Causality & Advertising

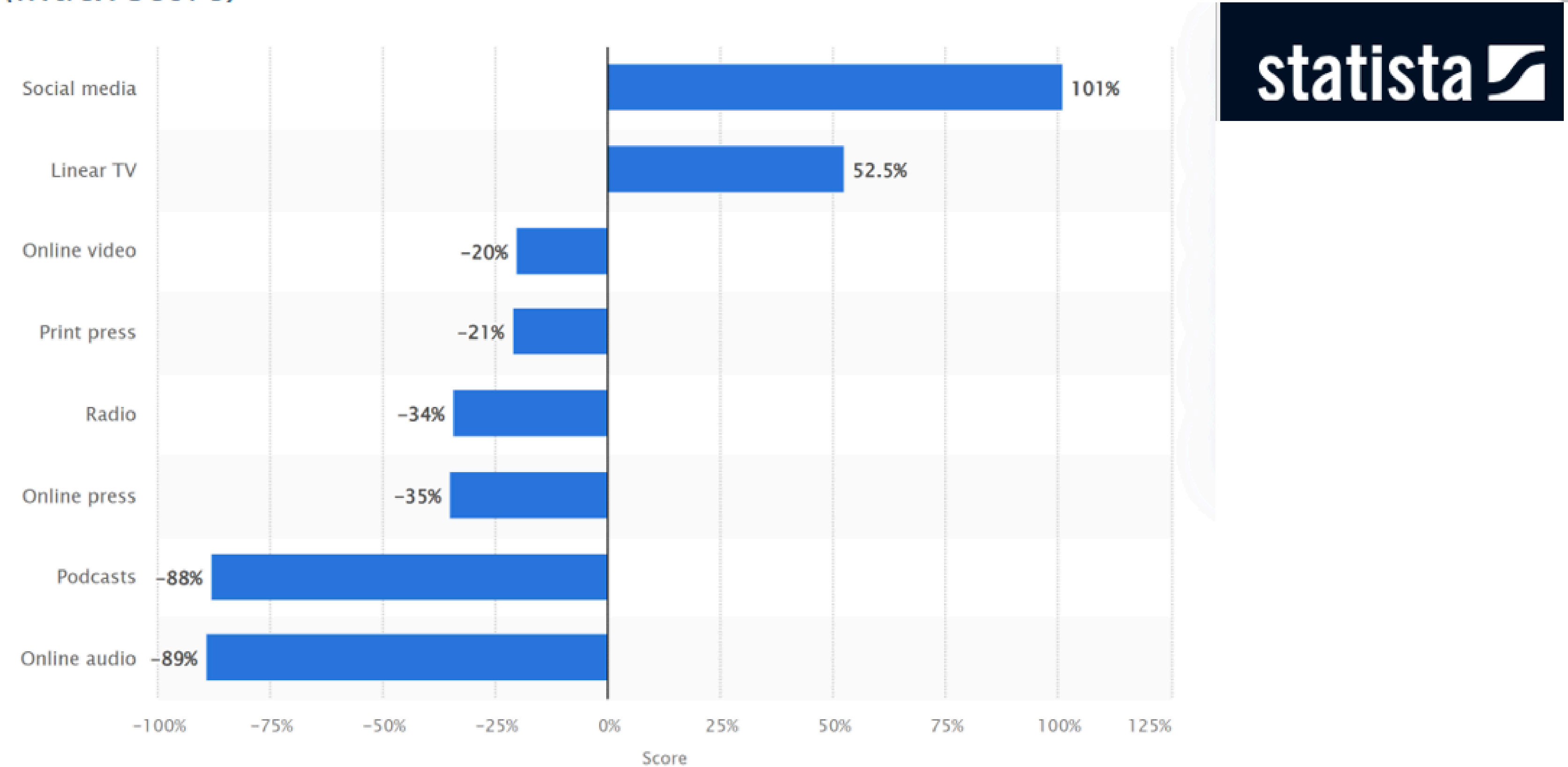
UCSD MGTA 451-Marketing

Kenneth C. Wilbur

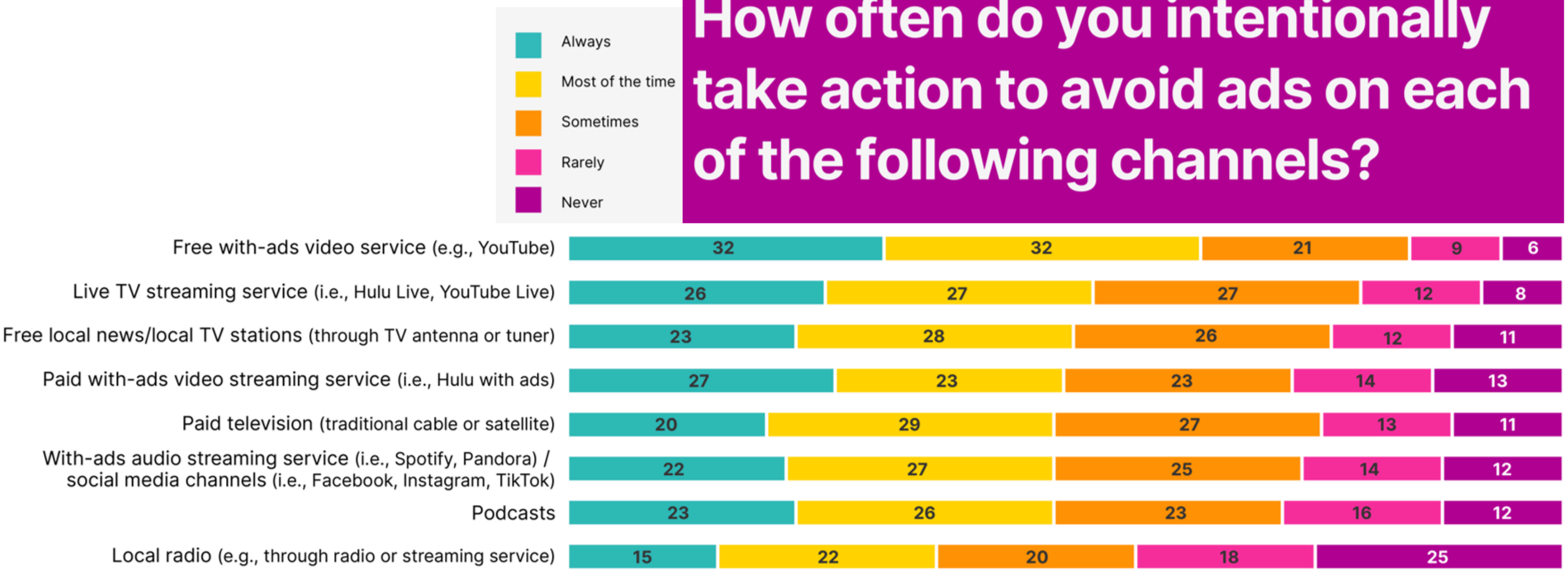
Advertising

