Dynamic Competition In Elite Handbag Industry

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The global luxury handbag market was valued at approximately \$28.64 billion in 2024 and is projected to grow at roughly 6% per year in the next decade Group, 2025. For instance, LVMH is estimated to have spent 9.8 billion Euros on advertisement worldwide in 2024 which is approximately 11.5% of its revenue. Other top players in this industry are Gucci (founded in 1921), Hermes (1837), Chanel (1910) and Dior (1946) to name a few Cage, 2025.

There is surprisingly little rigorous economic research on this industry in the IO literature (see KonishiWang, 2025 for a recent exception[1]. Building on the long tradition in the economics of advertising (see Bagwell, 2007) and recent advances in the field (see Blake, 2015; Goeree, 2008; DecarolisRovigatti, 2021 and Shapiro, 2021), my goal is to fill an evident gap in the literature by conducting a detailed and rigorous empirical analysis of this significant global industry. Firstly, I aim to quantify the structure of advertising investments in this sector; general wisdom in the industry is that ads show up in print media such as magazines to display a perception of exclusivity as opposed to TV; in recent years social media marketing for such brands has also increased. Secondly, I aim to quantify *market power* dynamics across time and states[2] in this sector.

Model

Demand: $p_{j,s,t} = f(Q_{s,t}, q_{1,s,t}, q_{2,s,t}, \tau_{s,t}, B_{1,s,t}, B_{2,s,t})$ is the stochastic inverse demand function where $Q_{s,t}$ is aggregate industry capacity constraint; $q_{1,s,t}$, $q_{2,s,t}$ are firm level quantities produced, $\tau_{s,t}$ is a positive taste shock for firm 1; lastly, $B_{1,s,t}, B_{2,s,t}$ are brand-images for each of the two firms. All these variables can vary across time and states of nature.

For ease of expression and model solution, I assume the following functional forms:

$p_{1,s,t} = \alpha_{s,t} - v_{s,t}q_{1,s,t} + \psi(\tau_{s,t}, m_{1,t}) \times (B_{1,s,t} - B_{2,s,t})$

$p_{2,s,t} = \alpha_{s,t} - v_{s,t}q_{2,s,t} + (1 - \psi(\tau_{s,t}, m_{1,t})) \times (B_{2,s,t} - B_{1,s,t})$. For complete description of the model, refer to the appendix.

[1] This paper builds a model for durable goods in the fashion industry but does not conduct any empirical analysis.

[2] States could be recessions or seasonal fluctuations in demand such as Christmas or summer.

Prestige and Branding: $\psi(\tau_{s,t}, m_{s,t}) = \frac{\tau_{s,t} \ln\left(1+\frac{q_{1,s,t}}{Q_{s,t}}\right)}{\ln 2}$ is the brand dominance amplifier which is concave and increasing in market share of firm 1; $\tau_{s,t} \in [0,1]$ is the prestige shock for brand 1.

$B_{1,s',t} = \sum_s \Pi(s'|s)\rho(I_{1,s,t-1})B_{1,s',t-1} + I_{1,s,t}$ and $B_{2,s',t} = \sum_s \Pi(s'|s)\rho(I_{2,s,t-1})B_{2,s,t-1} + I_{2,s',t}$ are the laws of motion for brand capital over time; $P_j \in [0, 0.3]$ is capturing that brand image needs to be maintained for all players due to depreciation driven by loss of memory, death of old consumers and need to repeatedly emphasize exclusivity to encourage conspicuous consumption but $P_1 > P_2$ since LVMH has a first mover advantage.

Supply-Side: $q_{1,s,t} + q_{2,s,t} \leq Q_{s,t}$ is the aggregate resource constraint and cost of advertising/marketing investment function is the following: $\mathbb{C}(I_{1,s,t}, \psi) = \frac{1}{\psi(\tau_{s,t}, m_{s,t})}(I_{1,s,t})^2$ and $\mathbb{C}(I_{2,s,t}, \psi) = \frac{1}{1-\psi(\tau_{s,t}, m_{s,t})} \times (I_{2,s,t})^2$. This is an otherwise standard convex cost function but $\frac{1}{\psi(\tau_{s,t}, m_{s,t})}$ captures the idea that when firm 1 has higher prestige or higher market share, it can avail bulk ad discounts and also prestige discounts since demand for their ads in magazine or social media platforms will increase; this is motivated by how advertising auctions and pricing works.

