Leeds University Business School

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Managing Resource Trade-Offs II
Marketing Experiment

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Agenda

- **Marketing experiment**
- **AB testing**
- **Multivariate testing**
- **Natural experiment**
- **Research examples**

Marketing Experiment

- **Marketing experiments test how customers might respond to marketing decisions, while ruling out confounds that otherwise would be present when comparing a treatment to a control group.**

- **When to use it?**
  - To determine if there is a direct relationship between a specific marketing investment and customer or firm outcomes.
  - To choose among a set of investment strategies and tactics, according to their financial impacts (e.g., lift in sales).

Marketing Experiment: Components

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- **The experimental attribution approach involves intervention, outcome, design of the treatment condition, and a control condition.**

Component	Definition
Intervention	A key marketing action whose effectiveness the firm seeks to document
Outcome	The key marketing gain for the firm implementing the experiment
Treatment	When, where, and to whom the firm administers the intervention
Control	A region, customer, or situation similar to the experimental intervention that remains unchanged during the experimental process

- **Deciding which factors to test is critical, and experiments can quickly grow very complex.**

Marketing Experiment: How it works

- **An experiment seeks to establish a relationship between an independent variable (marketing investment) and an outcome.**
  - A good treatment and a comparison (control) group needs to be in place. A treatment group is the group of subjects (e.g., consumers, salespeople) who receive this treatment. A comparison group keeps the causal factor constant (e.g., commissions to another group of salespeople stay the same).
  - The treatment and control groups must be similar in all other respects (e.g., sample size, demographic makeup, selling motivation, experience). All other factors (at least those under the firm's control) that can influence outcome (e.g. sales) are purposefully kept constant between experimental condition and control condition.
  - To achieve this criterion, random assignment is commonly used. With a random assignment, in a probabilistic sense, the chances of subjects receiving the treatment are equal across the different groups.

Marketing Experiment: How it works

- **Then, in the below equation:**

  $Y_i = \beta_0 + \beta_1 T_i + \varepsilon_i$

  – Y_i is the dependent variable of interest;

  – T_i is coded 1 if subject i is assigned to the treatment group and 0 otherwise,

  – the coefficient β_1 is the treatment effect.

  – ε_i captures random statistical error.

  – β_0 is intercept.

- **After conducting the experiment, if β_1 is statistically significant, the treatment effect is legitimate.**

Marketing Experiment: How it works

- **Depending on the goal of the analysis, experiments can feature two different designs:**
  - "after-only" design: measures the effect of a marketing action on customer behavior after customers have been exposed to marketing action
  - "before-and-after" design: measures the effect of the marketing action both before and after customers have been exposed to it

Marketing Experiment: Example

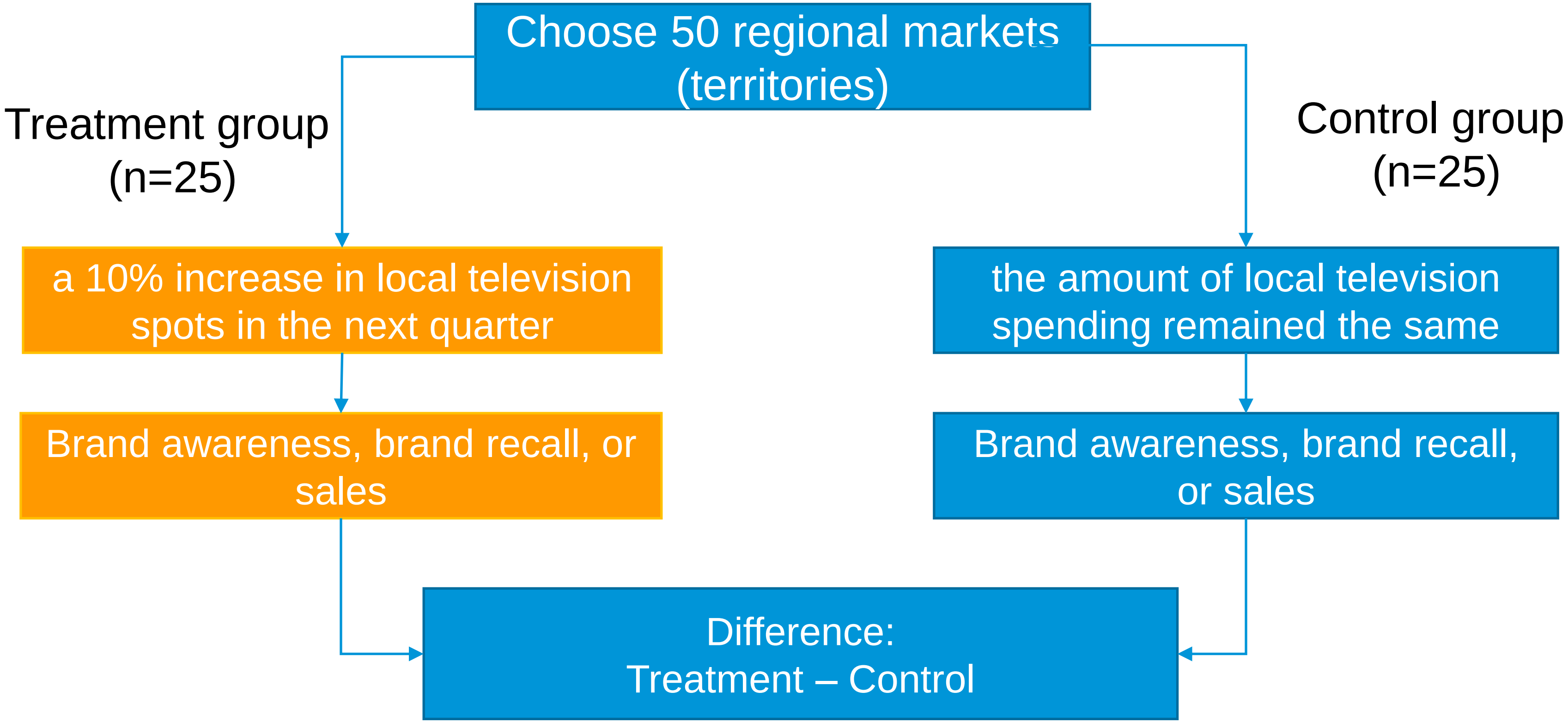
The floral delivery company DFG business was in the midst of its quarterly marketing budget meeting. Noting the company spent $250,000 in annual advertising, one manager questioned whether it was warranted, or if DFG was overspending.