Difference between advertising spending and time spent with selected media in the United States in 2022

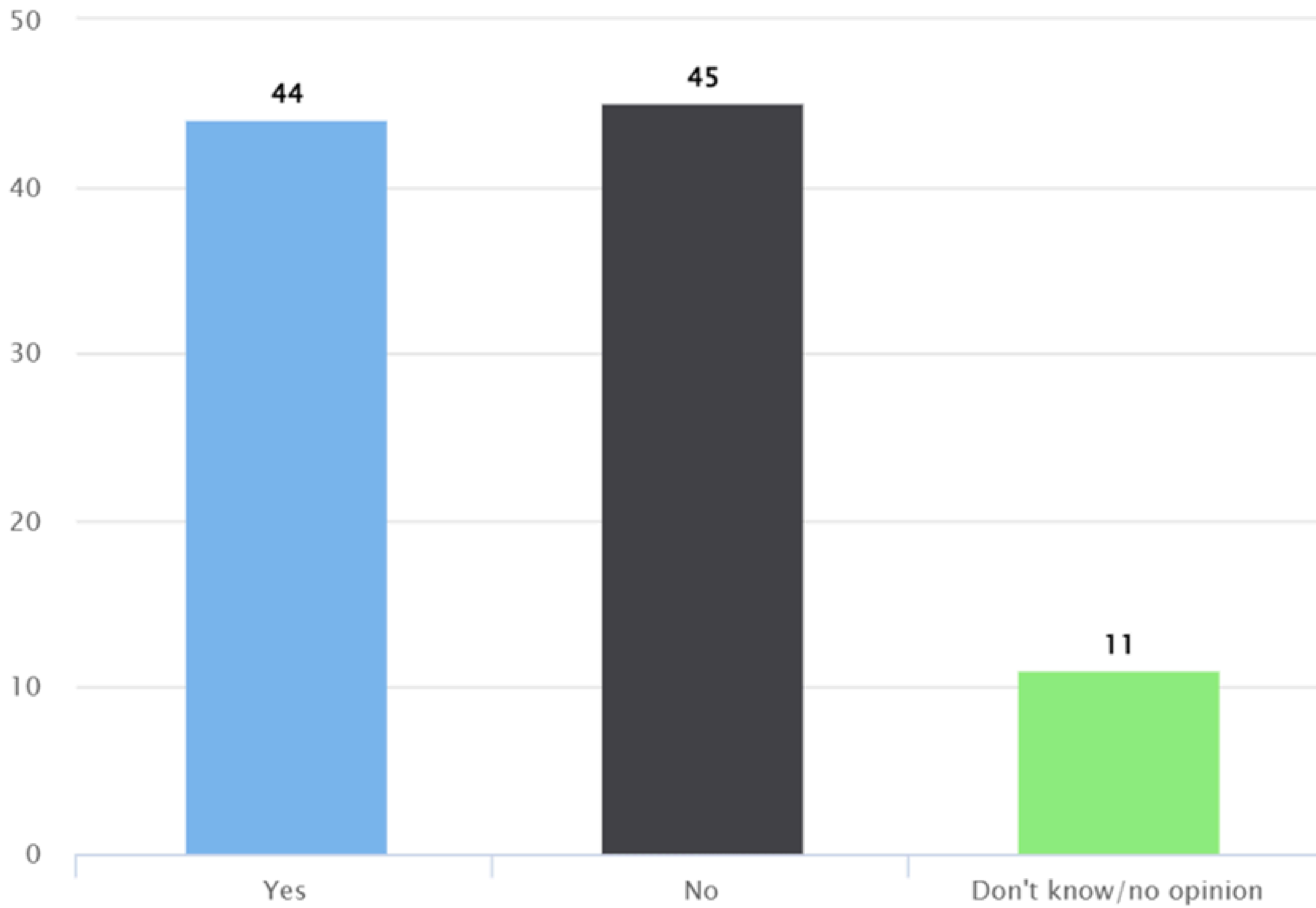
(index score)



