PRICING STRATEGY
& DATA-DRIVEN DECISION MAKING

CONTEXT

The Company manages a diverse catalog of eco-friendly tableware SKUs across online marketplaces.

Current pricing challenges:

- Pricing decisions are reactive and inconsistent
- Margin performance varies widely across SKUs
- Inventory pressure caused by over- and under- pricing
- Limited linkage between demand signals and pricing actions
- Prices sometimes drift away from the market without clear justification

Need:

A structured, repeatable, and data-driven pricing framework that balances

- Profitability
- Demand responsiveness
- Inventory health
- Market alignment

PRICING PHILOSOPHY

Value-Anchored, Data-Driven Framework

The proposed pricing framework is built on a value-based pricing foundation, where each SKU’s base price reflects customer-perceived value, sustainability positioning, and market expectations.

Dynamic pricing is applied as a controlled adjustment mechanism, using demand, inventory, performance, and competitive signals to optimize prices within defined guardrails.
This ensures pricing decisions are:

Strategic, not reactive
Data-driven, not arbitrary
Scalable and explainable across the catalog

HOW I APPROACH THE PROBLEM

I do not begin with formulas or tools. I begin by reframing the problem. The organization lacks a structured, repeatable pricing framework that balances profitability, demand, inventory health, and competitive positioning. Current pricing decisions are largely reactive rather than signal-driven.

Based on the business context and available data, I designed a value-based pricing foundation, supported by a rule-based dynamic pricing mechanism. This approach allows prices to adapt to real operational signals while consistently respecting cost and margin guardrails.

Pricing must:

- Protect margins
- Respond to demand signals
- Manage inventory risk
- Remain explainable to business stakeholders

OBJECTIVE

The objective is not to identify a single “optimal price”, but to design a pricing decision framework that:

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- Can be applied consistently across SKUs
- Adapts dynamically to changing signals
- Is understandable and usable by non-technical business teams

This ensures pricing decisions are scalable, repeatable, and operationally practical, rather than onetime analytical outcomes.

UNDERSTANDING THE DATASETS
(WHAT I USE VS IGNORE)

Given the multiple datasets provided, my first step is to identify which signals genuinely influence pricing decisions.
Key Principle.

	Dataset	Key Fields Used	Purpose in Pricing
	Pricing_Data	Cost, FBA Fee, Storage Fee, Handling Cost, Minimum & Target Margin	Establish cost floor and margin guardrails
	Historical_Sales	Units Ordered, Ordered Product Sales, Sessions	Measure demand strength and sales velocity
	Inventory_Health	Available units, sell-through, days-of-supply, weeks-of-cover	Identify stock pressure or overstock risk
	Ads_Performance	ROAS, ACOS, ad-attributed sales	Understand price sensitivity and efficiency
	Competitor_Data	Avg, Lowest, Highest competitor prices	Prevent price drift from the market

