Retail and Marketing Analytics

Session 2

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Outline

Morning session:

- Retail promotions
- SCAN*PRO model
- Advertising effects
- ADSTOCK model

Afternoon session:

- R tutorial
- Simulation Game

Retail Promotions

POLL

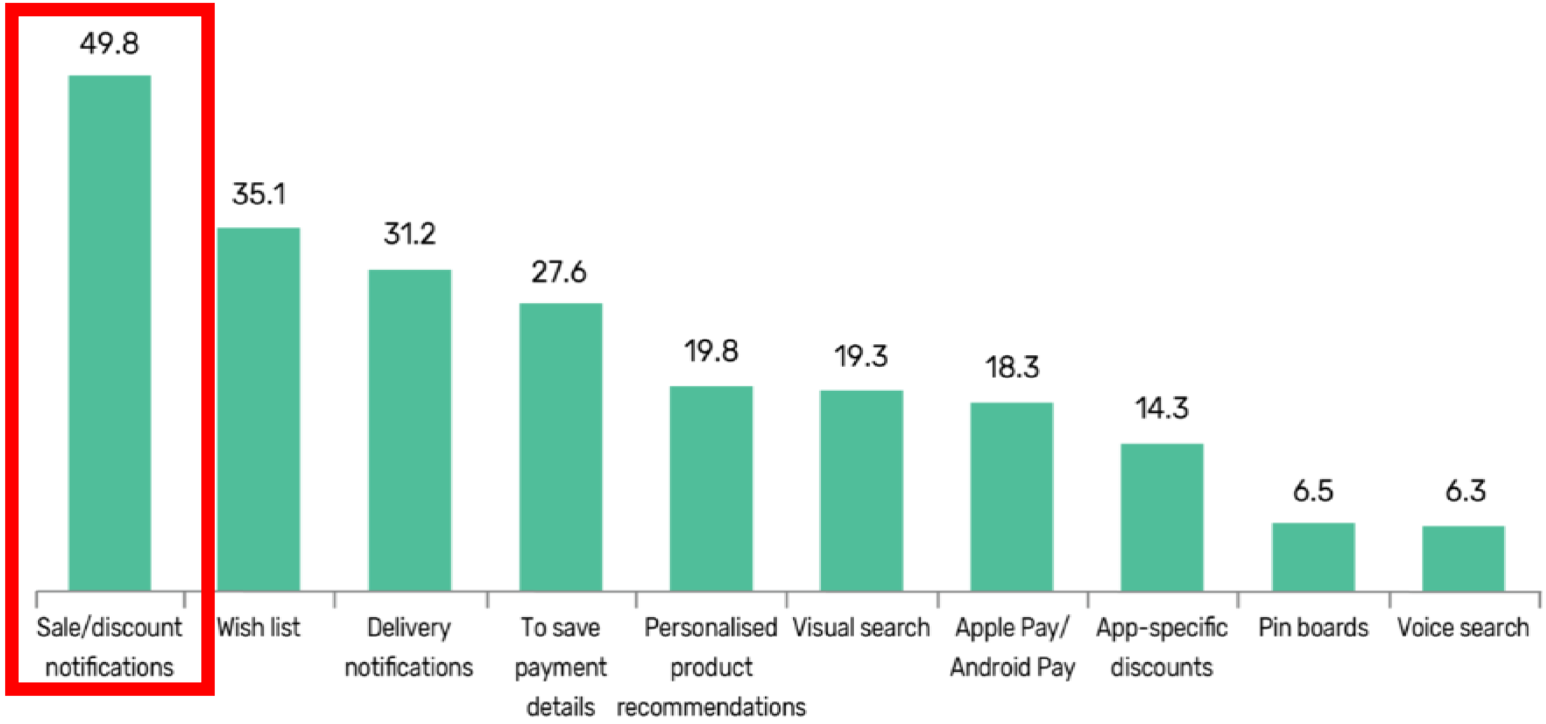
1. What percentage of **food products** do you think are sold on promotion in the UK?

A) 20%	B) 30%	C) 40%	D) 50%	E) Over 50%

2. What percentage of **non-food products** do you think are sold on promotion in the UK?

A) 20%	B) 30%	C) 40%	D) 50%	E) Over 50%

What do UK consumers use retailer apps for?



GlobalData's Monthly Spend Tracker Report, January 2019

Why run promotions?

To boost sales:

Remind existing customers to buy:
- More quantity
- Higher frequency

Trigger **new product trials** and make new customers switch permanently

Promotion effects

POLL

1. One chocolate bar is constantly sold on promotion. How does this affect your perception of the quality of the chocolate?

- ❑ No impact on my perception of quality
- ❑ I perceive the product to have a lower quality

2. You purchase a flat screen TV that is on promotion on Amazon. You are really happy with it. You want another one. But it's not on promotion anymore. What do you do?

- ❑ Buy it at the higher cost
- ❑ Buy another brand at a lower price
- ❑ Wait until the same TV goes back on promotion

Price promotions in turbulent times

Price promotions in a recession

Are price promotions less effective in a recession?

Are price promotions less effective in a recession?

vs.

Growth mindset

Prevention focus

Are price promotions less effective in a recession?

