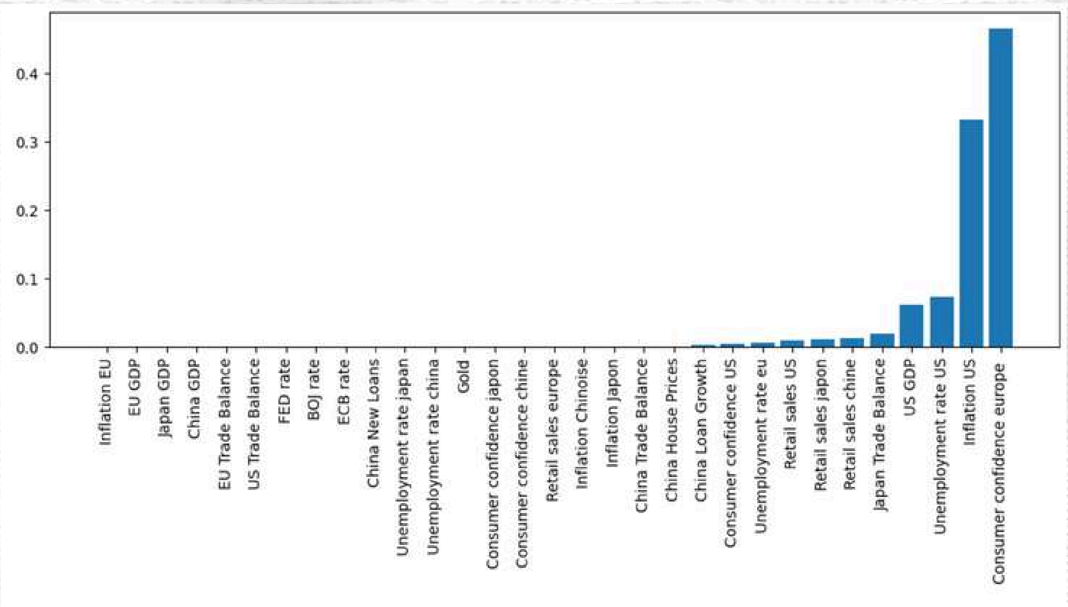
	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	484.2859	51.512	9.401	0.000	382.956	585.616
Q("000300.SS")	0.0340	0.015	2.271	0.024	0.005	0.063
Q("^STOXX50E")	0.6337	0.028	22.836	0.000	0.579	0.688
Q("^N225")	-0.0017	0.001	-1.217	0.225	-0.004	0.001
Q("GC=F")	-0.1334	0.022	-6.050	0.000	-0.177	-0.090
Q("^HSI")	-0.0137	0.002	-5.564	0.000	-0.019	-0.009
Q("^KS11")	-0.1784	0.018	-9.966	0.000	-0.214	-0.143
Q("^NSEI")	-0.0287	0.003	-10.907	0.000	-0.034	-0.024
Q("FTSEMIB.MI")	-0.0358	0.004	-9.344	0.000	-0.043	-0.028

Omnibus:	12.001	**Durbin-Watson:**	1.958
Prob(Omnibus):	0.002	**Jarque-Bera (JB):**	15.920
Skew:	0.298	**Prob(JB):**	0.000349
Kurtosis:	3.872	**Cond. No.**	1.33e+06