BASE PRICE FLOOR

Value-Based Base Price & Cost Guardrails

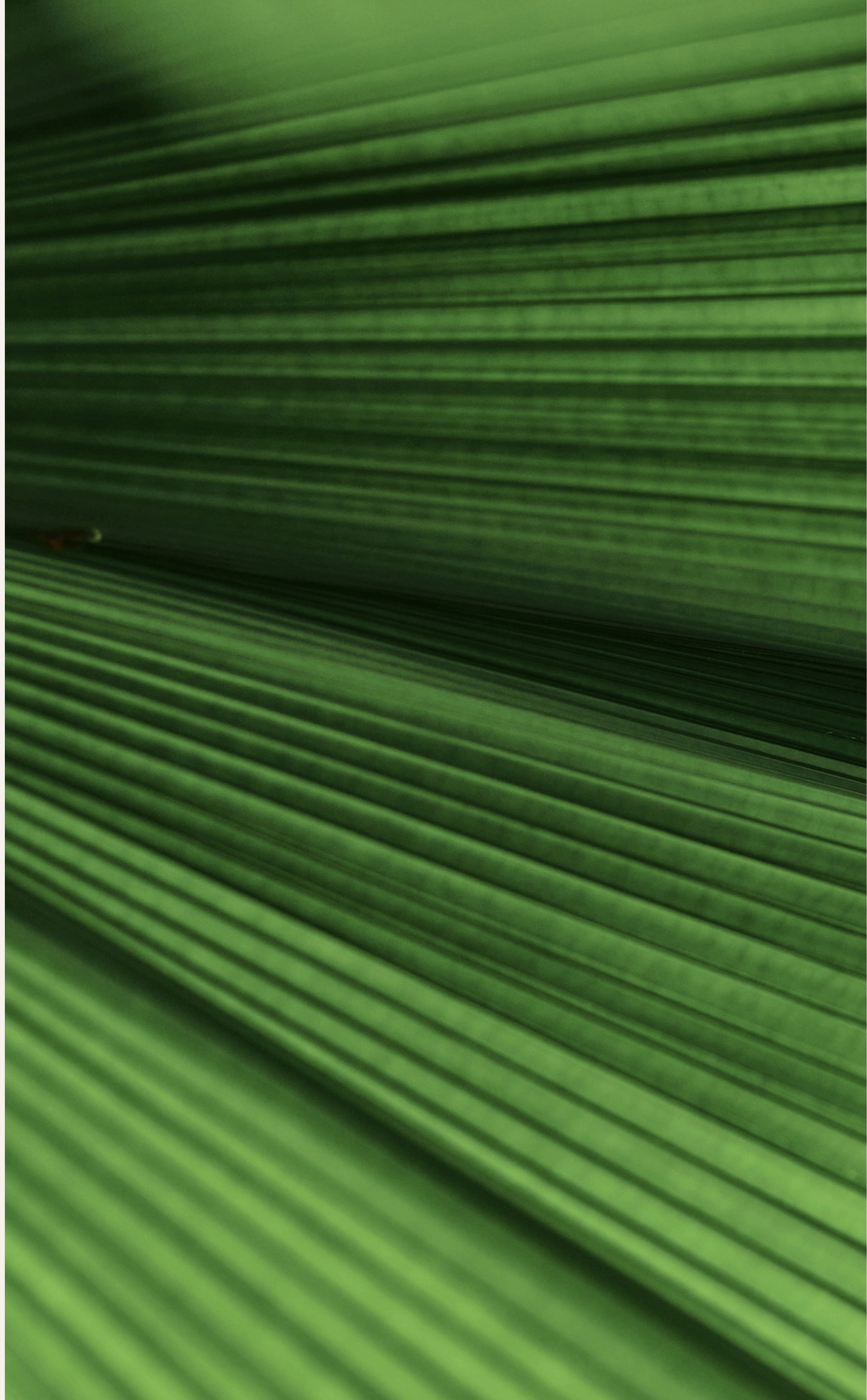
The first rule of pricing is loss prevention.
All pricing decisions are anchored to a value-based base price, validated by a cost-derived price floor:

Floor price is calculated by dividing the landed cost by one minus the minimum acceptable margin.

Cost + FBA Fee + Storage Fee + Handling Cost
→ Floor price

This ensures:

- No SKU is priced below sustainable profitability
- Margin discipline is enforced consistently
- Pricing decisions are protected from short-term pressure



ADJUSTMENTS & GUARDRAILS

Demand Signal Adjustment

Demand was evaluated using:

- Units ordered
- Sessions / impressions
- Conversion rate

High demand with strong conversion indicates pricing power, while high traffic with weak conversion indicates price resistance. Adjustments were applied only relative to the value-based base price and within guardrails.

Inventory Health Adjustment

- Low inventory + strong demand → controlled price increase
- Inventory + weak demand → price correction to improve sell-through

This prevents stockouts caused by underpricing and excess inventory caused by overpricing.