Effective if:

- consumers are price-sensitive, AND
- brands are happy with the lower margin.

Price Wars

Price wars

MarketingWeek

Tesco becomes first supermarket to directly price match with Aldi

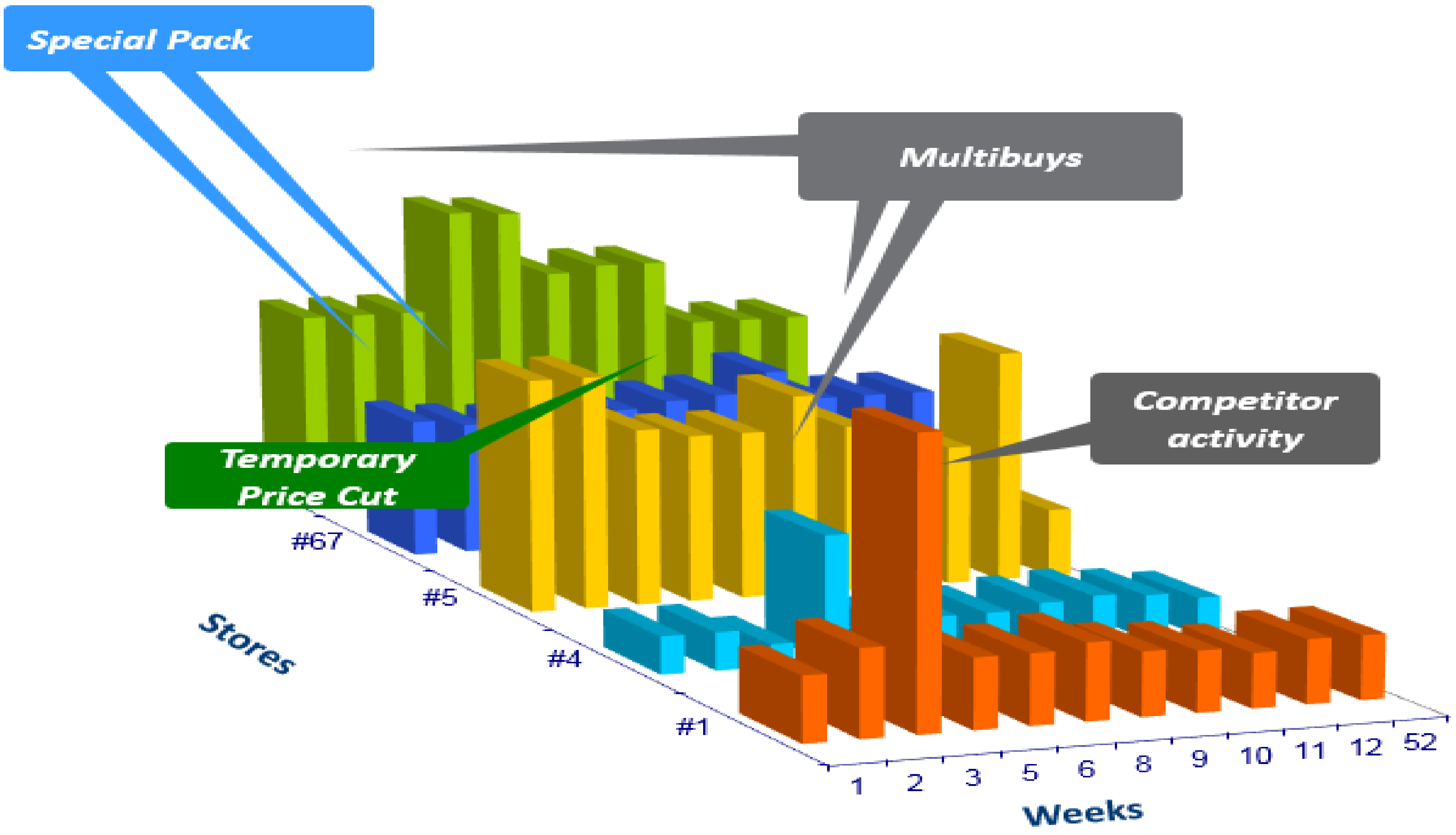
Tesco will hope that by price-matching with the discounter on both own-brand and branded products it can curb Aldi's growth and win back customers.

Price wars

Tesco initiated a price war, followed by Sainsbury’s.

Would you follow Tesco and Sainsbury’s?

SCAN*PRO Model


Special Pack
Multibuys
Competitor activity
Temporary Price Cut
#67
#5
#4
#1
Stores
1
2
3
5
6
8
9
10
11
12
52
Weeks

Why at store-level?