2 - MICROECONOMIC VIEW: DECISION TREES

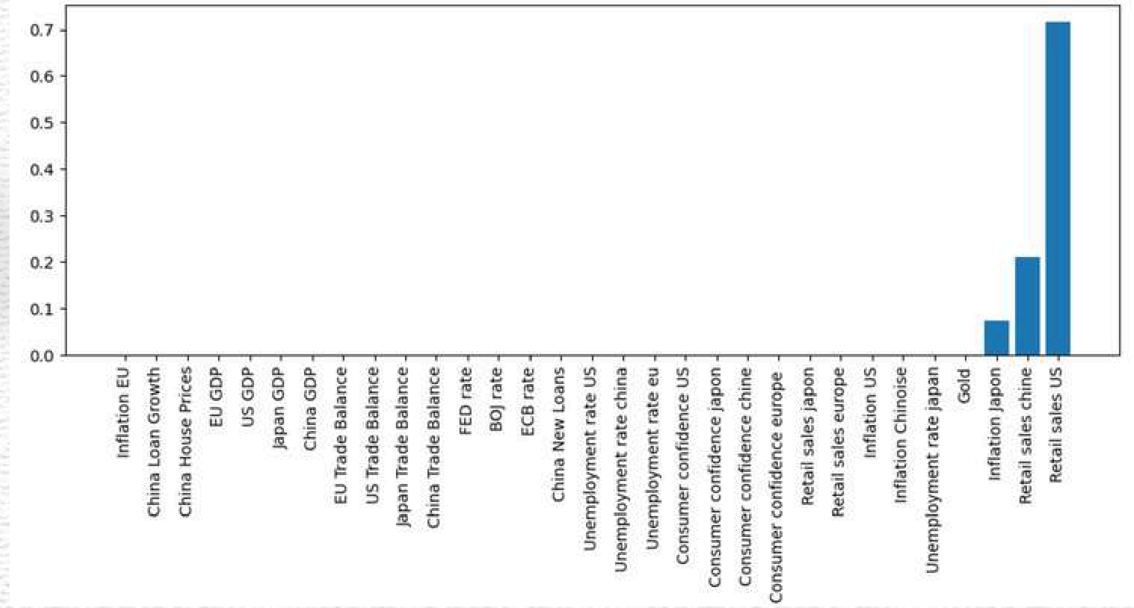
GUCCI

ID	Business Rule	Revenue Change
16	Consumer Confidence Europe > 11.2%; US GDP > 2.9%; Retail Sales US > 9.6%	**35.80%**
15	Consumer Confidence Europe > 11.2%; US GDP > 2.9%; Retail Sales US <= 9.6%	**30.20%**
13	Consumer Confidence Europe > 11.2%; US GDP <= 2.9%; Retail Sales China > 6.1%; China Loan Growth <= 12.7%; Unemployment Rate EU > 7.8%	**20.10%**
6	Consumer Confidence Europe <= 11.2%; Inflation US <= 7.3%; Consumer Confidence US > 102.95; China Trade Balance > 264.31	**19.60%**
7	Consumer Confidence Europe <= 11.2%; Inflation US > 7.3%; China Loan Growth <= 8.4%; China House Prices <= 4.7%	**-13.80%**
9	Consumer Confidence Europe <= 11.2%; Inflation US > 7.3%; China Loan Growth > 8.4%	**-14.20%**
11	Consumer Confidence Europe > 11.2%; US GDP <= 2.9%; Retail Sales China <= 6.1%; Japan Trade Balance > -1203.3	**-20.10%**
10	Consumer Confidence Europe > 11.2%; US GDP <= 2.9%; Retail Sales China <= 6.1%; Japan Trade Balance <= -1203.3	**-22.60%**



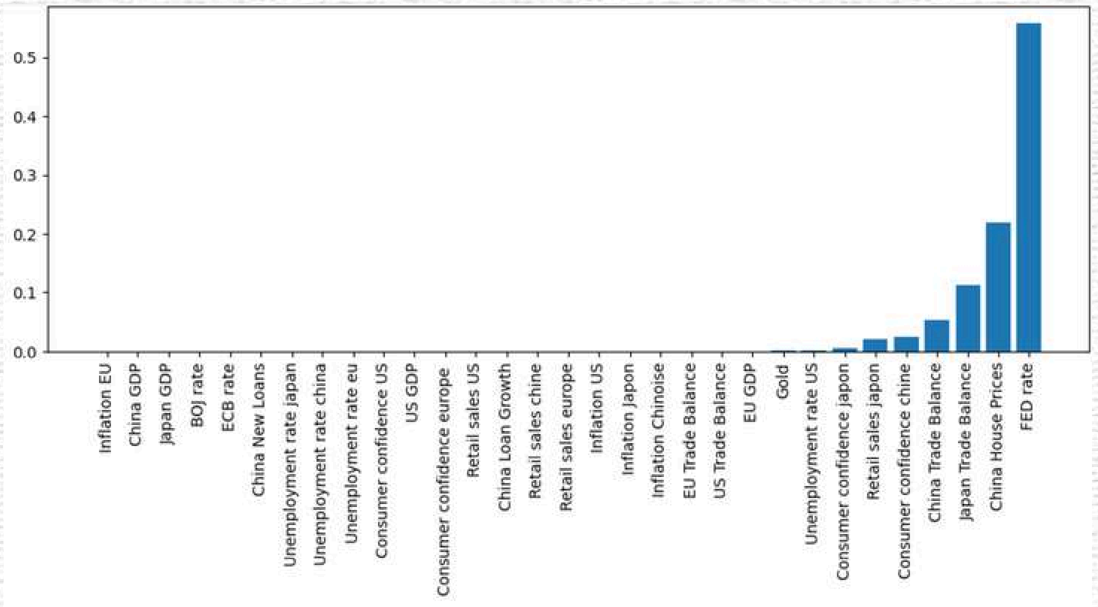
YSL

ID	Business Rule	Revenue Change
4	Retail Sales US > 6.5%; Inflation Japan > 0.5%	**43.10%**
3	Retail Sales US > 6.5%; Inflation Japan <= 0.5%	**23.30%**
2	Retail Sales US <= 6.5%; Retail Sales China > 7.6%	**16.00%**
1	Retail Sales US <= 6.5%; Retail Sales China <= 7.6%	**-5.50%**