In the ensuing internal discussion, some managers insisted that that local television advertising was crucial to creating brand equity and generating revenues; others believed the company was heavily overspending.

Marketing Experiment: “after-only”

- **DFG decided to use a controlled marketing experiment**

Match treatment and control groups on known attributes (e.g. demographics)



Marketing Experiment: “before-and-after”

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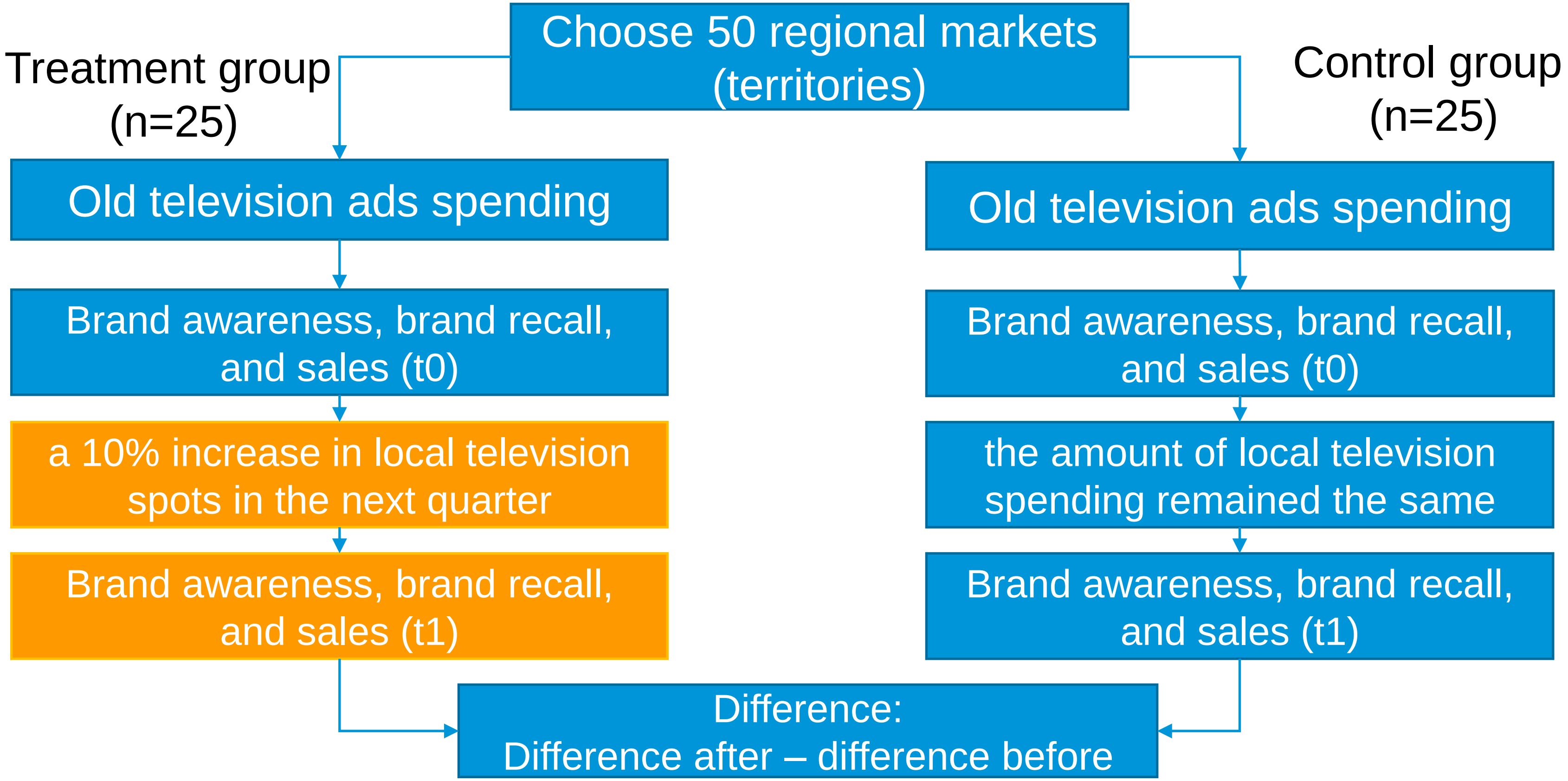
- **DFG decided to use a controlled marketing experiment with a before-and-after design**