	Week 1	Week 2
Store 1		
Price	$4.00	$5.00
Sales	100	90
Store 2		
Price	$5.00	$4.00
Sales	90	100
Market Level Aggregate		
Price	$4.47	$4.47
Sales	190	190

Price change at the store level

No price change at the market level

SCAN*PRO Model

$$q_{kjt} = \left[\prod_{r=1}^{n}\left(\frac{p_{krt}}{\bar{p}_{kr}}\right)^{\beta_{rj}}\prod_{l=1}^{3}\gamma_{lrj}^{D_{lkrt}}\right]\left[\prod_{t=1}^{T}\delta_{jt}^{X_t}\right]\left[\prod_{k=1}^{K}\lambda_{kj}^{Z_k}\right]e^{\varepsilon_{kjt}}$$

SCAN*PRO Model

It is a multiplicative model

$$q_{kjt} = \left[\prod_{r=1}^{n}\left(\frac{p_{krt}}{\bar{p}_{kr}}\right)^{\beta_{rj}}\prod_{l=1}^{3}\gamma_{lrj}^{D_{lkrt}}\right]\left[\prod_{t=1}^{T}\delta_{jt}^{X_t}\right]\left[\prod_{k=1}^{K}\lambda_{kj}^{Z_k}\right]e^{\varepsilon_{kjt}}$$

SCAN*PRO Model

$$q_{kjt} = \left[\prod_{r=1}^{n} \left(\frac{p_{krt}}{\bar{p}_{kr}} \right)^{\beta_{rj}} \prod_{l=1}^{3} \gamma_{lrj}^{D_{lkrt}} \right] \left[\prod_{t=1}^{T} \delta_{jt}^{X_t} \right] \left[\prod_{k=1}^{K} \lambda_{kj}^{Z_k} \right] e^{\varepsilon_{kjt}}$$

PRICE

FEATURE and DISPLAY PROMOTIONS

RANDOM TERM

UNIT SALES

WEEK

STORE

SCAN*PRO Model

Model parameters to estimate

$$q_{kjt} = \left[\prod_{r=1}^{n}\left(\frac{p_{krt}}{\bar{p}_{kr}}\right)^{\beta_{rj}}\prod_{l=1}^{3}\gamma_{lrj}^{D_{lkrt}}\right]\left[\prod_{t=1}^{T}\delta_{jt}^{X_t}\right]\left[\prod_{k=1}^{K}\lambda_{kj}^{Z_k}\right]e^{\varepsilon_{kjt}}$$

SCAN*PRO Model

D_{1krt}= 1 if brand r is featured but not displayed by store k, in week t; 0 otherwise.

D_{2krt}= 1 if brand r is displayed but not featured by store k, in week t; 0 otherwise.

D_{3krt}= 1 if brand r is featured and displayed; 0 otherwise.

Unit price for brand r in store k, week t

$$q_{kjt} = \left[\prod_{r=1}^{n}\left(\frac{p_{krt}}{\bar{p}_{kr}}\right)^{\beta_{rj}}\prod_{l=1}^{3}\gamma_{lrj}^{D_{lkrt}}\right]\left[\prod_{t=1}^{T}\delta_{jt}^{X_t}\right]\left[\prod_{k=1}^{K}\lambda_{kj}^{Z_k}\right]e^{\varepsilon_{kjt}}$$

Unit sales of brand j in store k, week t;

Median regular unit price (in non-promoted weeks) for brand *r* in store *k*

X_t=1 if observation is in week t

Z_k=1 if observation is in store k

SCAN*PRO Model: Estimation

Log-transformation makes the model linear…

$$q_{kjt} = \left[\prod_{r=1}^{n}\left(\frac{p_{krt}}{\bar{p}_{kr}}\right)^{\beta_{rj}} \prod_{l=1}^{3} \gamma_{lrj}^{D_{lkrt}}\right]\left[\prod_{t=1}^{T} \delta_{jt}^{X_t}\right]\left[\prod_{k=1}^{K} \lambda_{kj}^{Z_k}\right] e^{\varepsilon_{kjt}}$$

$$\Downarrow$$

$$ln(q_{kjt}) = \sum_{r=1}^{n} \beta_{rj}\, ln\left(\frac{p_{krt}}{\bar{p}_{kr}}\right) + \sum_{r=1}^{n}\sum_{l=1}^{3} ln(\gamma_{lrj}) D_{lkrt} + \sum_{t=1}^{T} ln(\delta_{jt}) X_t + \sum_{k=1}^{K} ln(\lambda_{kj}) Z_k + \varepsilon_{kjt}$$

Simplifying the model further…

Let $\gamma'_{lrj} = ln(\gamma_{lrj}), \;\; \delta'_{jt} = ln(\delta_{jt}), \;\; \lambda'_{kj} = ln(\lambda_{kj})$

Then, the model becomes:

$$ln(q_{kjt}) = \sum_{r=1}^{n} \beta_{rj}\, ln\left(\frac{p_{krt}}{\bar{p}_{kr}}\right) + \sum_{r=1}^{n}\sum_{l=1}^{3} \gamma'_{lrj} D_{lkrt} + \sum_{t=1}^{T} \delta'_{jt} X_t + \sum_{k=1}^{K} \lambda'_{kj} Z_k + \varepsilon_{kjt}$$

Two-brand example

Assume that there is **no competitive feature and display activity**.

$$ln(q_{kjt}) = \sum_{r=1}^{n} \beta_{rj}\, ln\left(\frac{p_{krt}}{\bar{p}_{kr}}\right) + \sum_{r=1}^{n}\sum_{l=1}^{3} \gamma'_{lrj} D_{lkrt} + \sum_{t=1}^{T} \delta'_{jt} X_t + \sum_{k=1}^{K} \lambda'_{kj} Z_k + \varepsilon_{kjt}$$