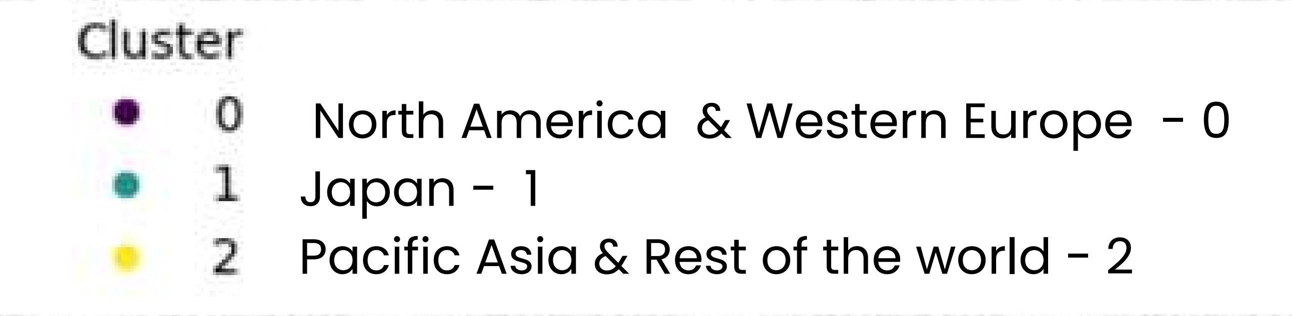


BOTTEGA

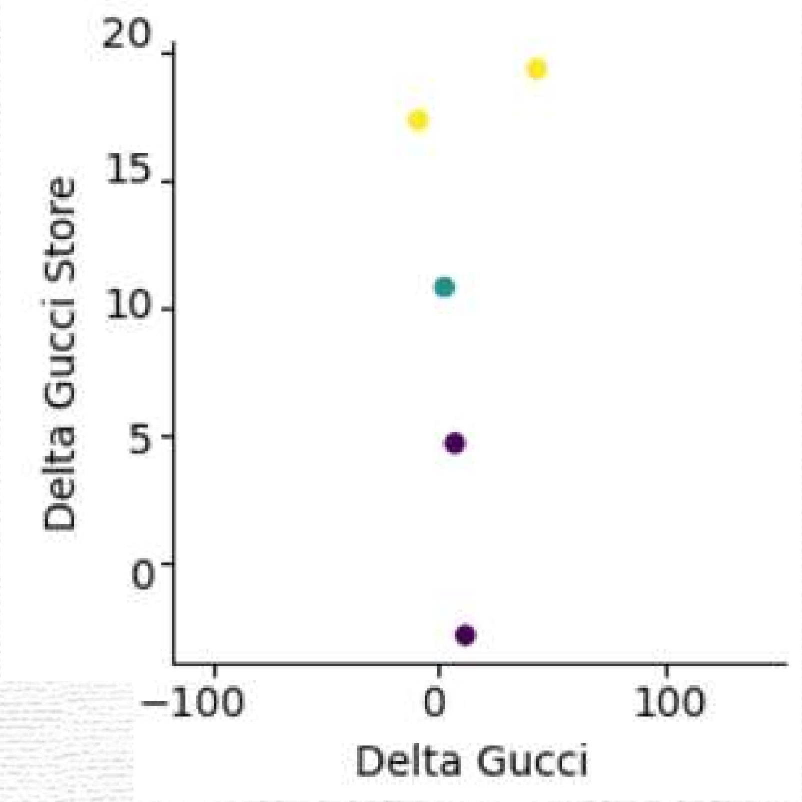
ID	Business Rule	Revenue Change (%)
4	FED rate <= 0.048; China House Prices <= 0.093; China Trade Balance > 250.0; EU GDP > 0.005	**20.60%**
3	FED rate <= 0.048; China House Prices <= 0.093; China Trade Balance > 250.0; EU GDP <= 0.005	**20.40%**
1	FED rate <= 0.048; China House Prices <= 0.093; China Trade Balance <= 250.0; Consumer confidence China <= 73.025	**14.00%**
2	FED rate <= 0.048; China House Prices <= 0.093; China Trade Balance <= 250.0; Consumer confidence China > 73.025	**8.80%**
7	FED rate > 0.048; Japan Trade Balance <= -1418.55; Japan Trade Balance <= -1686.65; Unemployment rate US <= 0.037	**-0.30%**
8	FED rate > 0.048; Japan Trade Balance <= -1418.55; Japan Trade Balance <= -1686.65; Unemployment rate US > 0.037	**-2.50%**
6	FED rate <= 0.048; China House Prices > 0.093; Retail sales Japan > 0.007	**-5.00%**
10	FED rate > 0.048; Japan Trade Balance > -1418.55; Consumer confidence Japan <= 36.2	**-12.80%**