Marketing Experiment:

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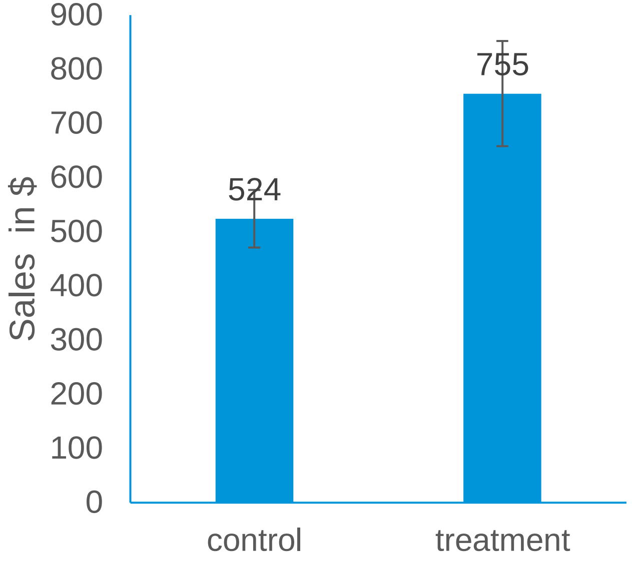
- **Randomly assign customers**
- **Analysis**

  -Comparing groups to determine
  if difference in means is significant

  -T-test/ANOVA/regression

	Control	Treatment
	$771	$345
	$447	$1,280
	$772	$441
	$333	$967
	$71	$992
	$452	$234
	$771	$761
	$340	$449
	$883	$1,671
	$911	$567
	$716	$290
	$392	$1,712
	$345	$28
	$149	$564
	$717	$386
	$278	$912
	$456	$937
	$397	$0
	$12	$706
	$285	$394
	$828	$1,616
	$856	$512
	$570	$1,450
	$895	$564
	$456	$1,090
Mean	**$524**	**$755**
Median	**$456**	**$567**
Std Dev	**$265**	**$486**



Difference in two groups

$231	average
$111	midpoint
$221	"+/- 1 std dev captures 68% of sample, +/- 2 is 95%"

68-95-99.7 rule

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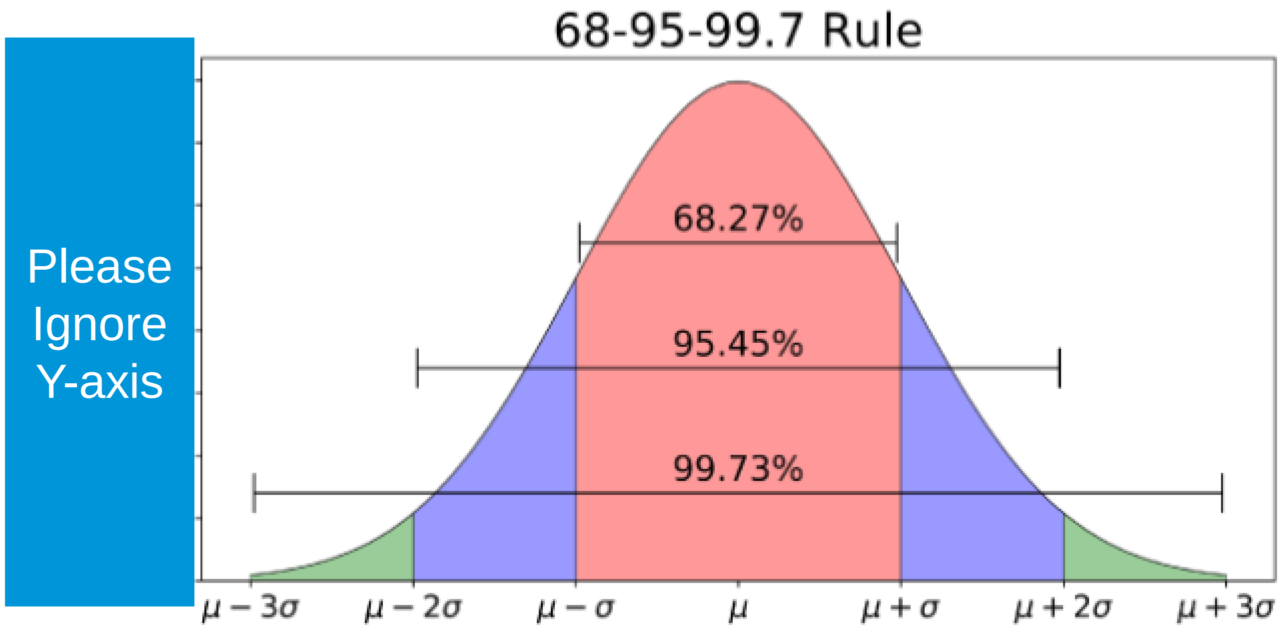


68% of the data is within 1 standard deviation, 95% is within 2 standard deviation, 99.7% is within 3 standard deviations