How often do you intentionally take action to avoid ads on each of the following channels?



U.S. consumers who purchased products after seeing an internet ad



Toy economics of advertising

- Suppose we pay $20 to buy 1,000 digital ad OTS. Suppose 3 people click, 1 person buys.
- Ad profit > 0 if transaction margin > $20

```
    - But we also had to advertise to 999 people who didn't buy
```

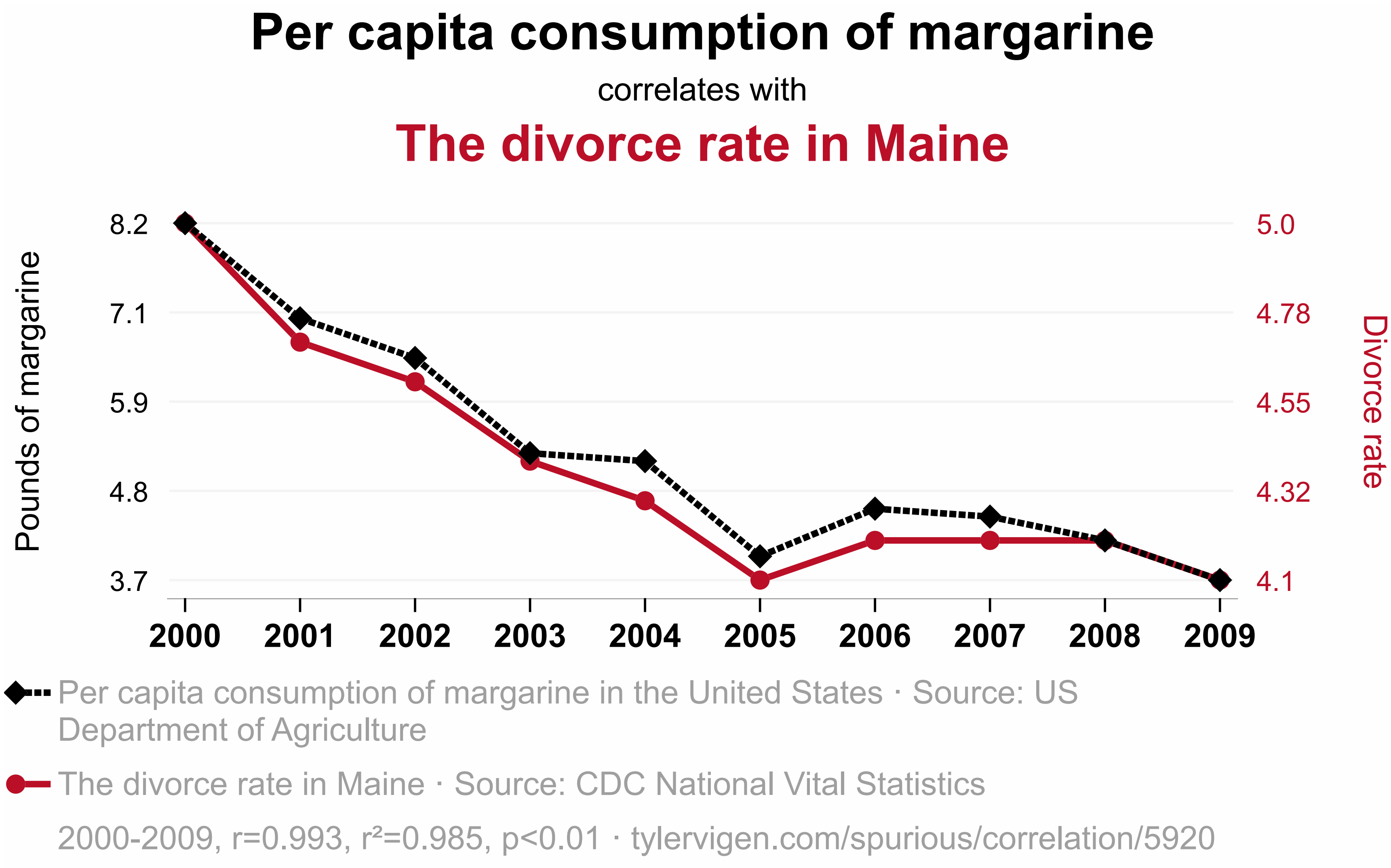
- Or, ad profit > 0 if customer CLV > $20 *and* if the customer would not have purchased otherwise

```
    - This is "incrementality"
    - But how would we know if they would have purchased otherwise?
```