The model for the **focal brand *j*** becomes:

$$ln(q_{kjt}) = \sum_{r=1}^{n} \beta_{rj}\, ln\left(\frac{p_{krt}}{\bar{p}_{kr}}\right) + \sum_{l=1}^{3} \gamma'_{lj} D_{lkjt} + \sum_{t=1}^{T} \delta'_{jt} X_t + \sum_{k=1}^{K} \lambda'_{kj} Z_k + \varepsilon_{kjt}$$

Two-brand example

- For brand j = 1

$$ln(q_{k1t}) = \beta_{11} ln\left(\frac{p_{k1t}}{\bar{p}_{k1}}\right) + \beta_{21} ln\left(\frac{p_{k2t}}{\bar{p}_{k2}}\right) + \gamma'_{11} D_{1k1t} + \gamma'_{21} D_{2k1t} + \gamma'_{31} D_{3k1t} + \sum_{t=1}^{T} \delta'_{1t} X_t + \sum_{k=1}^{K} \lambda'_{k1} Z_k + \varepsilon_{k1t}$$

- For brand j = 2

$$ln(q_{k2t}) = \beta_{12} ln\left(\frac{p_{k1t}}{\bar{p}_{k1}}\right) + \beta_{22} ln\left(\frac{p_{k2t}}{\bar{p}_{k2}}\right) + \gamma'_{12} D_{1k2t} + \gamma'_{22} D_{2k2t} + \gamma'_{32} D_{3k2t} + \sum_{t=1}^{T} \delta'_{2t} X_t + \sum_{k=1}^{K} \lambda'_{k2} Z_k + \varepsilon_{k2t}$$

Interpretation of coefficients

For brand $j = 1$

Cross price elasticity

Display-only multiplier

Seasonality

$$ln(q_{k1t}) = \beta_{11} ln\left(\frac{p_{k1t}}{\bar{p}_{k1}}\right) + \beta_{21} ln\left(\frac{p_{k2t}}{\bar{p}_{k2}}\right) + \gamma'_{11} D_{1k1t} + \gamma'_{21} D_{2k1t} + \gamma'_{31} D_{3k1t} + \sum_{t=1}^{T} \delta'_{1t} X_t + \sum_{k=1}^{K} \lambda'_{k1} Z_k + \varepsilon_{k1t}$$

Own price elasticity

Feature-only multiplier

Feature & Display multiplier

Difference in sales across stores

Estimation

$$ln(q_{kjt}) = \sum_{r=1}^{n} \beta_{rj}\, ln\left(\frac{p_{krt}}{\bar{p}_{kr}}\right) + \sum_{r=1}^{n}\sum_{l=1}^{3} \gamma'_{lrj} D_{lkrt} + \sum_{t=1}^{T} \delta'_{jt} X_t + \sum_{k=1}^{K} \lambda'_{kj} Z_k + \varepsilon_{kjt}$$

Log-transformed model is linear in variables → Simple OLS

Endogeneity problem: bias in the estimated parameters of the model.

If there is price endogeneity, use instrumental variable (IV) regression.

Baseline and Incremental Sales

Baseline sales= Estimated sales without promotions (feature and display)

$$ln\left(q_{kjt}\right)_{baseline} = \sum_{r=1}^{n} \beta_{rj}\, ln\left(\frac{p_{krt}}{\bar{p}_{kr}}\right) + \sum_{t=1}^{T} \delta'_{jt} X_t + \sum_{k=1}^{K} \lambda'_{kj} Z_k + \varepsilon_{kjt}$$

Incremental sales = Actual sales (observed) - Baseline sales (estimated)

Profitability of promotion= Incremental revenue – Costs of promotion

Measuring advertising effects

Advertising effects

In reality, **consumer response to advertising can be delayed.**

Not accounting for carry-over effects of advertising can cause advertising elasticities to be under-valued.

Modeling carryover effects

- **Advertising adstock** measures the effect of advertising beyond the current time period

$$\boxed{Adstock_t = Advertising_t + \lambda \ Adstock_{t-1}}$$

- In each time period, you are assumed to retain a fraction (λ) of your previous advertising stock

- For example, if λ equals 0.3, then adstock from one time period ago still has a 30% effect in the current time period

Modelling carryover effects

How to calculate Adstock levels?

$$\text{Adstock}_t = \text{Advertising}_t + \lambda \text{ Adstock}_{t-1}$$

Week	Advertising	Adstock
1	450	450
2	100	235[a]
3	0	71[b]
4	200	221
5	800	866
6	400	660
7	300	498

$\lambda = 0.30$

[a] 100 + 0.3*450 = 235

[b] 0 + 0.3*235 = 71

Integrating Adstock into MMM

Example in R:

```
adstock <- function(x, rate=0.1){return(as.numeric(stats::filter(x=x, filter=rate, method="recursive")))}

spending.data <- spending.data %>%
  mutate(tv_adstock = adstock(tv),
         newspaper_adstock = adstock(newspaper),
         radio_adstock = adstock(radio))

regression <- lm(log(sales) ~ log(radio+0.01) + log(tv_adstock) + log(newspaper), data=spending.data)

summary(regression)
```

- “rate=0.1” sets λ to 0.1 (i.e. 10%)
- You can empirically test multiple values of λ or optimize it.