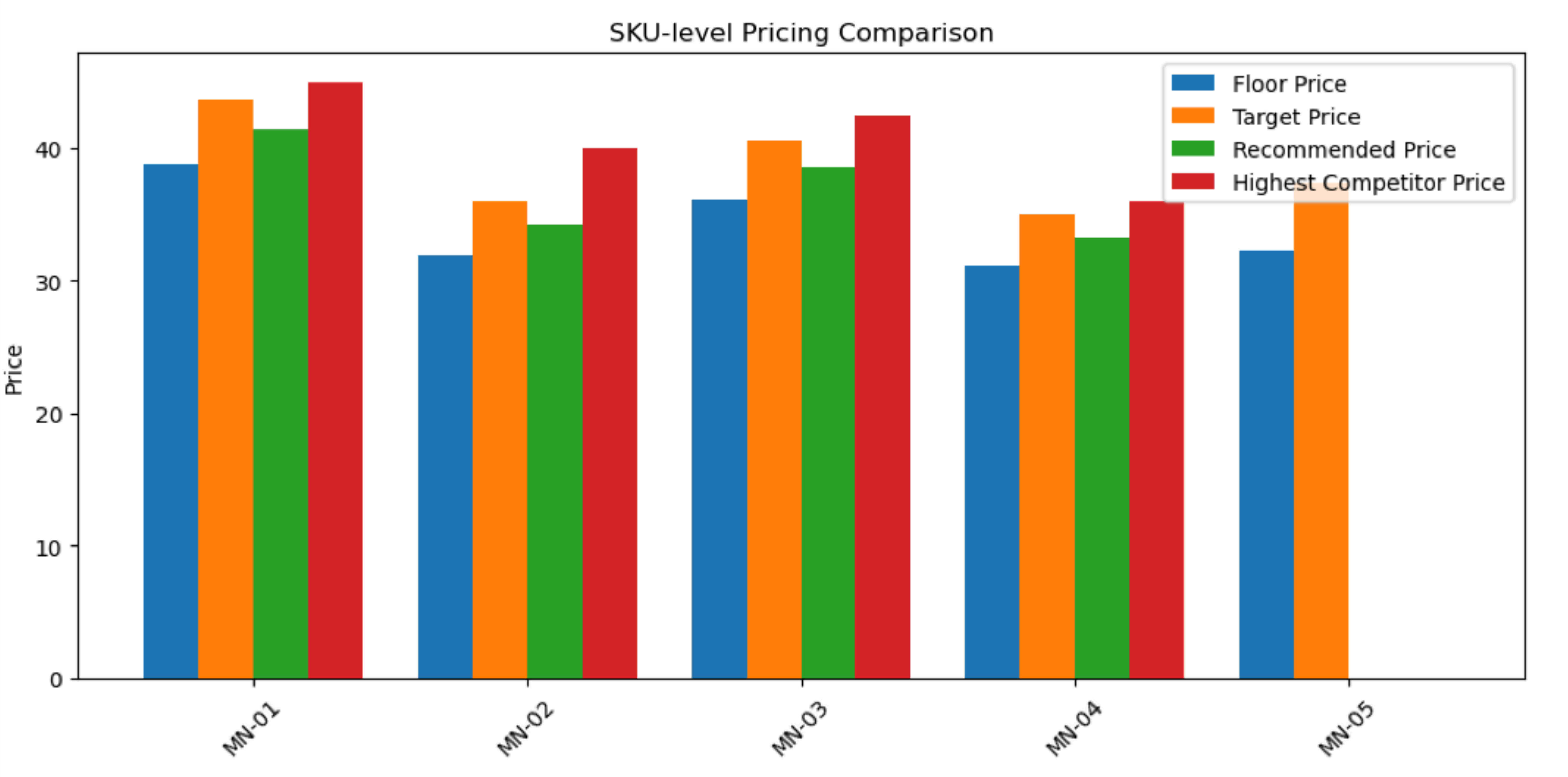
Advertising Efficiency as Validation

Advertising performance was used as a validation layer, not a pricing driver. Poor conversion efficiency highlighted pricing friction, while strong efficiency supported margin protection.