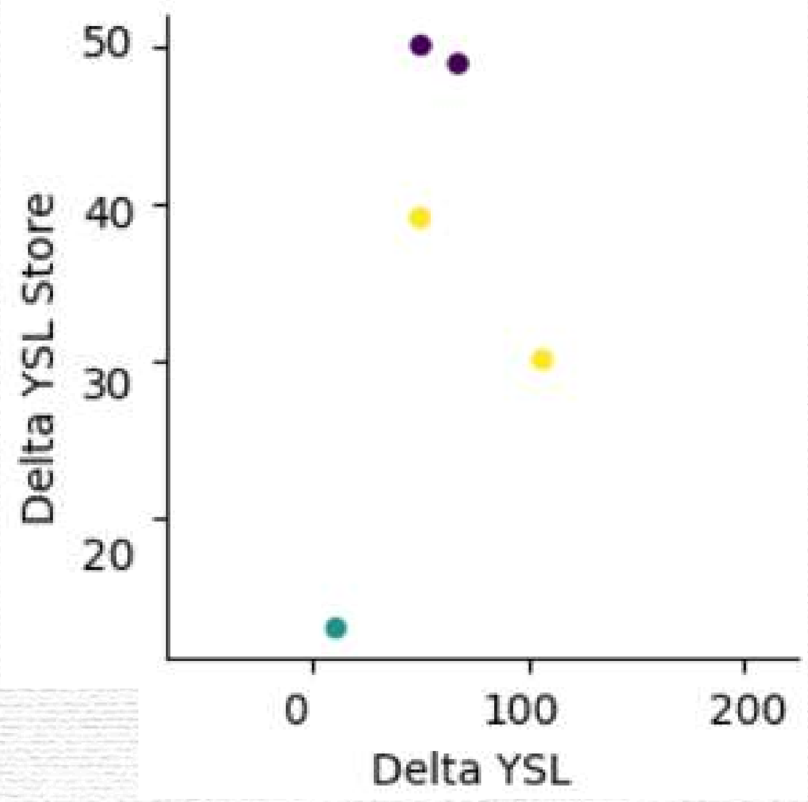
3 - BRAND SPECIFIC: CLUSTERING



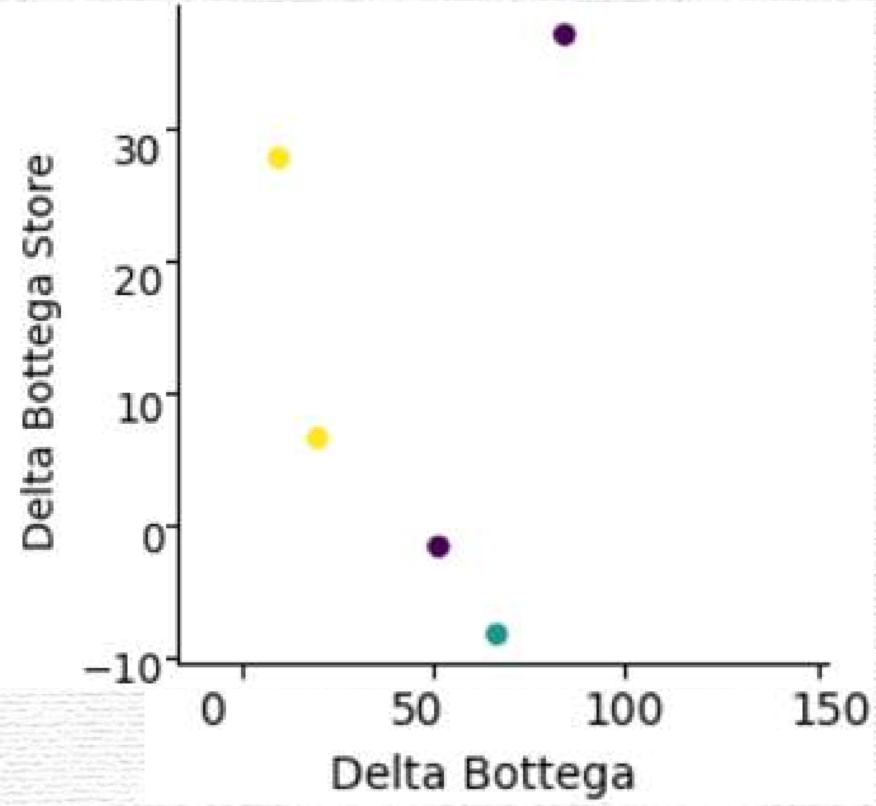
GUCCI



YSL

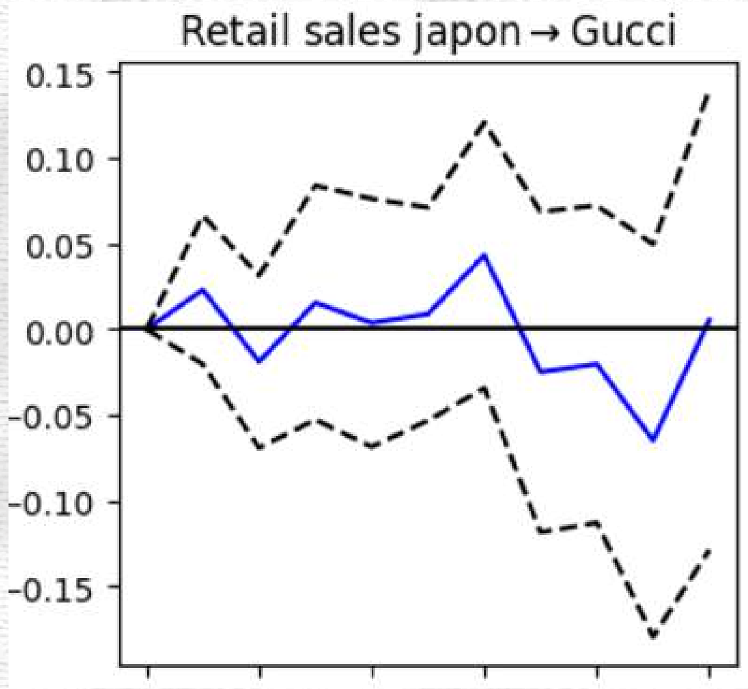


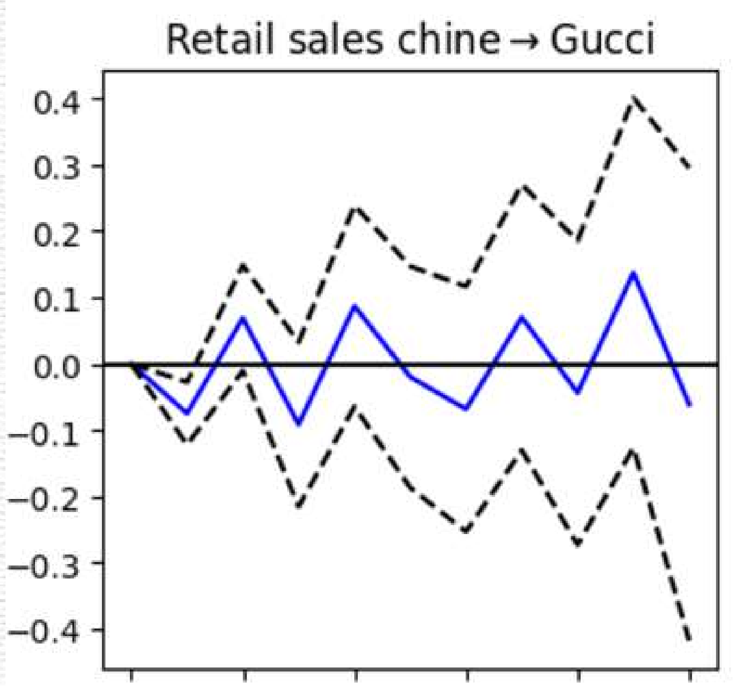
BOTTEGA