Value Function: Lastly, each firm has a discounted value function shown below which is maximized for a finite horizon:

$$V_j = \sum_{t=0}^{T-1} \beta^{T-1} \sum_{s=0}^{S_t} \pi_{s,t} \left(p_{j,s,t}q_{j,s,t} - c(q_{j,s,t}) - \mathbb{C}(I_{i,s,t}, \psi(.))\right) + \beta^T \sum_{s=0}^{S_2} \pi_{s,T} \left(p_{j,s,T}q_{j,s,T} - c(q_{j,s,t})\right) \tag{1}$$

The definition of equilibrium is as follows where unlike complete markets, I assume that aggregate industry feasibility is not necessarily satisfied with equality [3].

Equilibrium: Given exogenous parameters, a Bayesian Nash equilibrium of the dynamic game consists of strategies: $\{q_{j,s,t}\}$, $\{I_{j,s,t}\}$, $\forall s,t,j$ such that given $\{\pi_{s,t}\}, \{Q_{j,s,t}\}$ $\{\alpha_{s,t}, v_{s,t}, \tau_{s,t}\}$, $\forall s,t,j$, firms optimize by choosing optimal production and marketing investment decisions given the goal to maximizes stream of discounted profits over finite horizon T; aggregate industry feasibility is satisfied with *equality or inequality*.

[3]This captures imperfect foresight of demand. Unlike food or oil industry where demand is less volatile and can be estimated with higher precision, elite handbag industry is constantly advertising to increase market share and capture a wider consumer base from among the upper middle class and elites of the world; since new consumers are always coming, demand will be difficult to forecast and the fact that elite handbag industry does not engage in significant hording or maintenance of inventories over time. There is a myth in this market that LVMH burns every unsold product rather than storing it to maintain a reputation of exclusivity.

In the appendix, I illustrate a dynamic game (for review of dynamic games refer to Parilina, 2022) with $T = 2$ which can be solved through stochastic backward induction.

Structural Empirical Model

The dynamic game estimation algorithm will follow the insights of PakesMcGuire, 2001. Since the model represents a finite-horizon dynamic game, the algorithm will be adapted using *stochastic backward induction*. At each period t, the value function in recursive form is:

$$V_j(B_{j,s,t},\, m_{j,s,t},\, s) = \max_{\{I_{j,s,t},\, q_{j,s,t}\}} \left\{ U_{j,s,t}\big(B_{j,s,t},\, m_{j,s,t},\, I_{j,s,t},\, q_{j,s,t},\, s\big) + \beta\, \mathbb{E}_{s'|s} \left[V_j\big(B_{j,s',t+1},\, m_{j,s',t+1},\, s'\big) \right] \right\}. \tag{2}$$

At the terminal period T, the value function satisfies equation 3 below; empirically K_j can be estimated using long-term trends or estimates of profits[4] across the two firms, discounted by β^T. My preliminary code implementing this stochastic backward induction is available here: dynamic-game.jl.

$$V_{j,s,T+1} = \beta^T K_j \tag{3}$$

Luxury brands such as LVMH and Gucci advertise extensively on digital platforms as well as in high-profile print magazines. To quantify firms' marketing decisions, I will assemble a data set combining web-scraped advertising records from X, Instagram and Facebook with archival print-advertising data from Vogue and Harpers' Bazaar. These data can be used to construct measures of advertising frequency, linguistic analysis of ads using tools from computational linguistics such as LDA Blei, 2003[5] and average product prices. Although product prices vary substantially within each brands' portfolio, all items belong to a narrow luxury handbag segment and have high prices. I will therefore abstract from within-brand price heterogeneity by using average prices at the brand level (e.g., LVMH, Gucci).

Brand image and market share: $B_{j,s,t}$ and $m_{j,s,t}$ are not directly observable and will be treated as latent structural state variables, estimated via maximum likelihood (see appendix for details). Advertising investments will be approximated using information on

[4] For instance, $V_{1,s,T+1} > V_{2,s,T+1}$ where long-term price, sales averages and costs can be used to measure this; the goal of model is to explain market share dynamics over time/transitional dynamics, not long-term trends.