Carryover effects for other advertising variables…

	$\lambda = 0.1$	$\lambda = 0.3$	$\lambda = 0.5$
Radio adstock	0.21	0.28	0.37
TV adstock	0.46	0.62	0.77
Newspaper adstock	0.02	0.01	0.03

Integrating Adstock into MMM

$$Sales_t = \beta_0 \left({\beta_1}^t + \beta_2 Adstock_t\right) Price_t^{\beta_3} \; (Seasonal\ Index) + \varepsilon_t$$

Base level for sales in the absence of seasonality and advertising and adjusts the base level based on the current level of Adstock.

Adjusts the base level based on the current price and seasonal period.

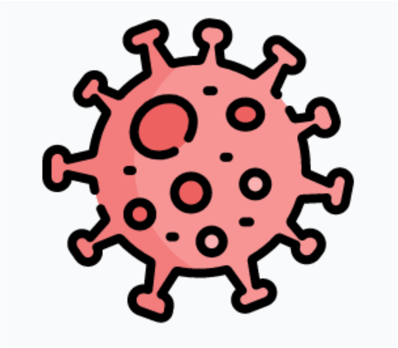
Other methods

Other approaches to evaluate ad performance:

1. Recognition test
2. Unaided recall test
3. Aided recall test
4. Association test

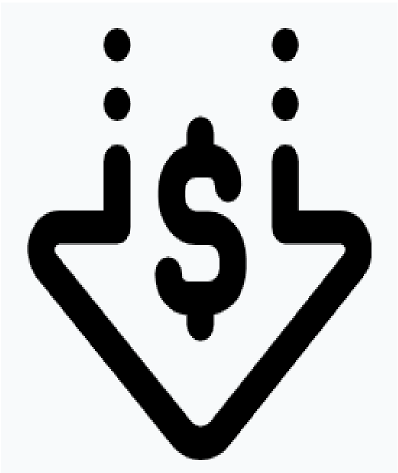
Ad spending in turbulent times

Advertising in tough times



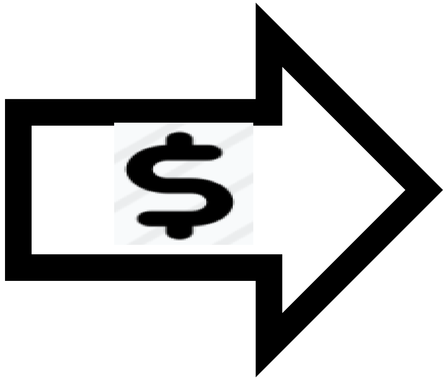
What should marketers do with their advertising spending in turbulent times?

A.



B.

C.



ANALYTIC PARTNERS

- 700 brands in over 45 countries
- The majority saw ROI increase in the last recession.

J. of the Acad. Mark. Sci.
DOI 10.1007/s11747-017-0542-9

CONCEPTUAL/THEORETICAL PAPER

Business cycle research in marketing: a review and research agenda

Marnik G. Dekimpe[1,2] · Barbara Deleersnyder[1]

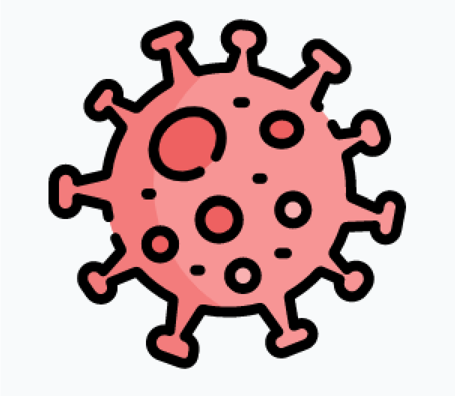
Received: 31 August 2016 / Accepted: 27 April 2017

Abstract Business cycles (BCs) may affect entire markets, and significantly alter many firms' marketing activities and performance. Even though managers cannot prevent BCs from occurring, marketing research over the last 15 years has provided growing evidence that their impact on consumers, and hence on firm and brand performance, depends to a large extent on how

twenty-first century, after more than a ‹
prosperity, a severe contraction hit the glo
reminded marketers that BCs can sever
activities, and even threaten many firms'
An often-used definition of BCs goes
study of Burns and Mitchell (1946, p. 3),

- **Tens of studies reviewed.**
- **It is typically better to maintain or increase marketing spending in a recession.**

Managing ad budget in tough times



- **Optimization of the advertising budget (Wright 2009, JAR):**
- Optimal budget= Gross contribution * Elasticity

= Unit contribution*Expected Sales*Elasticity

Summary

Summary

SCAN*PRO model helps us predict the impact of in-store price reductions and other types of promotions such as feature and display.

It can be used for online promotions (non-targeted) as well.

The model allows for the decomposition of sales into baseline and incremental sales due to promotions.

Different **types of promotions** can affect revenues and margins in different ways.