3 - BRAND SPECIFIC: IMPULSE RESPONSE ANALYSIS

GUCCI





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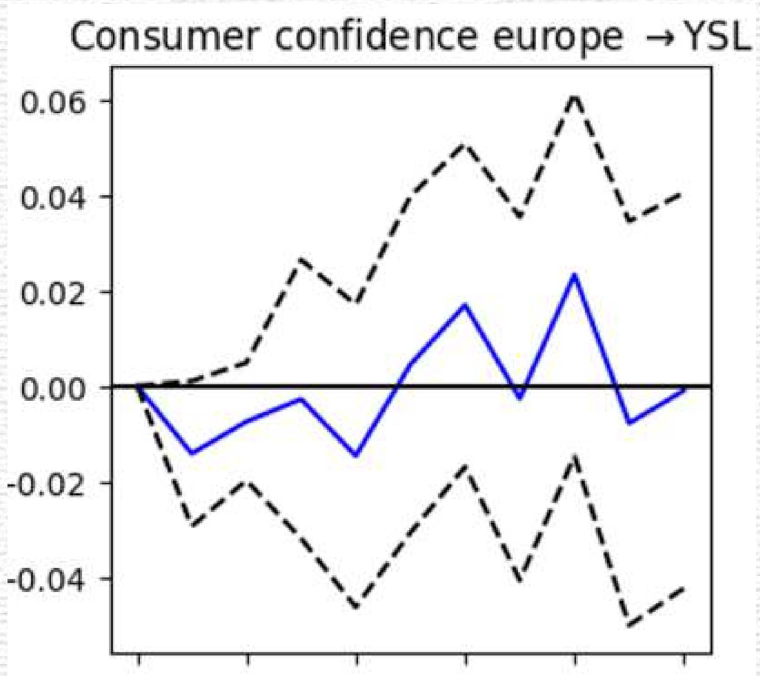
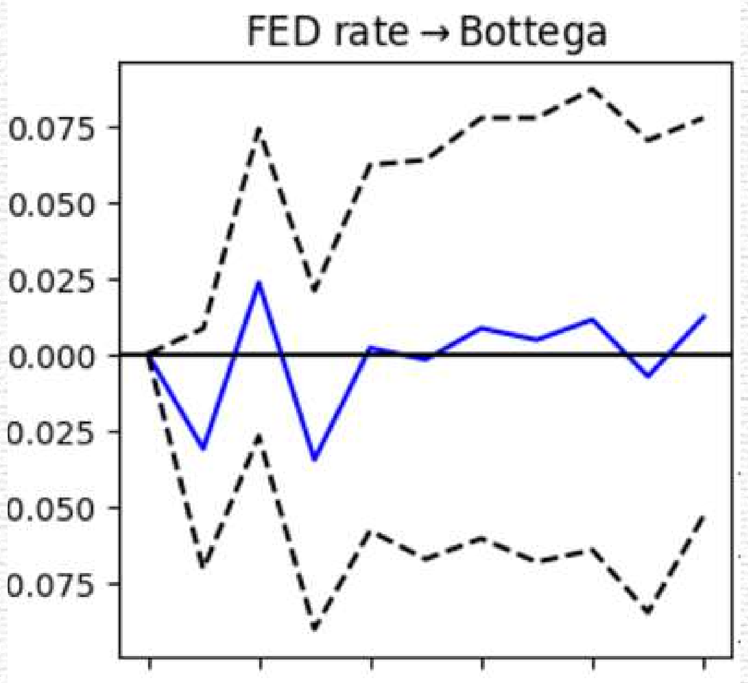
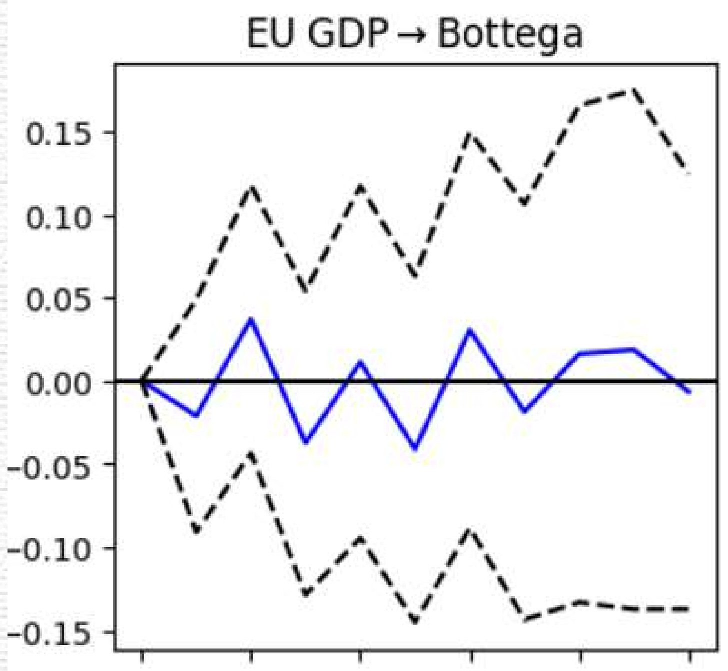