- Ad effects are often subtle, but ad profit can still be robust

```
    - Ad profit depends on ad cost, conversions, margin, objective
formulation
```

Causality


Per capita consumption of margarine
correlates with
The divorce rate in Maine
Pounds of margarine
8.2
7.1
5.9
4.8
3.7
Divorce rate
5.0
4.78
4.55
4.32
4.1
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
Per capita consumption of margarine in the United States · Source: US Department of Agriculture
The divorce rate in Maine · Source: CDC National Vital Statistics
2000-2009, r=0.993, r²=0.985, p<0.01 · tylervigen.com/spurious/correlation/5920

- Suppose 10 outcomes, 1000 predictors, N=100,000 obs

```
    - Outcomes might include visits, sales, reviews, ...
    - Predictors might include customer attributes, session attributes, ...
```

- Suppose everything is noise, no true relationships

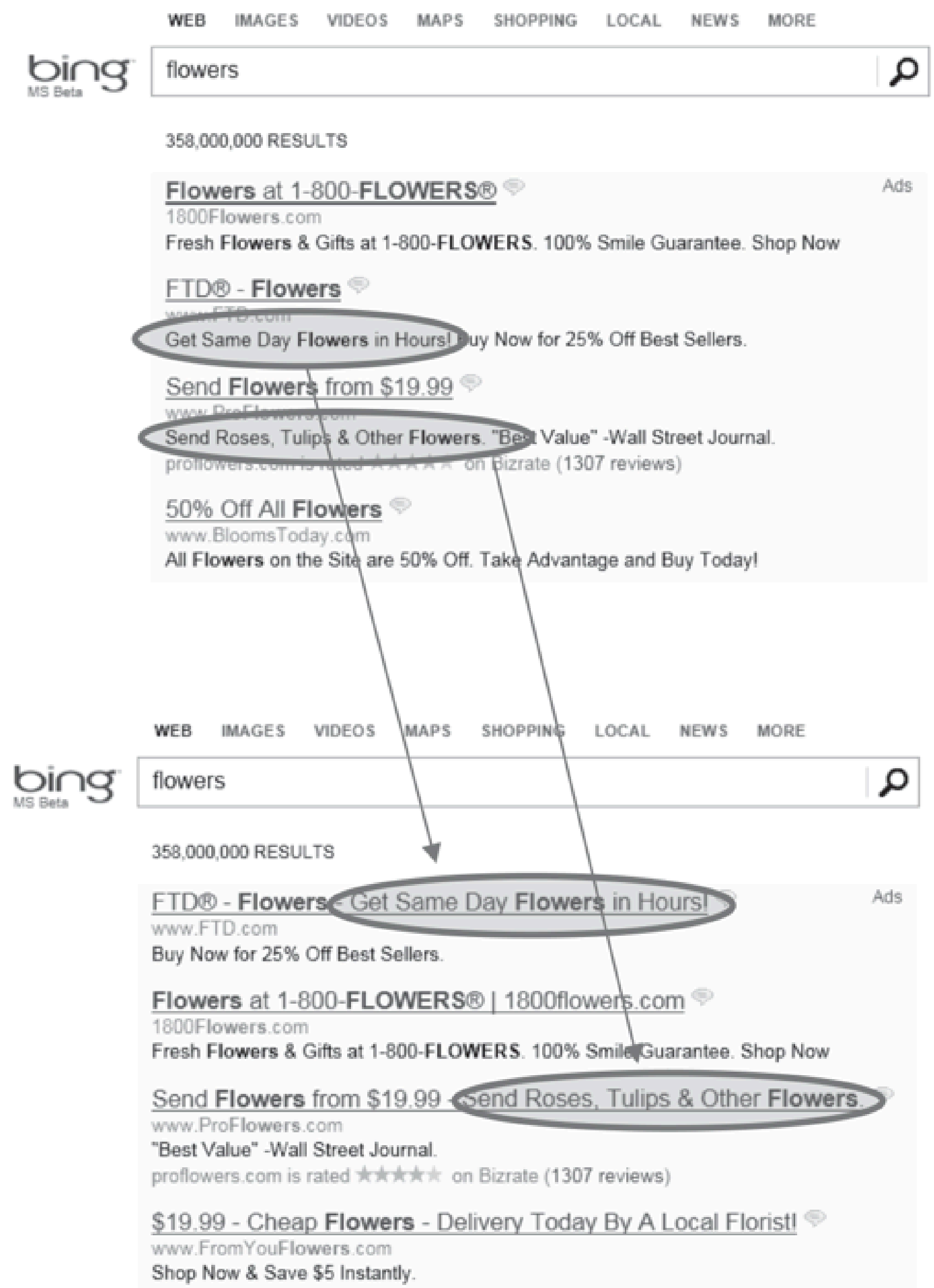
```
    - The distribution of the 10,000 correlation coefficients would be
Normal, tightly centered around zero

    - A 2-sided test of {corr == 0} would reject at 95% if |r|>.0062
```