Source: Galarnyk 2018

Marketing Experiment: Example

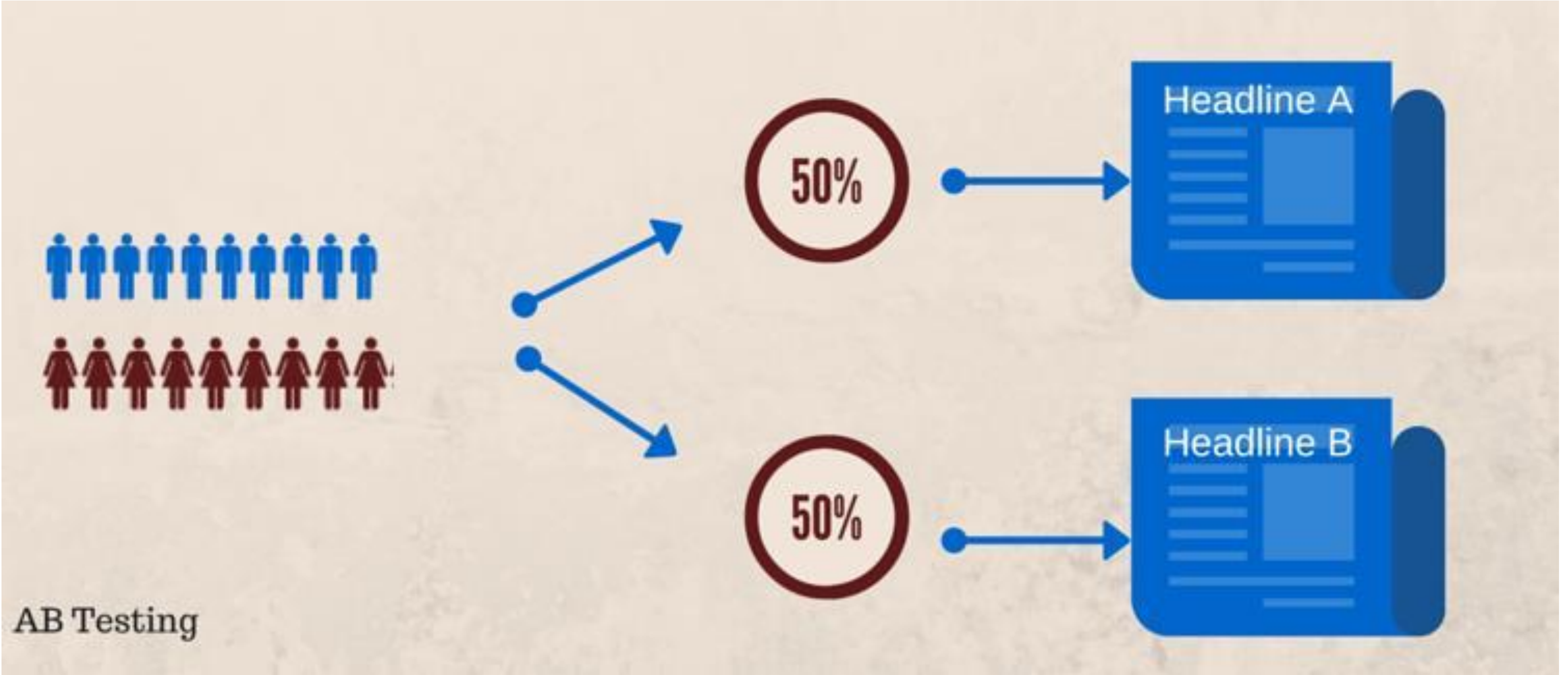
- **The company estimated three regression equations to obtain the coefficient β_1 from three different models, capturing the statistical changes in brand awareness, brand recall, and sales, respectively, due to increases in local television advertising relative to the control condition.**

- **The treatment effect was significant in each regression:**
  - The growth of brand awareness, brand recall, and sales in the treatment territories were 1.5%, 3.2%, and 3%, respectively, when DFG increased its local television advertising (cf. the control group).

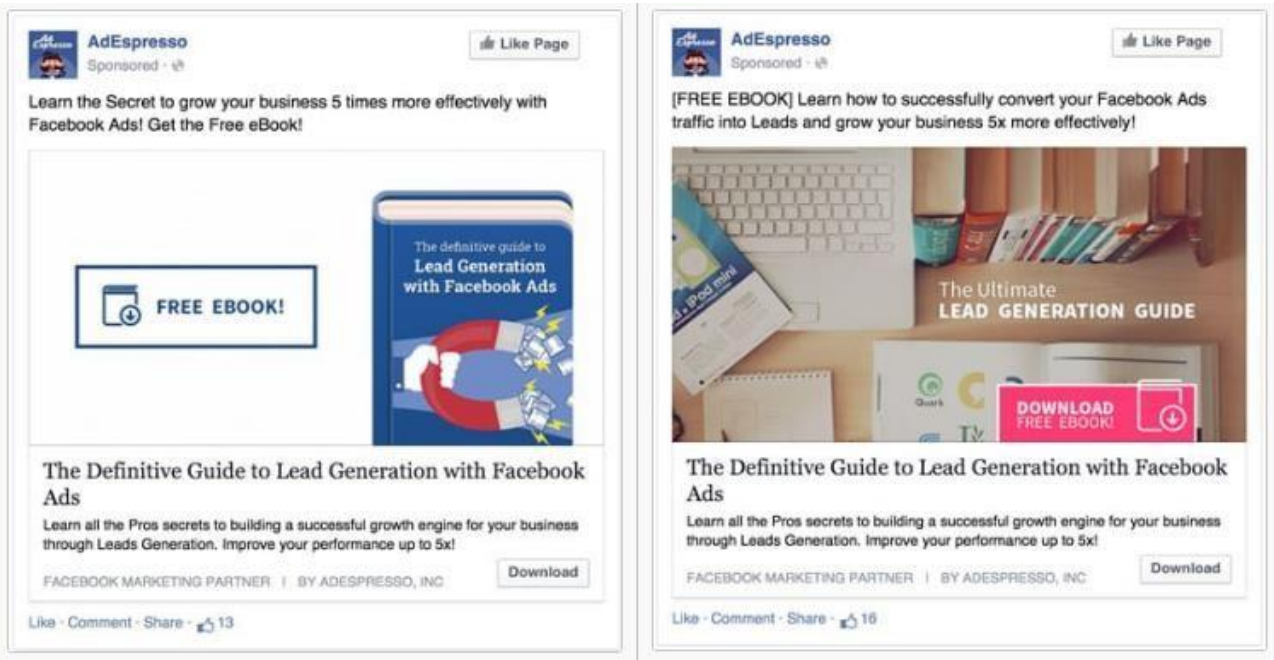
- **DFG earns $25,000,000 in sales annually, so the experiment gave confidence to the decision makers in the company that the growth in sales due to local television advertising would paid off. Thus, an experiment helped to resolve an internal conflict within DFG.**