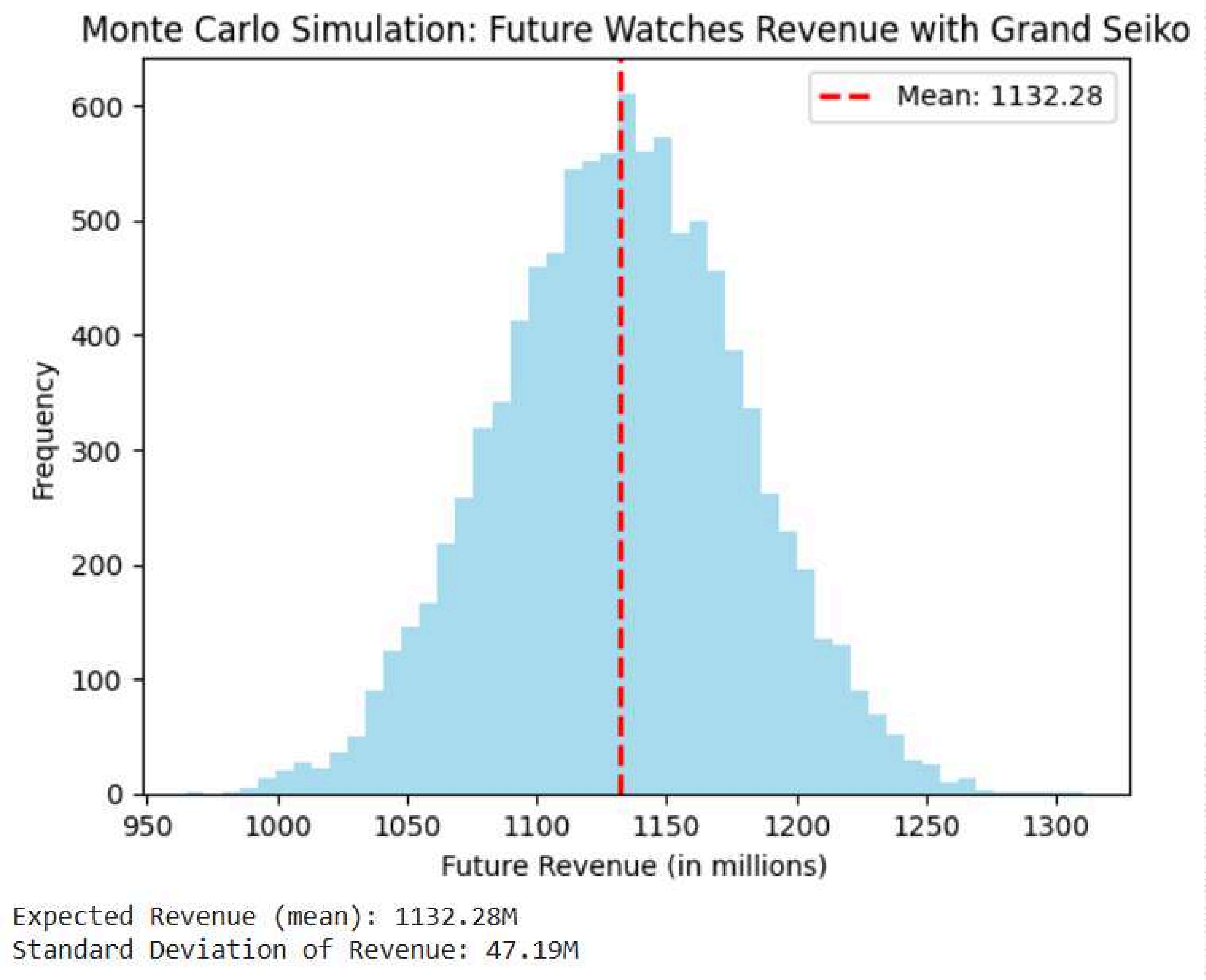
BOTTEGA



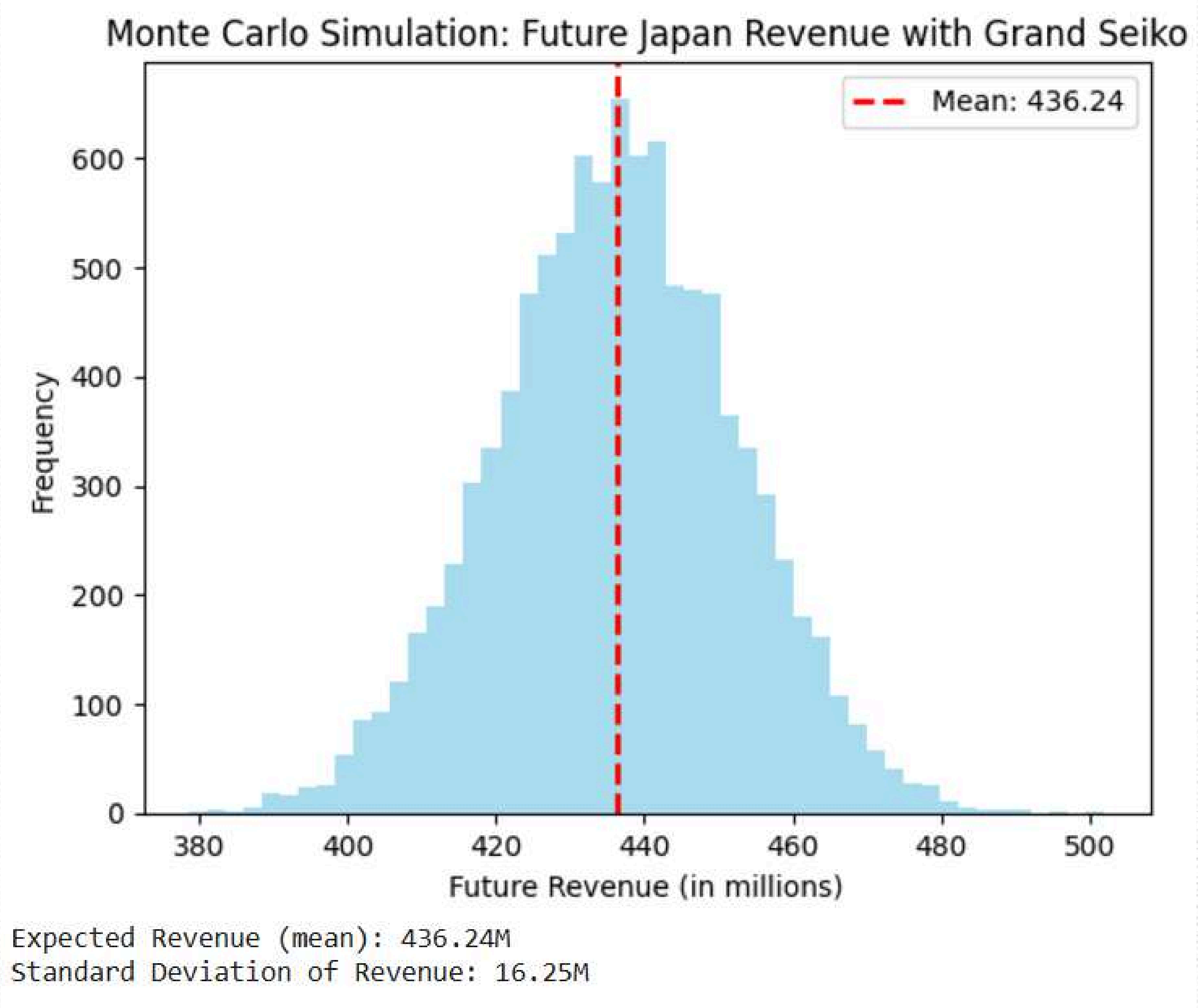


3 - BRAND SPECIFIC: MONTE-CARLO SIMULATION

WATCHES SEGMENT



JAPANESE MARKET



MAIN OBSTACLES AND SOLUTIONS

- **Data Availability:**

Gathering data across various sources was a key challenge: we lacked pre-compiled datasets for quarterly macroeconomic variables or brand-level financial performance.
To address this, we relied on multiple sources, including CapitalIQ, Investing.com, and YahooFinance, and manually extracted relevant information.

- **Impact of the COVID-19 Crisis:**

Data for Q2 2020 and Q2 2021 were heavily affected by the pandemic.
To ensure accuracy, we excluded these quarters to avoid misleading results.

- **Small Sample Size (19 observations for the decision tree):**

The limited dataset made traditional train-test splits impractical.
Instead, we minimized the decision tree depth to reduce overfitting, using the Mean Squared Error (MSE) as a criterion. R-squared metrics further validated model performance.

AVOID OVERFITTING (1/2)

- **Linear Regression:**

We split the data into training and test sets, using Root Mean Squared Error (RMSE) to evaluate performance. Minimal differences between the two sets confirmed the model's generalization capabilities.

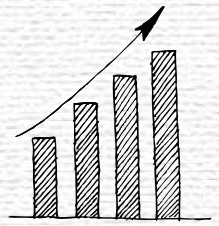
- **Decision Tree:**

Due to the small dataset, we adjusted tree depth to minimize overfitting, using MSE to select the optimal depth. The R-squared values validated the chosen depth and variable selection.

- **Clustering:**

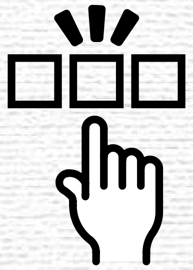
While clustering is less prone to overfitting, we ensured robustness by carefully selecting variables that reflected market and brand dynamics, such as store presence and regional revenue.

AVOID OVERFITTING (2/2)



- **Monte Carlo Simulation:**

The model relies on external assumptions.
To avoid overfitting, we grounded our inputs in real-world data and industry reports.