[5] Latent Dirichlet Allocation

print-advertising rate cards and sponsored search auction prices on Google, X, and Facebook (see AtheyNekipelov, 2010 for a structural treatment of search-advertising auctions).

Whereas, aggregate industry sales $\sum_j q_{j,s,t}$: will be estimated using U.S. Customs import data under HS Code 4202, since LVMH products are imported luxury goods. Estimates of $Q_{j,s,t}$ can come from FRED data on Real Gross Domestic Product for "Apparel, Leather, and Allied Product Manufacturing (NAICS 315-316)" in the United States.

Lastly, assumptions regarding hyper-parameters such as discount factor: $\beta = 0.95$ and brand persistence: $P_j \in [0, 0.3]$ will be made.

1. APPENDIX

LIKELIHOOD FUNCTION

Observable variables at each time t consist of prices $\{p_{j,s,t}\}_{j=1}^{J}$ ($J = 2$ in my setting: number of firms.), advertising investments: $\{I_{j,s,t}\}_{j=1}^{J}$ and industry aggregate quantity $Q_{s,t} = \sum_j q_{j,s,t}$. Firm-specific quantities $\{q_{j,s,t}\}$, market shares $\{m_{j,s,t}\}$, and brand images $\{B_{j,s,t}\}$ are latent variables: not observed

Given the assumed law of motion

$$B_{1,s',t} = \sum_s \Pi(s^{'}|s)(\rho(I_{1,s,t-1})B_{1,s,t-1}) + I_{1,s',t}$$

,

if $\{I_{j,s',t}\}_{j=1}^{J}$ and $\{m_{j,s',t}\}_{j=1}^{J}$: investments and market shares are known, brand images can be estimated.

The likelihood contribution at time t has three components: the probability of observed advertising choices: $L_t^I(\theta)$, the density of observed aggregate industry quantity: $L_t^Q(\theta)$ and the transition density of the latent state variables which are not observed: $L_t^s(\theta)$; θ is the set of parameters.

Combining the three components, the full likelihood for period t is

$$L_t(\theta) = L_t^I(\theta) \cdot L_t^Q(\theta) \cdot L_t^s(\theta).$$

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Once we have the above likelihood function, we can use maximum likelihood to estimate market shares and quantities sold across firms.

2. APPENDIX: FULL MODEL

Demand: $p_{j,s,t} = f(Q_{s,t}, q_{1,s,t}, q_{2,s,t}, \tau_{s,t}, B_{1,s,t}, B_{2,s,t})$ is the stochastic inverse demand function where $Q_{s,t}$ is aggregate industry capacity constraint; $q_{1,s,t}$, $q_{2,s,t}$ are firm level quantities prodcued, $\tau_{s,t}$ is a positive taste shock for firm 1; lastly, $B_{1,s,t}, B_{2,s,t}$ are brand-images for each of the two firms. All these variables can vary across time and states of nature.

For ease of expression and mode solution, I assume the following functional forms:

$p_{1,s,t} = \alpha_{s,t} - v_{s,t}q_{1,s,t} + \psi(\tau_{s,t}, m_{1,t}) \times (B_{1,s,t} - B_{2,s,t})$

$p_{2,s,t} = \alpha_{s,t} - v_{s,t}q_{2,s,t} + (1 - \psi(\tau_{s,t}, m_{1,t})) \times (B_{2,s,t} - B_{1,s,t})$

$(\alpha_{s,t}, v_{s,t})$ are state and time-level global shocks to demand and price elasticity; $\psi(m_{1,t})$ is the brand-image amplifier for firm 1 defined below and $(1 - \psi(m_{1,t}))$ is the same for firm 2. When the relative brand image of 1 is positive $(B_{1,s,t} - B_{2,s,t}) > 0$, firm 1 can charge higher prices; this relative brand dominance effect is amplified further by the following function of market share and an exogenous prestige shock:

Prestige and Branding: $\psi(\tau_{s,t}, m_{s,t}) = \frac{\tau_{s,t} \ln\left(1+\frac{q_{1,s,t}}{Q_{s,t}}\right)}{\ln 2}$. is the brand dominance amplifier which is concave and increasing in market share of firm 1; $\tau_{s,t} \in [0, 1]$ is the prestige shock for brand 1.

