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Hierarchical Models for Pricing in Consumer Packaged Goods Industry

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Who are we? What we do?

'Cogito ergo sum' – 'I think, therefore I am'

Provide strategic solutions for businesses across sectors such as FMCG, Media, E-commerce, Telecom etc

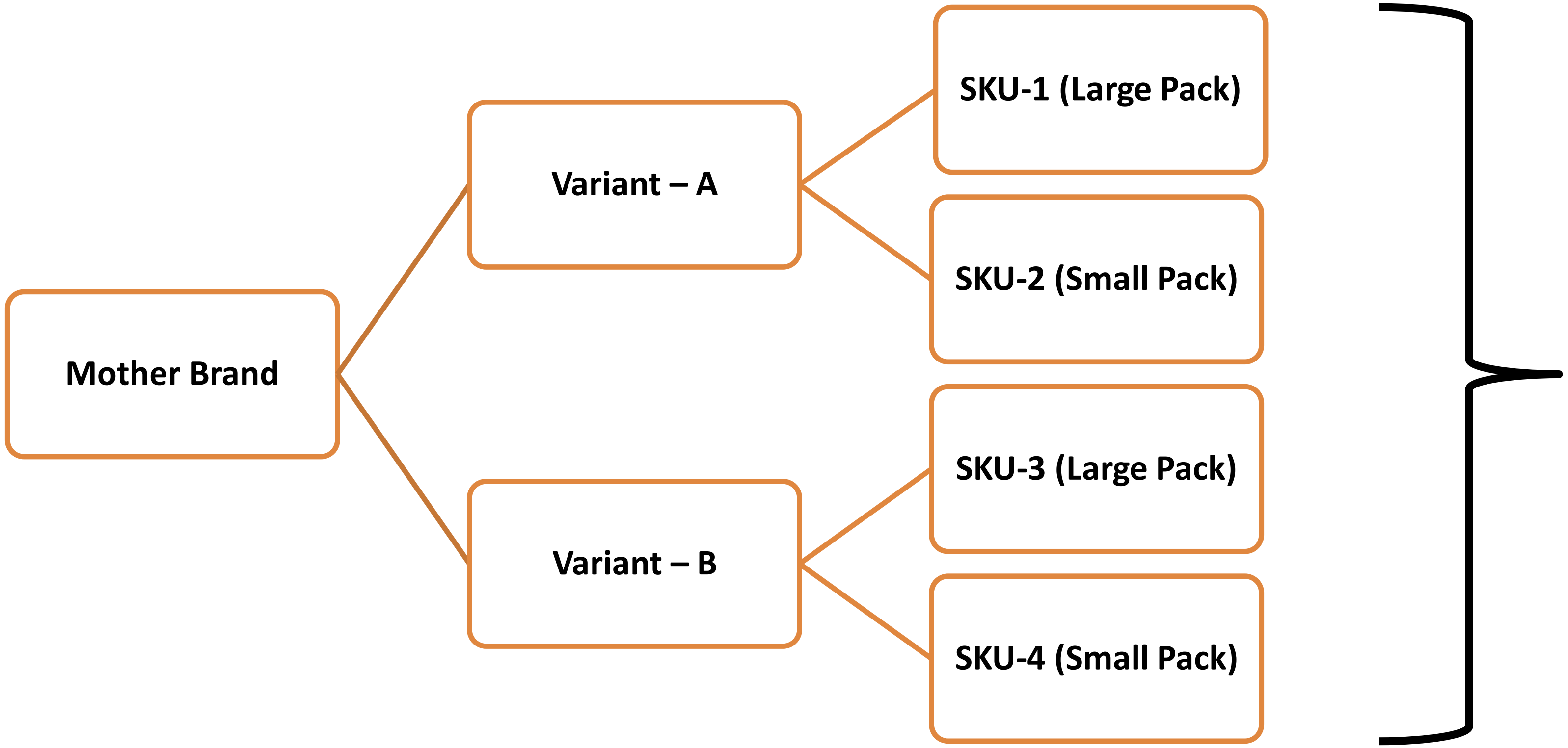
Build user friendly products through proprietary and customized solutions