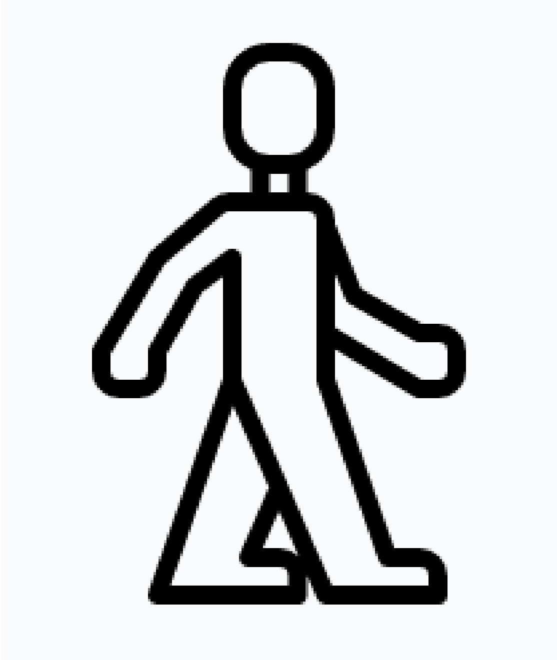
Unlike promotions, advertising effects are typically delayed.

Adstock model allows us to model advertising dynamics.

Price promotions and advertising decisions in turbulent times.

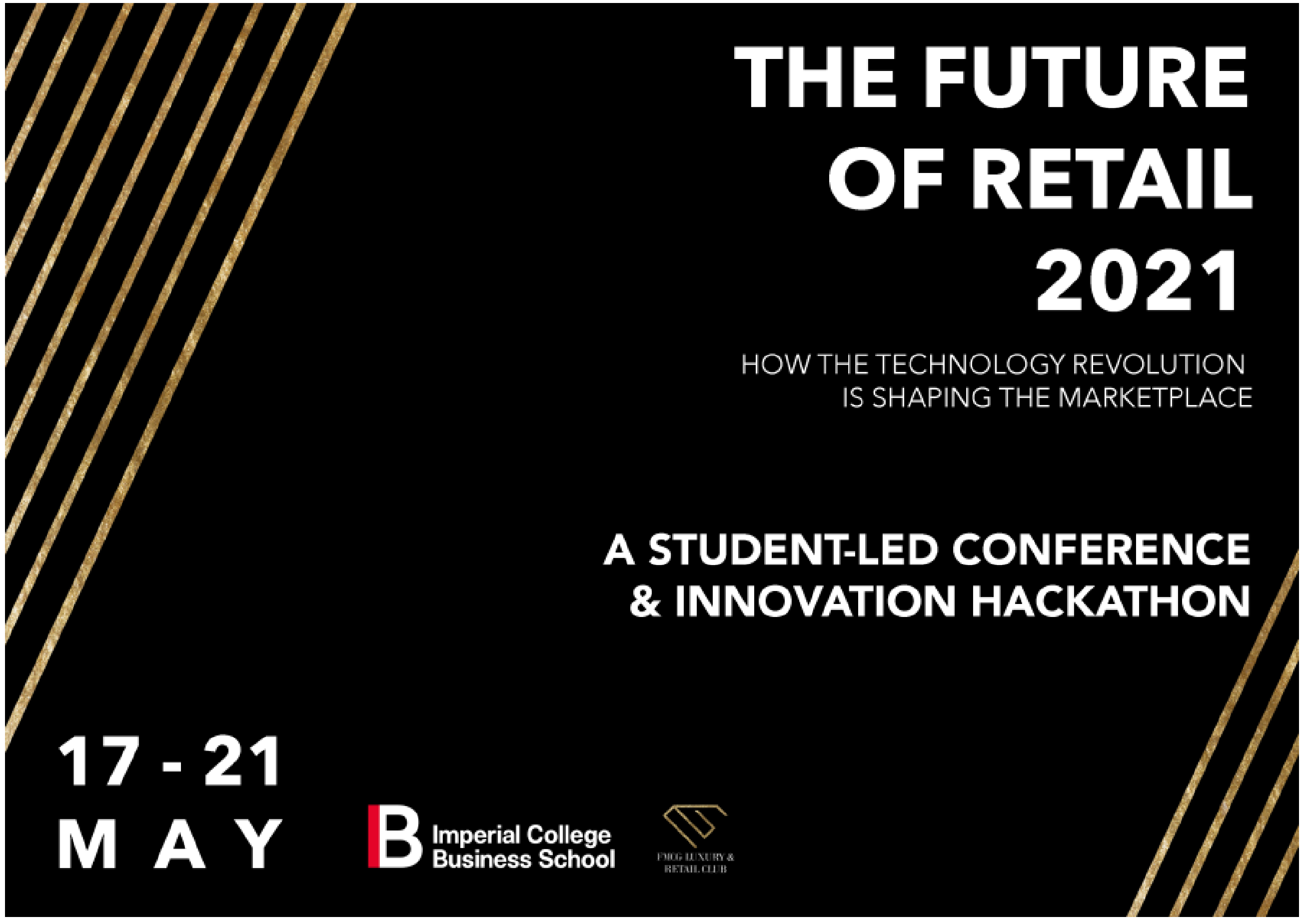
Thank you!


ANY
QUESTIONS
?