A/B testing

- **Using experimental design to compare two or more variants of a design**
  - New idea
  - Run experiment
  - Analyse results
  - Picking wining idea



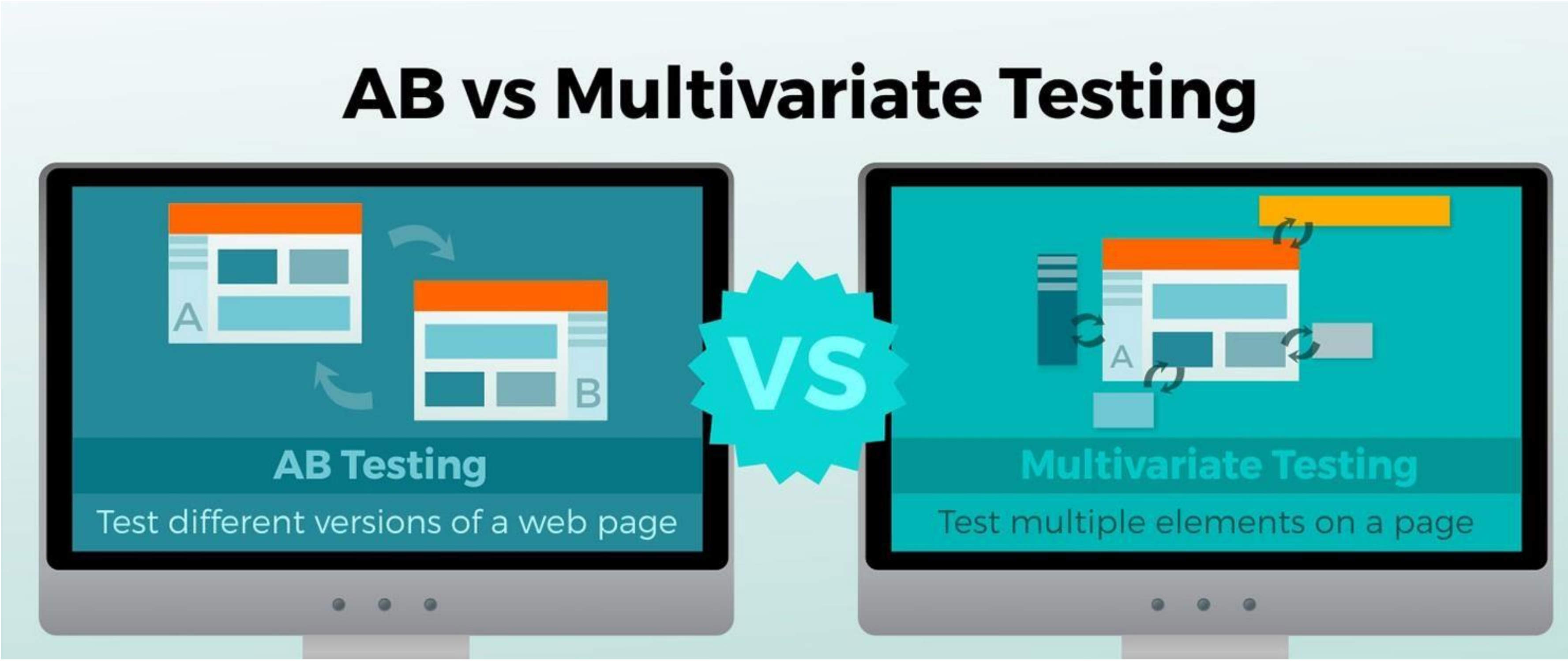
A/B testing



10,000 Impression	10,000 Impression
237 Clicks *(CTR: 2.37%)*	187 Clicks *(CTR: 1.87%)*
28 Sales *(Conversion rate: 11.81%)*	16 Sales *(Conversion rate: 8.55%)*

- **Powerful and widely used measures**
  - Conversion rates (e.g. click-through rates)
  - Engagement rates (e.g. likes, shares)
  - Time spent (e.g. seconds spent on homepage)