Blending statistical techniques with marketing domain knowledge, as well as a deep understanding of economics, econometrics and organizational structures

PROBLEM STATEMENT

Problem: Identifying pricing opportunities among SKUs (Stock Keeping Units)

A popular hair color brand in India is selling two variants. Each variant is available in two different pack sizes (Large and Small)



- What is the optimum price range for these SKUs?
- Is a price cut necessary?
- Determine impact of cannibalization, if any

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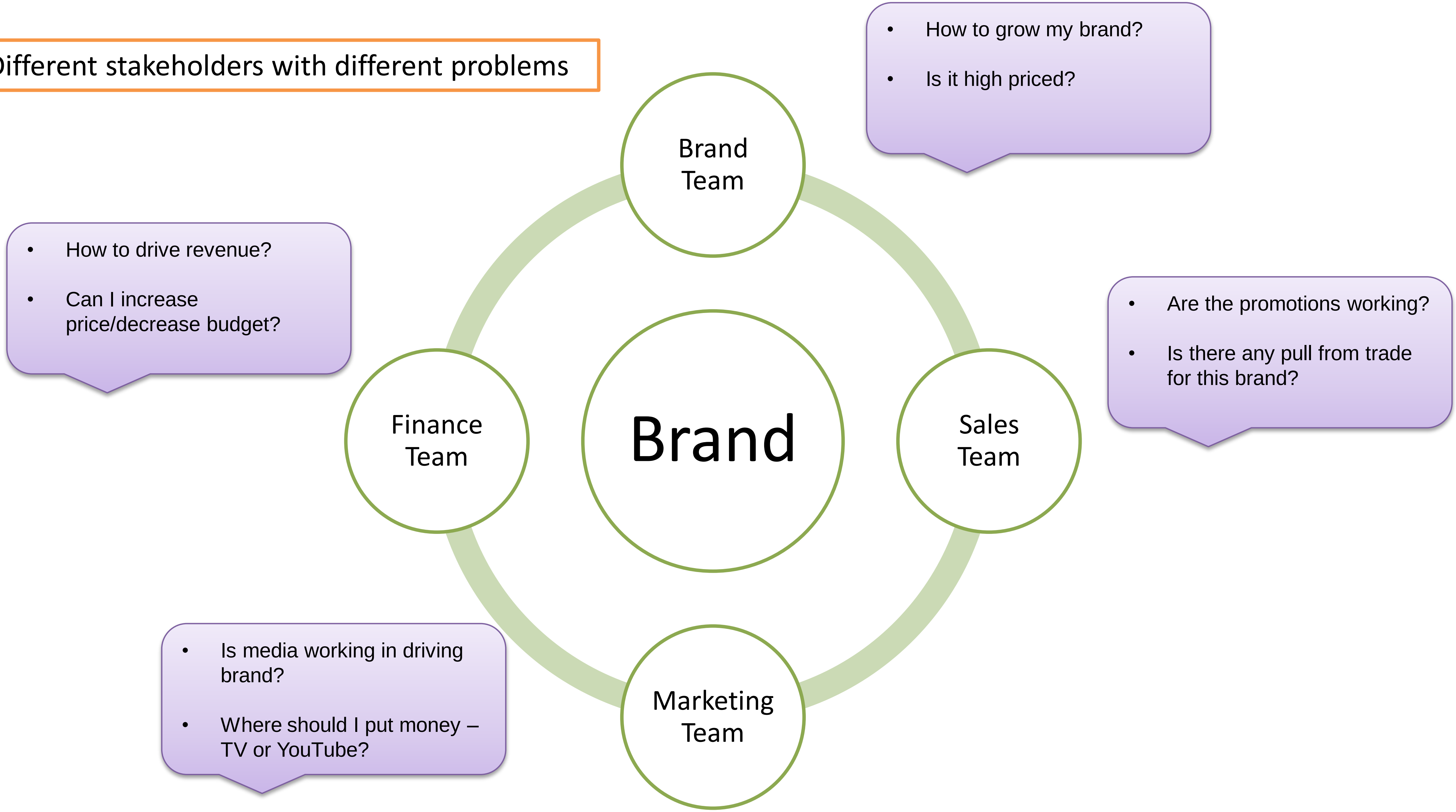
The Bigger problem (1/2)