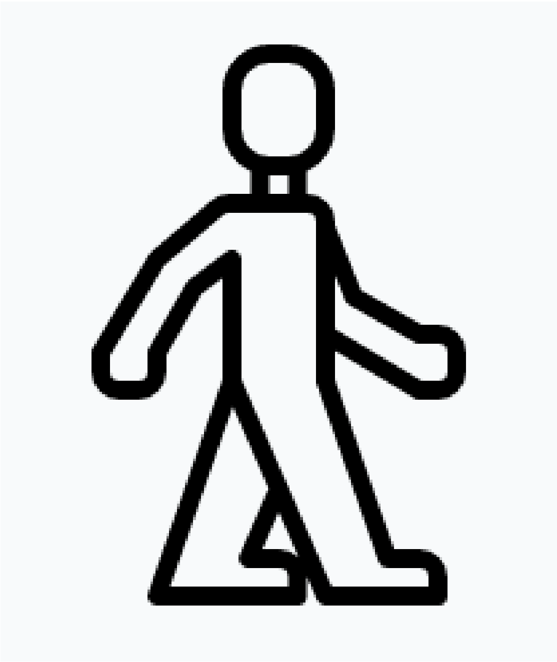


Announcement

Announcement



E-mail: ib-futureofretail@imperial.ac.uk



R Tutorial

SCAN*PRO Model

- How did feature and display promotions affect Snickers sales?
- How did Snickers sales respond to price changes?
- Did seasonality play a role in driving Snickers demand?

Adstock Model

A retail company dataset from Jan 2013 to December 2018.

Estimate the **Adstock Model for a seasonal price-sensitive product**.

Use the predicted **Adstock** measure in a **marketing mix model** to determine the effectiveness of advertising.