Multivariate testing



Multivariate testing

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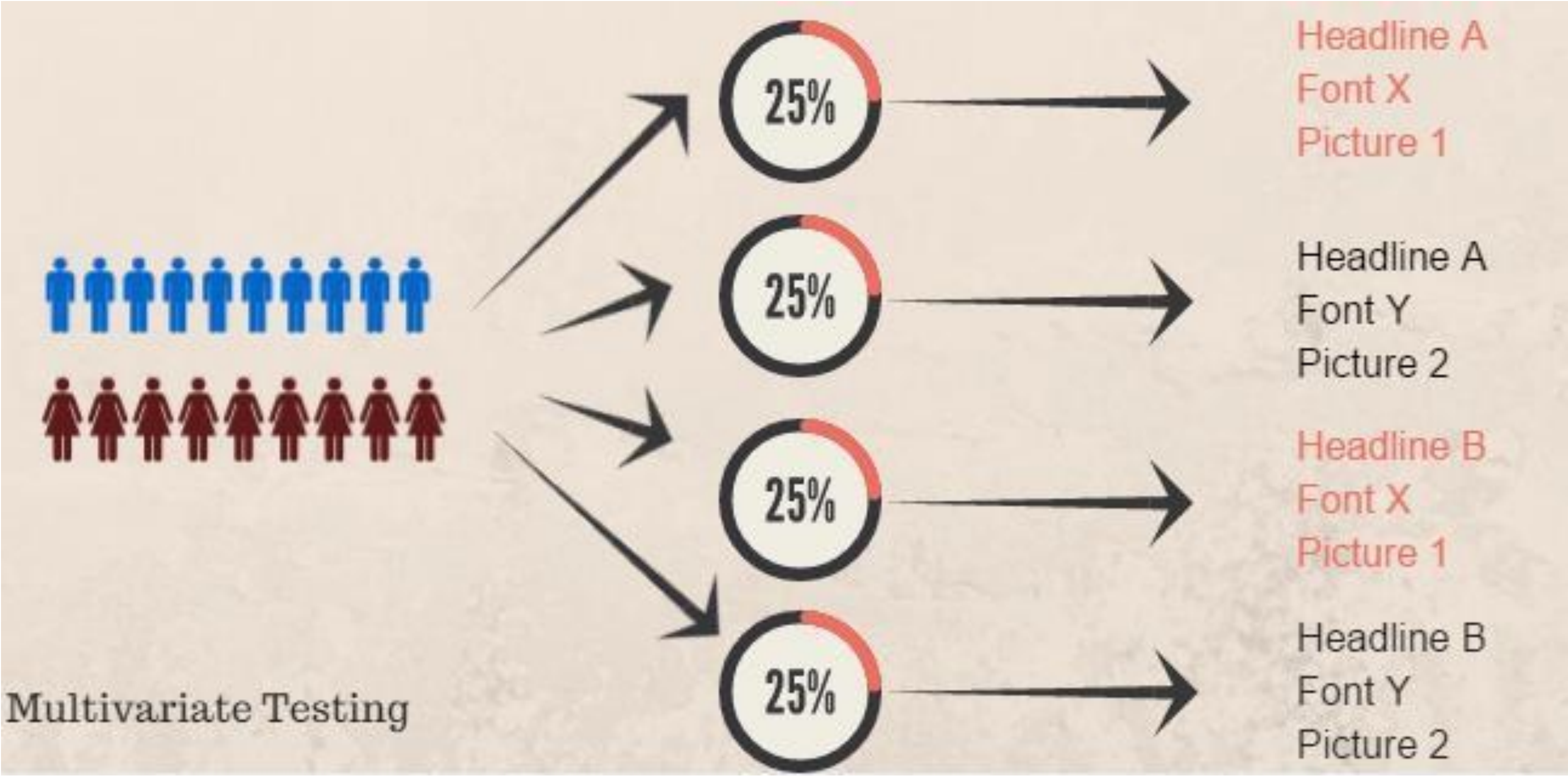
-It reduces the cost



