Dynamic Pricing & Elasticity-Based Profit Optimization

1. Cleaning and Preparing the Data - We started with raw sales files, including Amazon reports, international sales, inventory, and some price catalogs. These files were quite messy. They had different headers, mixed date formats, and sometimes missing prices. First, I standardized everything into five main fields: date, SKU, category, quantity, and price. If the price wasn't directly available, I calculated it by dividing Amount by Quantity. I also ensured the categories were consistent. Anything that was blank or unusual went into Uncategorized. In addition, I merged cost information from the catalogs. We used the lowest TP column per SKU as the cost price. If we couldn't match a SKU, we used a safe unit cost by default. Finally, I included warehouse costs such as shipping and returns. This way, every transaction had revenue and profit associated with it.

2. Preliminary Checks - Before modeling, I conducted some diagnostics. We had over 130,000 usable transactions across about ten categories. Most categories had very little historical price variation, which means demand didn't get tested much. Still, a few categories like Saree and Blouse showed some variation we could learn from.

3. Estimating Demand Elasticity - Next, I fit demand models. The idea here is simple: how do units sold change when the price changes? I regressed ln(Qty) against ln(Price), controlling for seasonality (weekday, month). The slope on ln(Price) is the elasticity; that's our β. What we saw was that most categories are very inelastic. For example:

Kurta: $\beta \approx -0.001$ (almost flat).

Set: $\beta \approx -0.002$.

Saree: $\beta \approx -0.03$ (slightly more sensitive).

Uncategorized: $\beta \approx -0.14$ (the most sensitive of the group).

That means raising prices won't really hurt demand in most categories.

4. Price Simulation - Using those elasticities, I built a simulator. For each category, I tested price changes from -30% to +30% in increments. The simulator predicts the new demand, then calculates revenue and profit after costs. I added some guardrails: If elasticity was close to zero, I only allowed the model to test small ±5% changes to stay safe. Elasticities were limited between -5 and 0, since demand should never increase with price.

5. Results and Recommendations - Categories like Set and Kurta can handle a +5% price increase with positive results. Uncategorized showed the most potential for growth, with over 50% profit increase when prices go up. Niche categories like Saree and Blouse also showed strong percentage gains. However, their smaller base volume means the total dollar increase is limited.

Most of the business can raise prices because demand is quite insensitive.

The biggest opportunities lie in "Uncategorized" products, which appear to be underpriced right now.

This is a model; the next step should involve controlled experiments or A/B tests to confirm these suggestions in actual sales. Products like Saree and Blouse also showed strong percentage increases, but because their base volume is smaller, the overall dollar gain is limited.