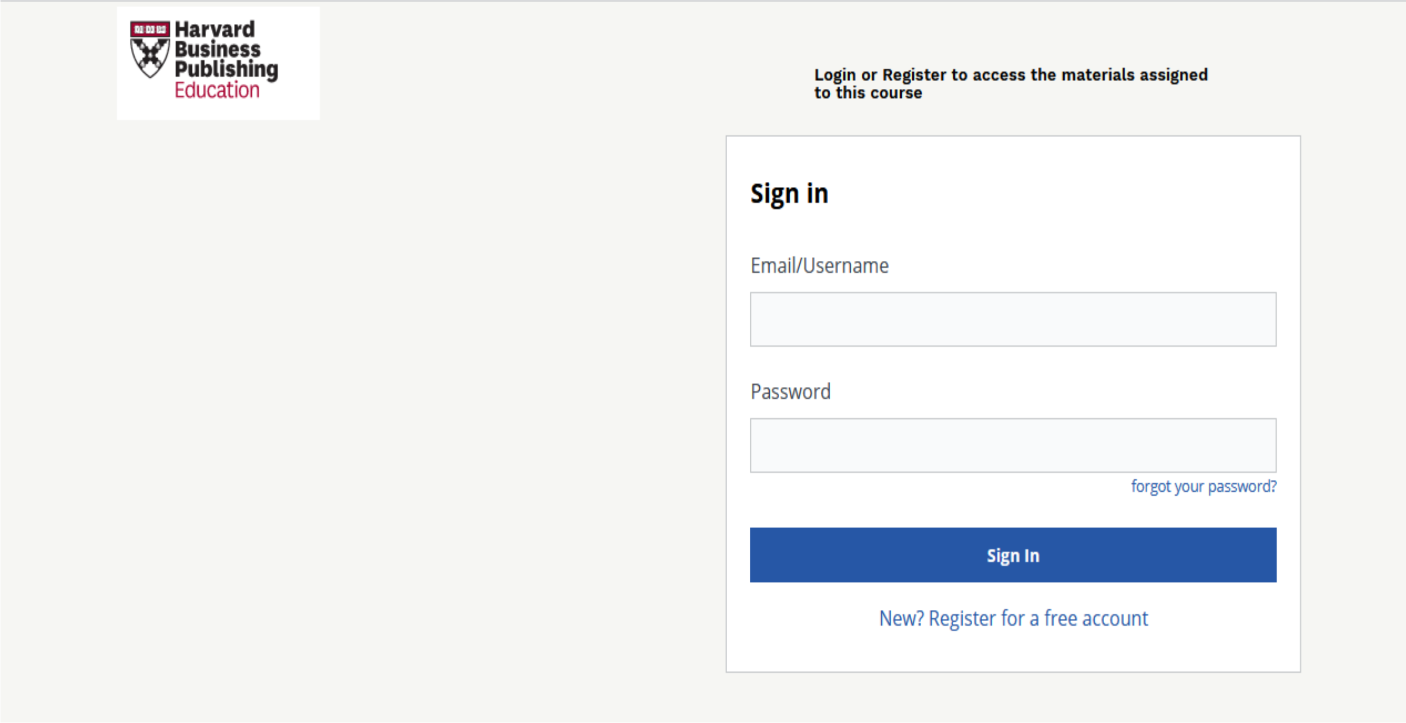
Simulation Game

Access to the game

1. Please visit hbsp.harvard.edu/import/795945

2. You need to sign in using your email address (username@ic.ac.uk) and then the password is RetMark2021#

3. Once you have logged in, **please make sure you change your password**



Case Study

ONLINE SIMULATIONS

HARVARD BUSINESS PUBLISHING

FEBRUARY 23, 2016

SIMULATION CASE

Data-Driven Management of Blue Detergent

Kelsey-White (K-W), an American multinational consumer goods company, manufactured and sold a variety of consumer packaged goods (CPG) around the world - generally through brick-and-mortar retailers. In the U.S., laundry detergent was a key product for K-W in the form of Blue, its primary brand. Blue came in several formulations – liquid, powder, and single-use pods (See Exhibit 1) – and had been a staple of the laundry marketplace for several decades. Pod sales had been slow compared to other competitors, and long-term Blue customers sometimes even felt that liquid was too modern for their tastes. As the average age of its customers rose, Blue's market share drifted downwards over the past

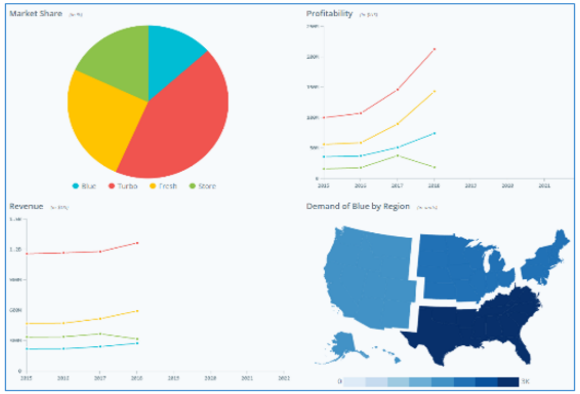
'How-To-Play' guide

HARVARD BUSINESS PUBLISHING

Data Analytics Simulation: Strategic Decision Making

HOW-TO-PLAY GUIDE

Dashboard



The **Dashboard** provides at-a-glance metrics:

- Market Share
- Profitability
- Revenue
- Demand of Blue by Region

On all screens, you can hover over any data point on the chart for more specific information.

Simulation Case

- You will act as a **brand manager** for a laundry detergent brand
- Your task is to improve the brand's performance by **leveraging data** to determine the best marketing strategy
- You will have to **make strategic decisions** about product composition, predict demand, set prices, and determine promotional spending, while communicating your strategy effectively to your managers
- The game makes use of **real-life consumer data** from a multinational consumer goods company

Blue and its competitors

Turbo

- Price per unit: $10
- Market share: 43.3%

Fresh

- Price per unit: $8
- Market share: 25.4%

Blue

- **Price per unit: $7**
- **Market share: 13.4%**

Store

- Price per unit: $6
- Market share: 18.0%

KPIs

You will play the simulation for **4 rounds** (years):

3 key metrics:

- Cumulative revenues
- Cumulative profits
- Final market share

Important info

- **Use only 1 account per team**
- **1 run per team per decision round**
- When you click “Submit decisions”, any submitted **decisions are final** and cannot be adjusted anymore
- Use report box to explain your strategy at each round.

FAQ

Q:How many attributes can I select on the Make Decisions screen under “Formulation” and “Product Features and Positioning” per year?

A: You can only choose one attribute per year for each

Q:What is the best strategy?

A:Just as in real life, there are a variety of strategies for winning in the market

Q:Should I change my strategy each year?

A: This is entirely up to you. It is possible to change your strategy in any decision-making year

FAQ

Q: How should I decide on sales forecasts?

A: The simulation is set such that there is <u>no inventory cost in the simulation</u>, and <u>unsold product</u> is held as <u>inventory</u>, and <u>charged as variable cost when sold in subsequent years</u>. You can therefore ignore the forecasting tool, it is beyond the scope of this module. Instead, use past sales, and add an estimated % depending on how much growth you expect.

Q: What do the various channels mean?

- Convenience: small stores (e.g. 7-eleven)
- Mass: one-stop shops (e.g. Wal-Mart)
- Club: wholesale (e.g. Makro)
- Grocery: 'general' supermarkets (e.g. Sainsbury's)

Some tips

- Carefully examine the past data to understand the **factors** that drive sales, operating profit, and market share. There is perhaps **more than one factor** that affects financial performance of the brand.

- Before you make your first round decisions, decide which **big-picture strategy** you would like to pursue.
  - What is the **KPI** that you aim to improve?
  - Which **customer groups** you'd like to target?
  - How would your **marketing mix communication** resonate with the **targeted segment**?

Some tips

- Check how **a change** you want make in a particular **marketing mix element** would **alter other decisions**. For example, you are planning to **lower prices**. How would that influence the **production level** that you have to decide?

- Communicate your **strategy** in a short **open-ended text box**. After each round you play the simulation, it may be useful to elicit **what strategies you used**, and **relate them to the outcomes you obtained**.

Some tips

- There are **a variety of strategies** for **playing** the simulation **successfully**.
- The **outcomes of some specific strategies make intuitive sense** and are consistent with what we would expect of good or bad business strategy in general.
- The key aspect of the game revolves around **identifying and matching the appropriate levers with the consumer segments of the chosen strategy**.

Marketing Analytics Award

for best data-driven brand manager of the year

Thank you!


ANY
QUESTIONS
?