- We should expect 500 false positives

```
    - What is a 'false positive' exactly?
```

- In general, what can we learn from a significant correlation?


WEB IMAGES VIDEOS MAPS SHOPPING LOCAL NEWS MORE
bing
MS Beta
flowers
358,000,000 RESULTS
Ads
Flowers at 1-800-FLOWERS®
1800Flowers.com
Fresh Flowers & Gifts at 1-800-FLOWERS. 100% Smile Guarantee. Shop Now
FTD® - Flowers
Get Same Day Flowers in Hours! Buy Now for 25% Off Best Sellers.
Send Flowers from $19.99
Send Roses, Tulips & Other Flowers. "Best Value" -Wall Street Journal.
on Bizrate (1307 reviews)
50% Off All Flowers
www.BloomsToday.com
All Flowers on the Site are 50% Off. Take Advantage and Buy Today!
WEB IMAGES VIDEOS MAPS SHOPPING LOCAL NEWS MORE
bing
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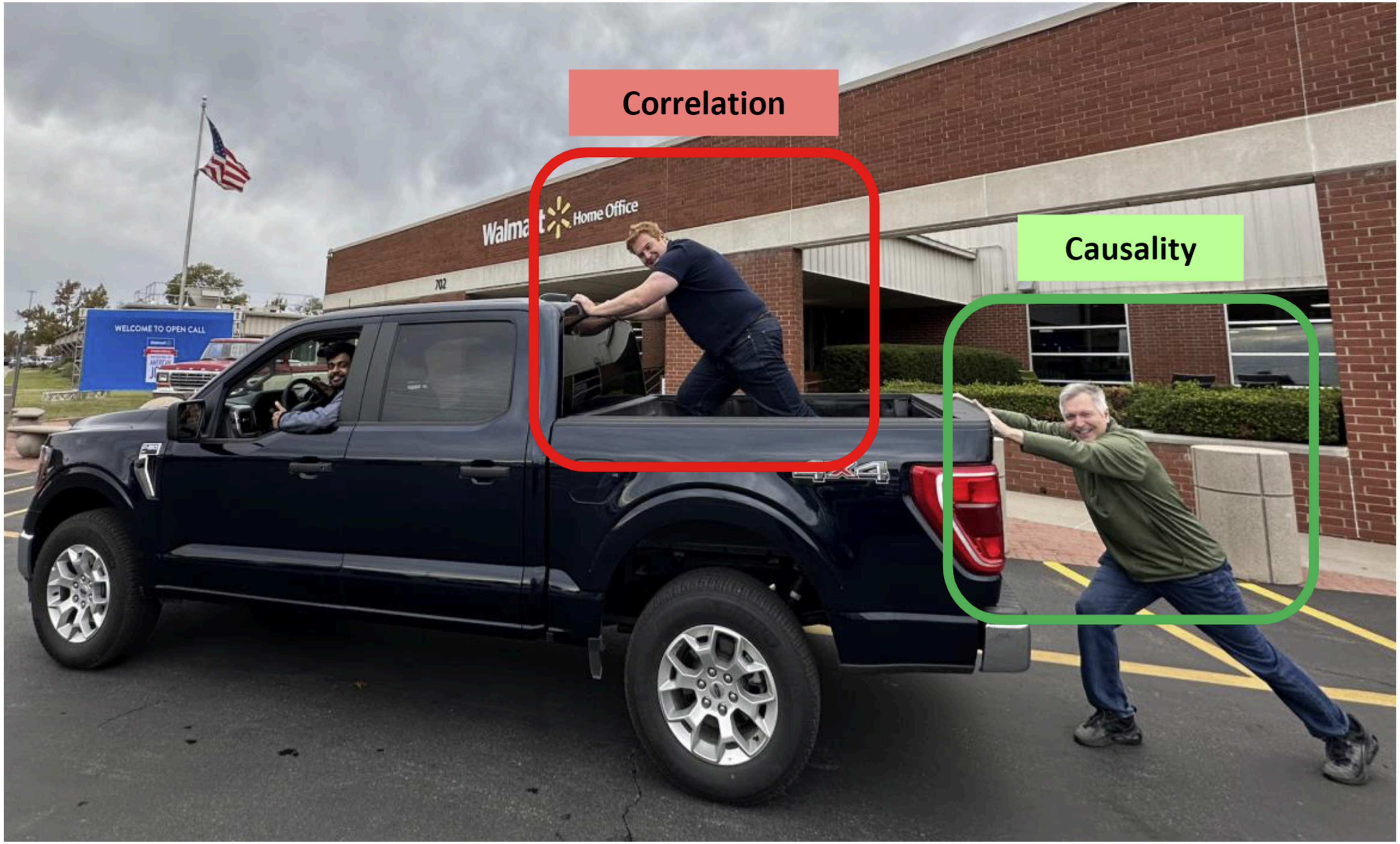
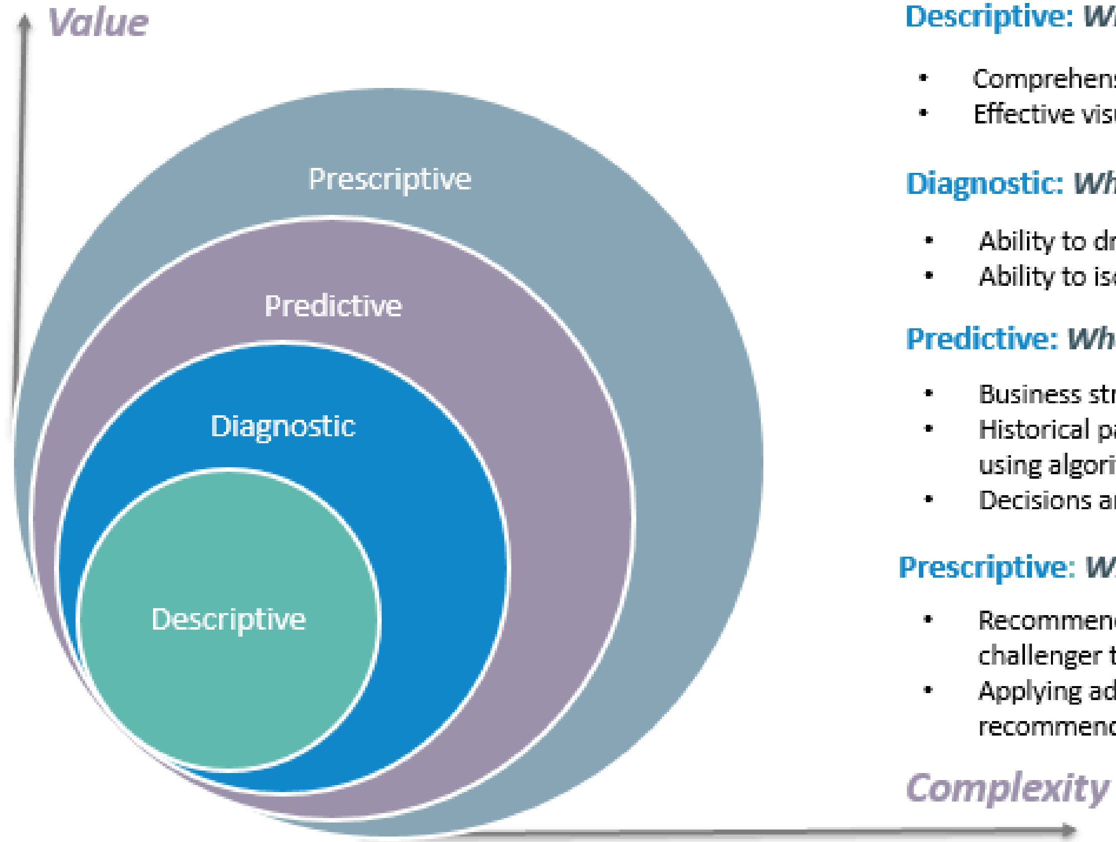
Ads
FTD® - Flowers - Get Same Day Flowers in Hours!
www.FTD.com
Buy Now for 25% Off Best Sellers.
Flowers at 1-800-FLOWERS® | 1800flowers.com
1800Flowers.com
Fresh Flowers & Gifts at 1-800-FLOWERS. 100% Smile Guarantee. Shop Now
Send Flowers from $19.99 - Send Roses, Tulips & Other Flowers.
www.ProFlowers.com
"Best Value" -Wall Street Journal.
proflowers.com is rated on Bizrate (1307 reviews)
$19.99 - Cheap Flowers - Delivery Today By A Local Florist!
www.FromYouFlowers.com
Shop Now & Save $5 Instantly.