Different stakeholders with different problems



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The Bigger problem (2/2)

- **Each team is interested in results at different granularity**
  - Marketing – Brand level analysis
  - Brand – Brand and SKU level analysis
  - Sales – SKU level analysis
  - Finance – SKU level analysis

- Should different models be built at different granularity? - *Sometimes difficult to align results from brand and SKU level*
- Can we answer these questions from fewer models?

DATA SUMMARY

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Data Description: weekly data from Jan 2015 to Dec 2016

SKU level

- Value and volume sales
- Price per pack
- Distribution – Number of stores
- Consumer promotion
- Trade promotion
- Visibility spends

Variant Level

- Offline media spends
  - TV/Radio/Print
- Online/digital media spends
  - YouTube/Facebook/Google search

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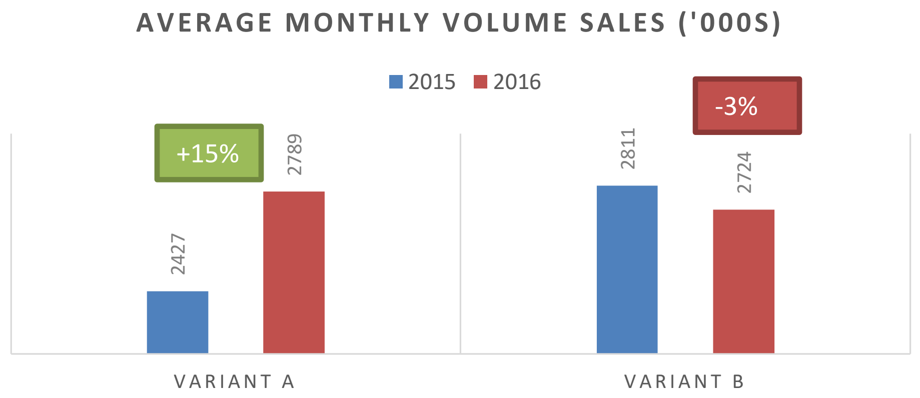
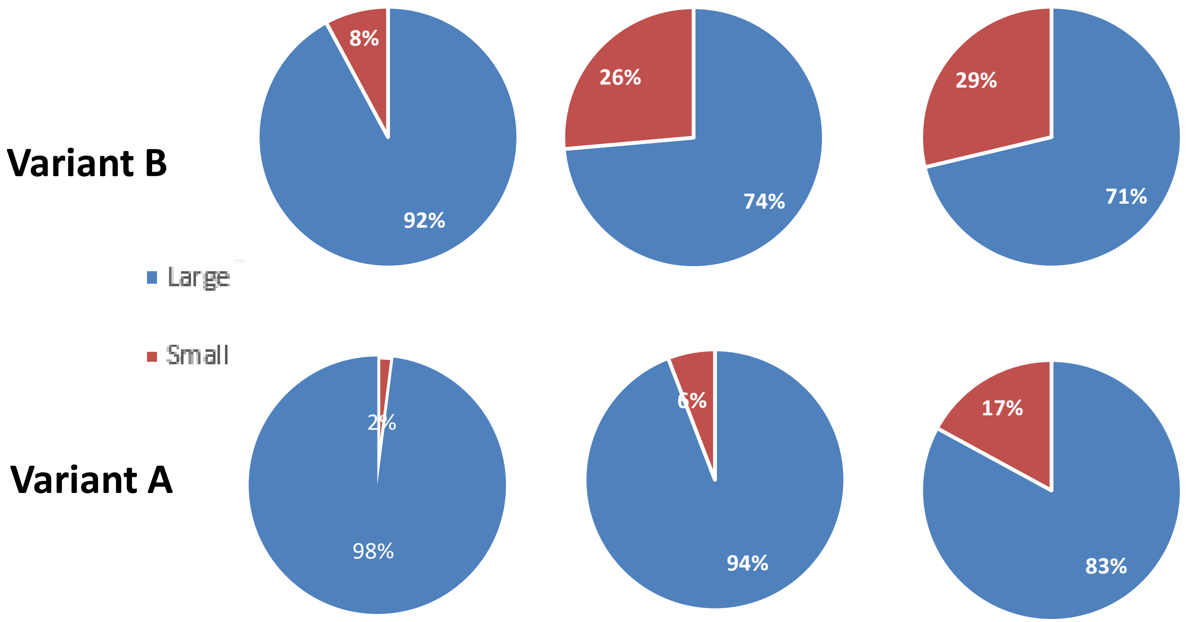
Some graphical summaries …