- **Variable Selection:**

Across all models, we focused on relevant macroeconomic and industry-specific variables, avoiding those with weak theoretical justification.
Additionally, we excluded COVID-impacted data points to reduce noise.

OUR RESULTS

Linear Regression Model

- **Key Findings for Kering:**
  - Strong correlations between stock price and macroeconomic variables in EU, US, China, and Japan.
  - Negative correlation with gold prices, reflecting cost pressures on margins.
- **Comparison with Competitors:**
  - Hermès: No correlation with gold prices; suggests efficient sourcing or strong pricing power.
  - LVMH: Less reliant on the Chinese market; benefits from diversified regional presence.
- **Model Robustness:**
  - Training Correlation: 0.903, Test Correlation: 0.910.
  - Training RMSE: 35.99, Test RMSE: 35.40.

Decision Tree Model

- **Kering:**
  - Revenue declines (-13.1%) when US retail sales weaken, China's retail sales are low, or adverse economic conditions occur, such as high EU inflation or low Japan GDP.
  - Optimal tree depth: 5; R^2: 0.9985.
- **Gucci:**
  - Revenue decreases (-22.6%) when China's retail sales are low, US unemployment is high, and Japan's trade balance is negative.
  - Optimal tree depth: 5; R^2: 0.9995.
- **YSL:**
  - Revenue peaks (+43.1%) with high US retail sales and moderate Japan inflation.
  - Optimal tree depth: 2; R^2: 0.901.
- **Bottega Veneta:**
  - Growth (+20.6%) driven by low FED rate and strong China trade balance.
  - Optimal tree depth: 4; R^2: 0.967.

OUR RESULTS

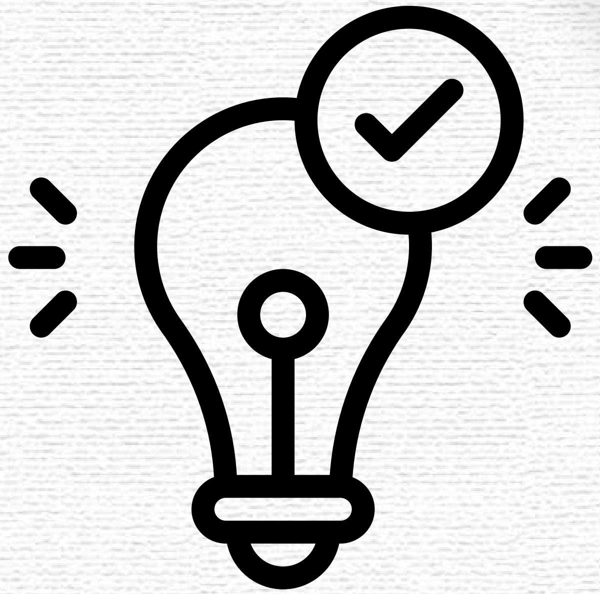
Clustering Insights

- **Store Distribution (2024):**
  - Gucci: Balanced presence across key markets.
  - YSL & Bottega: Over-concentrated in Pacific Asia; should expand in EU and North America.
  - Other Houses: Strong positioning in Japan, offering strategic insights.
- **Store Openings (2019–2024):**
  - Gucci: Stagnant openings; prioritize growth regions over Pacific Asia and Japan.
  - YSL: Growth driven by Europe, USA, and Rest of the World regions.
  - Bottega Veneta: Strong growth in North America and Japan but insufficient focus on Europe.
- **Investment in Brands:**
  - Significant investments in 2021–2022 correlated with higher growth.
  - Gucci: Underperformance linked to low investment levels.
  - YSL & Bottega (2019): Investments yielded limited results.

Monte-Carlo Simulation for Grand Seiko Acquisition

- **Predicted growth rates:**
  - Watch segment: +23.8% (current: 12%).
  - Japan region: +38% (current: 16.6%).

- **Based on realistic growth rates and integration cost analysis from past acquisitions.**



CONCLUSION

Our analysis demonstrates the complexity and interdependence of macroeconomic, brand-specific, and market dynamics on Kering's financial performance.

Using a combination of models, we revealed:

- **Macroeconomic Sensitivity:** gold prices, trade balances, retail sales in the US and China
- Brand-Specific Insights
- **Strategic Gaps:** oversaturation in specific markets (Pacific Asia for Gucci) and underutilized opportunities in Europe and North America for YSL and Bottega Veneta
- **Growth Drivers:** consumer confidence and trade balances
- **Risks:** inflation, slowing GDP growth, and regional market contractions
- **Scenario Testing:** importance of aligning strategic initiatives (acquisitions, store openings) with measurable market growth indicators to maximize ROI

➡ Resilience against macroeconomic shocks and strategic realignment at the brand level are crucial for sustained performance.

RECOMMENDATIONS

From a data analysis point of view:

- **Optimize Global Presence:**

Realign store openings in underpenetrated markets like North America and Europe.

- **Strategic Investments:**

Invest in brands to leverage growth and be active on the merging and acquisition market to better penetrate markets and extend the product range.

- **Leverage Brand Strengths:**

Enhance pricing strategies and marketing to strengthen resilience against economic shocks.

From luxury industry studies point of view:

Diversify: focus on luxury experiences, such as investing in sport events, to capture emerging customer interests.

Q&A