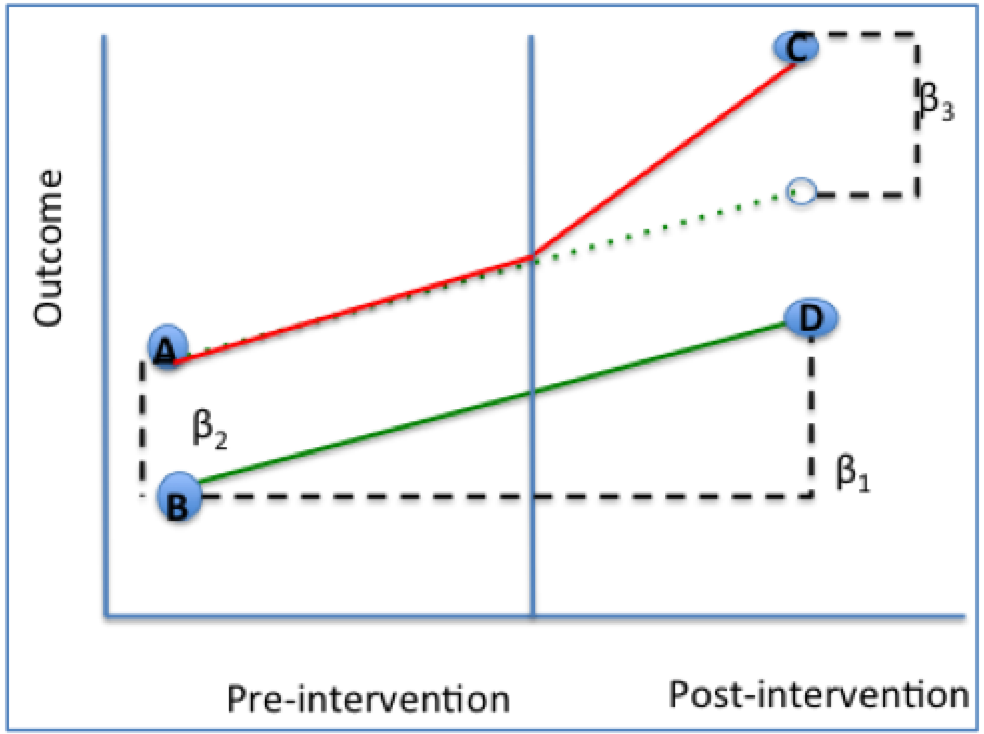
Natural Experiments: when to use

- **We can’t always do randomisation**

- **An unexpected change in policy could be seen as “natural experiment”. For example, a new return policy is introduced to some markets.**

- **Even in natural experiments, we need to identify which is the treatment and control group**
  - Treatment group: group that is influenced by the policy change; e.g. markets where return policy is changed.
  - Control group: group that is not affected by the policy change; e.g. markets where return policy remains the same.

Natural Experiments: Difference-in-Difference



Natural Experiments: Difference-in-Difference

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- **Difference in differences (DiD) attempts to mimic an experimental research design by studying the differential effect of a treatment on a 'treatment group' versus a 'control group' in a natural experiment.**

- **DiD uses panel data to measure the differences, between the treatment and control group, of the changes in the outcome variable that occur over time.**

- **Thus, in the below equation:**
- $Y_i = \beta_0 + \ \beta_1 \mathrm{t}_i + \beta_2 \mathrm{T}_i + \beta_3 (T_i \times t_i) + \varepsilon_i$
  - Y_i is the dependent variable;
  - t_i is coded 1 if post-intervention and 0 pre-intervention
  - β_1 is the time trend common to control and treatment group
  - T_i is coded 1 if subject i is assigned to the treatment group and 0 otherwise,
  - β_2 is the treatment effect.
  - The interaction $(T_i \times t_i)$ is the DiD term
  - β_3 is the true effect.
  - ε_i captures random statistical error
  - $\beta_0$is intercept

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Personalization in Email Marketing: The Role of Noninformative Advertising Content

Navdeep S. Sahni, S. Christian Wheeler, Pradeep Chintagunta

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Figure 1. A Typical Email Message Sent by Our Main Collaborator Company (C)

Subject: Learn Financial Modeling & Business Analytics from Industry Experts in Sydney

Dear %%First Name%%:

Greetings,

This e-mail is in regards to our upcoming Financial Modeling 4 Days Intense Classroom Training in Sydney this month.

This course will help you ...

Our offerings include:

- 4 days of classroom training
- ...
- 1 year online training (accredited best content)

Course Outline and Learning Outcomes:

- Techniques, tips & tricks to use Microsoft Excel to build financial models
- ...
- Macros and VBA to implement Monte Carlo Simulation

Standard Course Price: USD 1197

Register on or before 25th October 2014 to avail USD 1077 (Exam fee included).

Workshop Dates: 15th ,16th, 22nd, 23rd November 2014

I apologize if this course is not of your interest. You can easily reply back to this e-mail or click on the unsubscribe link below.

Best Regards,

%%Sender's Name%%

Unsubscribe me from this list

Sahni, Wheeler, and Chintagunta: *Personalization in Email Marketing*
Marketing Science, 2018, vol. 37, no. 2, pp. 236–258, © 2018 INFORMS

Table 2. Results from Experiment 1—Company C Adding the Recipient's Name to the Subject Line

	(1) Opens/Sent		(2) Leads/Sent		(3) Unsubscribes/Sent		(4) Leads/Opens		(5) Unsubscribes/Opens	
	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control	Treatment	Control
Mean (%)	10.80	9.05	0.51	0.39	1.00	1.20	4.72	4.29	9.24	13.28
Standard error (%)	(0.15)	(0.16)	(0.04)	(0.04)	(0.05)	(0.05)	(0.35)	(0.36)	(0.48)	(0.61)
Number of observations	33,322	34,766	33,322	34,766	33,322	34,766	3,599	3,146	3,599	3,146
p-value	<0.01		0.02		0.01		0.39		<0.01	
Effect size (Cohen's *d*)	0.06		0.02		−0.02		0.02		−0.13	

Notes. The table presents results from Experiment 1 in which the treatment group received the same emails as the control group, except that the subject line mentioned the recipient's name. For each experimental group we report (a) averages across individuals, (b) standard errors (in parentheses), (c) *p*-value testing whether the means are equal across the two conditions, (d) the number of observations, and (e) effect size in terms of Cohen's *d*. Column (1) shows the open rate (opens/sent). It shows that the treatment condition has a higher opens/sent relative to the control condition, and this increase is statistically significant. Column (2) compares the likelihood of a sales lead (leads/sent) across the two conditions and finds that the leads are also higher in the treatment condition. Column (3) shows that the unsubscription rate (unsubscribes/sent) is lower in the treatment condition. That is, the experimental treatment causes more people to open the emails and generate leads, but fewer people unsubscribe from the campaign. Columns (4) and (5) compare leads and unsubscribes conditional on opens and show that conditional on opening the email, unsubscribes reduce but the leads remain statistically similar.