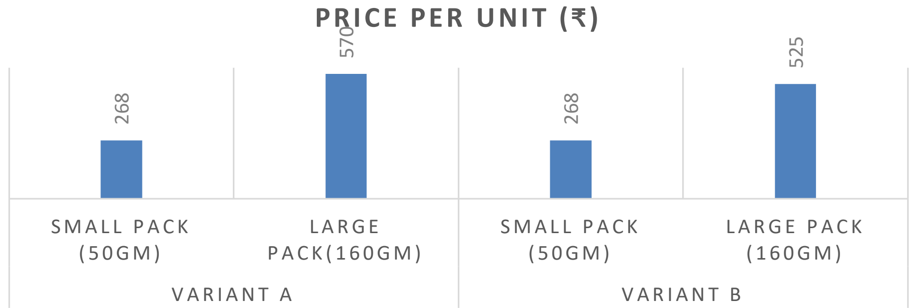
Volume sales of variant A grew by 15% and that of Variant B fell by 3% in 2016



There has been a significant shift from large packs towards small packs. Below is the Volume share for Variant A and Variant B– Large vs. Small



Small packs are relative more expensive on a per gram basis



MODELLING

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Marketing Mix Models (MMM) – an overview

- The marketing mix refers to variables that a marketing manager can control to influence a brand's sales or market share
- Traditionally, these variables are summarized as the four Ps of marketing: *product, price, promotion, and place (distribution)*
- Long history of modelling (Wilbur and Farris, 2014) with more focus on market response to pricing and advertising (Sethuraman and Tellis, 1991)
- Bayesian paradigms are used more frequently in marketing (Rossi, Allenby and McCulloch, 2005)

However, less literature on emerging markets …

- Conventional marketing strategies may not work in emerging markets

- Some differentiating characteristics of emerging markets are (Sheth, 2011)
    - Data issues
    - Market heterogeneity
    - Unbranded competition
    - Inadequate infrastructure

- Some notable works on marketing mix in emerging markets with focus on distribution and market share strategies are by Kumar and Fan (2009); Kumar, Sunder and Sharma (2015)

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3 different approaches …

- Simple linear models – develop independent models for each SKU and draw inference from each

- Seemingly Unrelated Regression (SUR) Models – model correlations among SKUs and draw inference from one model for all SKUs

- Hierarchical Models – exploit inherence hierarchy to draw inference at SKU, variant and mother brand levels

Method-1: Multiple linear regression

$$Y_i = x'_i \beta + \varepsilon_i, i = 1, \ldots, N; \ \varepsilon_i \overset{iid}{\sim} N(0, \sigma^2 I_N)$$

$$\text{where } x_i = (1, X_{i1}, \ldots, X_{ik})$$

$$sales = f(price, promotion, stores, media, competition) + \varepsilon$$

Issues with this approach

- Difficult to scale
  - 4 different models for SKUs
  - 2 different models for variants
- No dependence structure between SKUs

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Inference from multiple linear models

SKU	Price Elasticity (@5%)
Small pack (Variant A)	-12%
Large pack (Variant A)	-1%
Small pack (Variant B)	-6%
Large pack (Variant B)	-5%