Correlation
Causality
Walmart Home Office
WELCOME TO OPEN CALL
4X4

Agenda

- Causality
- Experiments
- Quasi-experiments
- Correlations
- Ad/sales frameworks

4 types of Data Analytics



What is the data telling you?

Descriptive: ***What's happening in my business?***

- Comprehensive, accurate and live data
- Effective visualisation

Diagnostic: ***Why is it happening?***

- Ability to drill down to the root-cause
- Ability to isolate all confounding information

Predictive: ***What's likely to happen?***

- Business strategies have remained fairly consistent over time
- Historical patterns being used to predict specific outcomes using algorithms
- Decisions are automated using algorithms and technology

Prescriptive: ***What do I need to do?***

- Recommended actions and strategies based on champion / challenger testing strategy outcomes
- Applying advanced analytical techniques to make specific recommendations

Principa
www.principa.co.za

Causal Inference

- Suppose we have a binary "treatment" or "policy" variable T_i that we can "assign" to person

```
- Examples: Advertise, Serve a design, Recommend
- "Treatment" terminology came from medical literature
```

- Suppose person could have a binary potential "response" variable

```
- Examples: Visit site, Click product, Add to Cart, Purchase, Rate, Review
- Looks like the marketing funnel model we saw previously
```

- Important: may depend fully, partially, or not at all on , and the dependence may be different for different people

Why care?

- We want to maximize profits
- Suppose contributes to revenue; then
- Suppose is costly; then
- We have to know to optimize assignments

```
- Called the "treatment effect" (TE)
```

- Profits may decrease if we misallocate

Fundamental Problem of Causal Inference

- We can only observe **either or** , but not both, for each person
- This is a missing-data problem that we cannot resolve. We only have one reality

```
- The case we don't observe is called the "counterfactual"
```

So what can we do?

1. Experiment. Randomize and estimate as avg

    ```
    - Creates new data; costs time, money, attention; deceptively difficult to design and then act on
    ```

2. Use assumptions & data to estimate a “quasi-experimental” average treatment effect using archival data

    ```
    - Requires expertise, time, attention; difficult to validate; not always possible
    ```

3. Use correlations: Assume past treatments were assigned randomly, use past data to estimate

    ```
    - Easiest approach; but T is only randomly assigned when we run an experiment, so what exactly are we doing here?
    ```

4. Fuhgeddaboutit, go with the vibes, do what we feel

How much does causality matter?

```
- How hard should we work?
```

- Organizational returns or costs of getting it right?
- Data thickness: How likely can we get a good estimate?
- How does empirical approach fit with organizational analytics culture? Will we act on what we learn?
- Individual: promotion, bonus, reputation, career; Will credit be stolen or blame be shared?
- Accountability: Will ex-post attributions verify findings? Will results threaten or complement rival teams/execs?

```
- Analytics culture starts at the top
```

Ad/sales example: Experiment

1. Randomly assign ads to customer groups on a platform; measure sales in each group, e.g. Link

```
 - Often called "incrementality" in ad/sales context

 - Pros: AB testing is easy to understand, easy to implement, easy to validate

 - Cons: Can we trust the platform's "black box"? Will we get the data and all available insights? Could
platform knowledge affect future ad costs?
```

2. Randomly assign messages within a campaign
3. Randomly choose times, places, segments or combinations; compare treated times to controls
4. Randomize over budgets and bids
5. Randomly choose platforms, publishers, behavioral targets, etc., to compare RoAS across options

```
RoAS = Return on Ad Spend. Usually, RoAS = Sales / AdSpend. Sometimes, =(Sales-AdSpend)/AdSpend
```

2. Ad/sales example: Experiment

Key issues for any experimental design:

```
    - Always run A:A test first. Validate the infrastructure before trusting a
result

    - Can we agree on the opportunity cost of the experiment? "Priors"

    - How will we act on the (uncertain) findings? Have to decide before we
design

    - Example: Suppose we estimate RoAS at 0.5 with a 95% confidence interval
of [0.45, 0.55]. Or, suppose we estimate RoAS at 0.5, but we have a 95%
confidence interval of [-2.1], 3.1]. What will we do with this information?
```

Before quasi-experiments: Vocab

Model: Mathematical relationship between variables that simplifies reality, eg y=xb+e

Identification strategy: Set of assumptions that isolate a causal effect from other factors that may influence

```
- A system to compare apples with apples, not apples with oranges
```

We say we “identify” the causal effect if we have an identification strategy that reliably distinguishes from possibly correlated unobserved factors that also influence

If you estimate a model without an identification strategy, you should interpret the results as correlational

You can have an identification strategy without a model, e.g.
avg

Usually you want both. Models help with quantifying uncertainty and estimating treatment effects by controlling for relevant observables