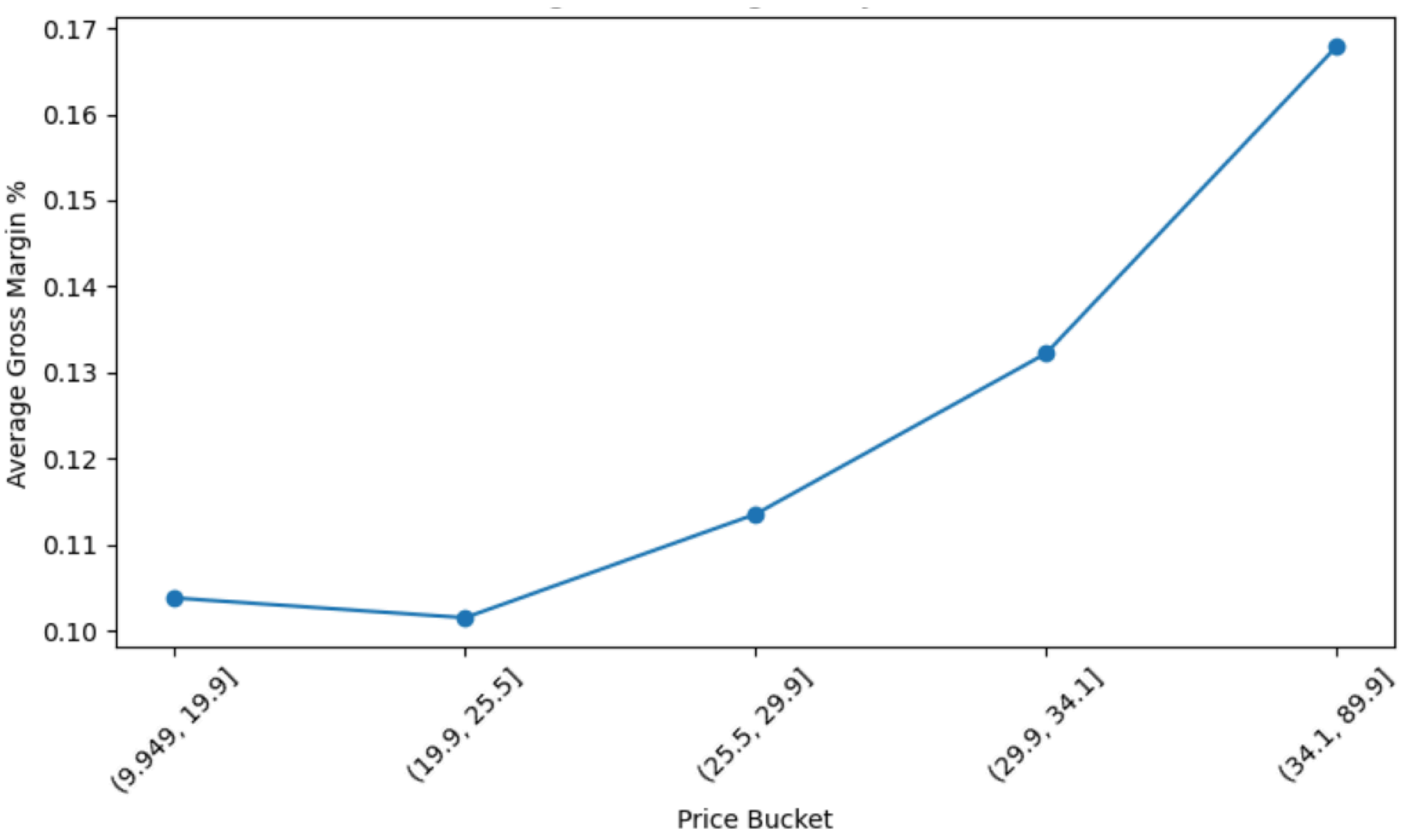
Competitive Market Guardrails

Competitor prices were used as boundaries, not primary drivers. Final prices were validated to ensure market alignment while avoiding race-to-the-bottom behavior.

KEY TRENDS ACROSS PRICE LEVELS



AVERAGE GROSS MARGIN % BY PRICE LEVEL



FINAL PRICING RECOMMENDATIONS & KEY INSIGHTS

Each SKU received:

- A single recommended price
- A clear pricing action (increase / decrease / maintain)
- A rationale linked to observed signals

Key Insights

- Several high-demand SKUs were underpriced relative to margin potential
- Some slow-moving SKUs showed price resistance despite advertising support
- Inventory pressure was often driven by pricing rather than traffic
- Competitive validation prevented unjustified price drift

SUPPORTING FILES & REPRODUCIBILITY

This pricing framework is fully implemented using Python and can be reproduced or extended using the linked notebook.

GitHub Repository:
https://github.com/Saranya-1994/Karmic-seed-assignment-Pricing-Strategy-Data-Driven-Decision-Making

Google Colab :
https://drive.google.com/file/d/1Xj9TjBTvGrlKvOnAhO4lpdpx6VWr3Xxn/view?usp=sharing

Notebook includes:

- Data cleaning and preparation
- Value-based base price calculation
- Cost floor and margin guardrails
- Demand & inventory-based dynamic adjustments
- Final SKU-level recommended prices

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