Variant A Price Elasticity (@5%) is -4.3%

Variant B Price Elasticity (@5%) is -5%

Note:

- 5% elasticity refers to the impact of change in volume when price is increased by 5%
- The elasticity numbers are from four different models
- Effect of cannibalization incorporated through relative price index among SKUs

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Method-2: SUR Model

The seemingly unrelated regressions (SUR) model, proposed by Zellner (1962), can be viewed as a special case of the generalized regression model

$$E(y) = X\beta; V(y) = \sigma^2 \mathbf{\Omega}$$

The basic SUR model assumes that, for each individual observation *i,* there are M dependent variables $x_{i1}, x_{i2} \cdots x_{ij}, \cdots x_{iM}$ available, each with its own linear regression model:

$$y_{ij} = \mathbf{x}'_{ij}\boldsymbol{\beta}_j + \varepsilon_{ij}, \qquad i = 1, ..., N,$$

or, with the usual stacking of observations over *i* ,

$$\mathbf{y}_j = \mathbf{X}_j \boldsymbol{\beta}_j + \boldsymbol{\varepsilon}_j$$

for $j = 1, ..., M$, where $\mathbf{y}_j$ and $\boldsymbol{\varepsilon}_j$ are N-vectors and $\mathbf{X}_j$ is an $N \times K_j$ matrix, where

$$K_j = \dim(\boldsymbol{\beta}_j)$$

is the number of regressors for the j^{th} regression.

Reasons to use SUR

- Correlated error structure – which brings dependencies across SKUs
  - SUR permits non-zero covariance between the error terms
- Reasonable assumption since there are certain common market factors which affect all 4 SKUs
- Although, SUR takes into account dependencies across SKUs, it does not necessarily account for cannibalization

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Inference from SUR model

SKU	Price Elasticity (@5%)
Small pack (Variant A)	-10%
Large pack (Variant A)	-1%
Small pack (Variant B)	-6%
Large pack (Variant B)	-4.2%

Variant level elasticity?

Note:
- 5% elasticity refers to the impact of change in volume when price is increased by 5%
- Not much of a difference when compared to price elasticities from independent models.
- No inference at variant level

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Method-3: Hierarchical Bayes Model

The model takes the following form

$$y_i = X_i\beta + w_i b_i + \varepsilon_i$$

Where each group *i* have k_i observations.

Where the random effects: $$b_i \sim N_p(0, V_b)$$

And the errors:

$$\varepsilon \sim N(0, \sigma^2 I_{k_i})$$

Assume standard conjugate priors

$$\beta \sim N_p(\mu_\beta, V_\beta)$$

$$\sigma 2 \sim IGamma(\upsilon, \frac{1}{\zeta})$$

$$V_b \sim IWishart(r, rR)$$

Prior information taken from classical linear mixed model

Two models, one for each variant

SKU	Price Elasticity (@5%)
Small pack (Variant A)	-7.5%
Large pack (Variant A)	-0.5%

Price elasticity of Variant A: -8%

SKU	Price Elasticity (@5%)
Small pack (Variant B)	-5%
Large pack (Variant B)	-3%

Price elasticity of Variant B: -3%

Price recommendation

- Consumers are more sensitive to price changes in Variant B as compared to Variant A
- Recommended to reduce price in Variant A by reducing price of small packs by 10%
- For Variant B, it is recommended to hold onto current price

Further insights from HB

- Using HB model, it was possible to account for impact of variant level spends – media, and visibility

- Media –
    - Digital and TV drive sales when used together. In the absence of TV, Digital's effectiveness also comes down

- Consumer promotion
    - Consumer promotion on Variant B was not driving incremental sales
    - Moreover, Variant A's consumer promotion has a negative impact on sales of Variant B;
    - Recommended to provide consumer promotion in smaller packs and that the promotion for two variants should be in unison

- Trade Promotion
    - Recommended to increase trade promotion for variant B

- Stores
    - High impact on sales. Recommended to drive number of stores

More questions

- Cannibalization
  - How to measure impact of cannibalization within a portfolio on account of price change?

Thank You!