$B_{1,s',t} = \sum_s \Pi(s'|s)\rho(I_{1,s,t-1})B_{1,s,t-1} + I_{1,s',t}$ and $B_{2,s',t} = \sum_s \Pi(s'|s)\rho(I_{2,s,t-1})B_{2,s,t-1} + I_{2,s',t}$ are the laws of motion for brand capital over time; this is motivated from the law of motion for physical capital but $\rho(.)$ is a function of endogenously determined market share over time. More precisely, $\rho(x, j) = P_j$[6] $\times \frac{\ln(x+\epsilon)-\ln(\epsilon)}{\ln(1+\epsilon)-\ln(\epsilon)}$, $\quad \epsilon = 10^{-2}$, where $\rho(x, j)$ captures the persistence of brand for firm j over time. $\rho(x)$ is increasing in consumer loyalty: P_j which may vary across brands due to historical privilege accumulation or in game theoretic sense, a first mover advantage for LVMH relative to Gucci; hence I assume $P_1 > P_2$: higher maximum level of prestige for older firm. Nevertheless, $P_j \in [0, 0.3]$ in my simulation, indicating that brand image needs to be repeatedly maintained for all players due to depreciation driven by loss of memory, death of old consumers and need to repeatedly emphasize exclusivity to encourage conspicuous consumption.

Cost of Production, Ads and Supply-Side:

$c(q) = \Omega_{s,t} \times q^2$ [7] is the standard, convex cost of producing the handbag.

$q_{1,s,t} + q_{2,s,t} \leq Q_{s,t}$ is the aggregate resource constraint.

[6] Notice that P_j is not a probability but imposes a bound on brand persistence.

[7] Ω can change when there are supply shocks in leather industry since handbags use leather as a raw material. Since supply shocks is not the focus of my proposal, I will assume $\Omega_{s,t} = 1$, $\forall s, t$)

Cost of advertising/marketing investment function is the following: $\mathbb{C}(I_{1,s,t}, \psi) = \frac{1}{\psi(\tau_{s,t}, m_{s,t})}(I_{1,s,t})^2$ and $\mathbb{C}(I_{2,s,t}, \psi) = \frac{1}{1-\psi(\tau_{s,t}, m_{s,t})} \times (I_{2,s,t})^2$. This is an otherwise standard convex cost function but $\frac{1}{\psi(\tau_{s,t}, m_{s,t})}$ captures the idea that firm 1 has higher prestige or higher $\psi(\tau_{s,t}, m_{s,t})$, it can avail bulk ad discounts and also prestige discounts since demand for their ads in magazine or social media platforms is higher; this is motivated by how advertising auctions and pricing works.

Value Function: Lastly, each firm has a discounted value function shown below which is maximized; I assume a finite horizon T which is capturing the idea that marketing decisions are made with a finite horizon in mind due to binding contracts with the ad industry; after the end of T, a new contract may be solved with new information.

$$V_j = \sum_{t=0}^{T-1} \beta^{T-1} \sum_{s=0}^{S_t} \pi_{s,t} \left(p_{j,s,t} q_{j,s,t} - c(q_{j,s,t}) - \mathbb{C}(I_{i,s,t}, \psi(.))\right) + \beta^T \sum_{s=0}^{S_2} \pi_{s,T} \left(p_{j,s,T} q_{j,s,T} - c(q_{j,s,t})\right) \tag{4}$$

The definition of equilibrium is as follows where unlike complete markets, I assume that aggregate industry feasibility is not necessarily satisfied with equality. This captures imperfect foresight of demand[8] and the fact that elite handbag industry does not engage in significant hording or maintenance of inventories over time[9].