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The Impact of Platform Protection Insurance on Buyers and Sellers in the Sharing Economy: A Natural Experiment

Xueming Luo, Siliang Tong, Zhijie Lin, and Cheng Zhang

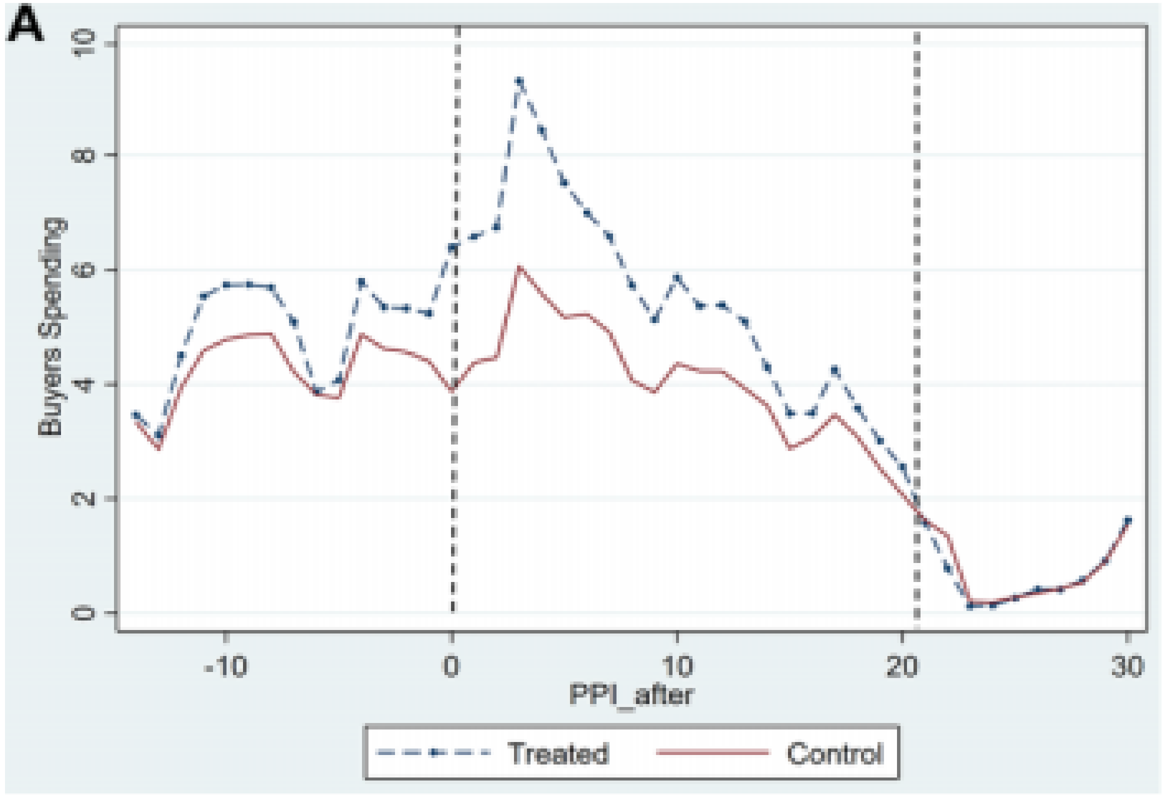
Abstract

The sharing economy has radically reshaped marketing thought and practice, and research has yet to examine whether and how platform-level buyer protection insurance (PPI) affects buyers and sellers in this economy. The authors exploit a natural experiment involving an unexpected system glitch during a PPI launch and estimate difference-in-differences models using over 5.4 million data points from a food sharing platform. Results suggest that PPI significantly increases buyer spending and seller revenue, affirming the benefits of this platform-level insurance in the sharing economy. The authors also uncover multifaceted buyer-side and seller-side responses that enable such benefits. PPI increases buyer spending by boosting product orders and variety-seeking behavior. Furthermore, it enhances seller revenue by increasing customer retention and acquisition. This work contributes to the literature by (1) putting a spotlight on the topic of PPI, a platform governance policy that reduces consumer risks and improves the efficacy of sharing platforms; (2) accounting for how PPI alters buyer and seller behaviors on a platform; (3) addressing what types of buyers and sellers benefit more or less from PPI; and (4) offering guidance for managers to improve platform reputation, marketplace efficiency, and consumer welfare in the context of the sharing economy.

Keywords

consumer protection insurance, customer retention and acquisition, peer-to-peer, platform regulation, sharing economy

Online supplement https://doi.org/10.1177/0022242920962510


A
Buyers Spending
0
2
4
6
8
10
-10
0
10
20
30
PPI_after
Treated
Control

Takeaways

- **Experiment assess cause and effect**
- **T-test, ANOVA, or Linear regression are normally used to compare groups to test whether the differences are significant**
- **Web experiments (A/B testing) are cheaper and faster**
  - Costs of experiments can be variable rather than fixed
- **Difference-in-Difference is used to examine quasi-experiment such as natural experiment. It measures the differences, between the treatment and control group, of the changes in the outcome variable occurs over time**