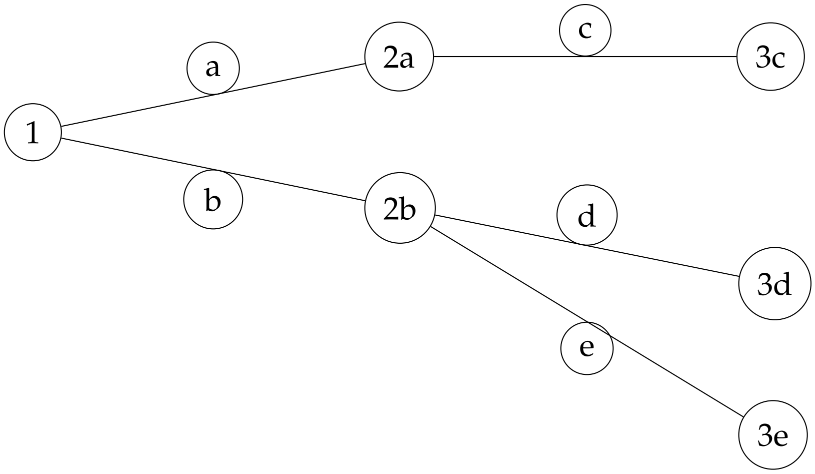
Equilibrium: Given exogenous parameters, a Bayesian Nash equilibrium of the dynamic game consists of strategies: $\{q_{j,s,t}\}$, $\{I_{j,s,t}\}$ $\forall s, t, j$ such that given $\{\pi_{s,t}\}$, $\{Q_{j,s,t}\}$ $\{\alpha_{s,t}, v_{s,t}, \tau_{s,t}\}$, $\forall s, t, j$ and other model primitives such as demand equation, cost functions etc, firms optimize by choosing optimal marketing and production decisions given the goal to maximize stream of discounted profits over finite horizon T; aggregate industry feasibility is satisfied with *equality or inequality*.

In the figure below, I illustrate a dynamic game (refer to Parilina, 2022 for review.) with $T = 2$; for instance a and b are the two states of nature following the initial node; if node is $2a$ is reached, all uncertainty is resolved since both brands have established market shares till the end of this finite game. Meanwhile, if node $2b$ is reached, one more round of play is needed to resolve market power competition[10]

[8]Unlike food or oil industry where demand is less volatile and can be estimated with higher precision, elite handbag industry is constantly advertising to increase market share and capture a wider consumer base from among the upper middle class and elites of the world; since new consumers are always coming, demand will be difficult to forecast.

[9]There is a myth in this market that LVMH burns every unsold product rather than storing it to maintain a reputation of exclusivity.

[10]Since LVMH has a first mover advantage, if it wins the first round of marketing competition, it contin-



3. Appendix: Stylized Model Simulation

I use the following state transition probabilities where the three states can be interpreted as recession, boom and normal times.

$$\Pi = \begin{bmatrix} 0.70 & 0.2 & 0.1 \\ 0.1 & 0.60 & 0.3 \\ 0.25 & 0 & 0.75 \end{bmatrix}$$

The simulated equilibrium dynamics after marketing competition begins at time 0 are provide below; the code can be found here: dynamic-game.jl. The key message is that while there is a persistent first-mover advantage for LVMH, Gucci is able to make some headway. Relative brand-power for Gucci was close to -0.5 at the star of play but it improves to -0.4l by the end of play; the key battle is in the domain of capturing market power through marketing tactics rather than improvement in product quality or prices; perceptions drive this industry more than anything else.

ues to maintain high market share regardless of whether the state is boom or recession afterwards. Whereas if it is not able to win the first round, then another round of competition will be played in which outcomes and strategies may vary across states of nature. The nodes in the game are capturing states of nature and evolve over time, not player strategies. At each node, both players will make decisions regarding quantities to produce and brand investments.

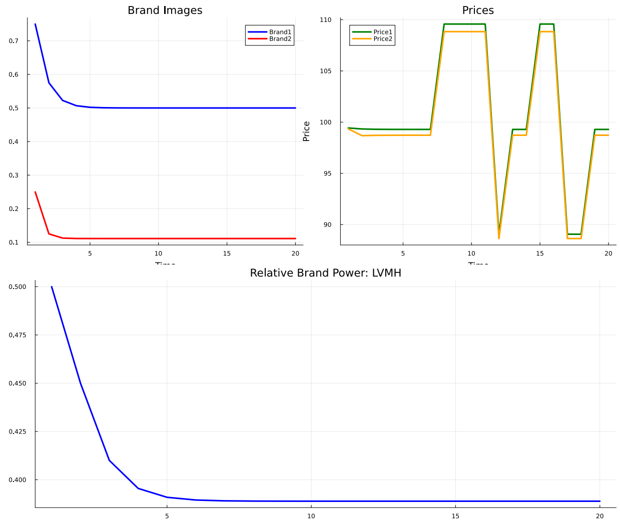

Brand Images
Brand1
Brand2
Prices
Price1
Price2
Price
Relative Brand Power: LVMH

Figure 1

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