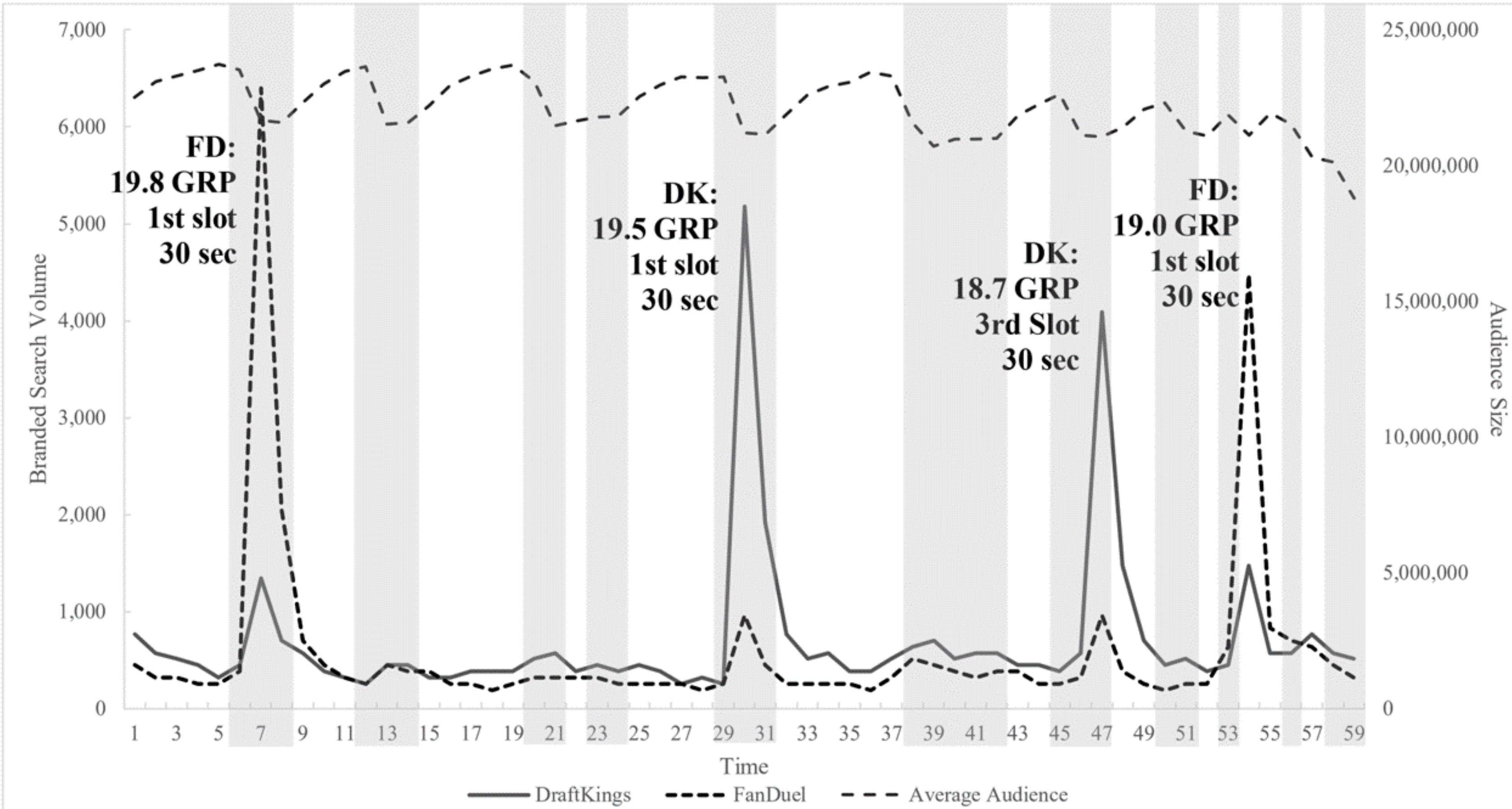
2. Ad/sales: Quasi-experiments

Goal: Find a “natural experiment” in which is “as if” randomly assigned, to identify

Possibilities:

```
      - Firm starts, stops or pulses advertising without changing other
variables, especially when staggered across times or geos
      - Competitor starts, stops or pulses advertising
      - Change in ad prices, availability or targeting for exogenous reasons
that don't affect Y (e.g., election or outage)
      - Discontinuous ad copy/campaign changes without changing other
variables
```

DraftKings and FanDuel TV ad effects on Google Search



Ad/sales: Quasi-experiments (2)

Or, construct a “control group”

- Customers or markets with similar demand trends where the firm never advertised
- Competitors or complementors with similar demand trends that don’t advertise

Techniques like “difference in differences,” “synthetic control,” “regression discontinuity,” “matching,” and “instrumental variables” can help

In each case, we try to predict our missing counterfactual data, then estimate the causal effect as observed outcomes minus predicted outcomes

3. Ad/sales example: Correlational

Just get historical data on and and run a regression

```
       Most people use OLS, but Google's CausalImpact R package is also
popular
```

The implicit assumption is either that there are no unobservables that influence both and ; or that we are OK with a correlation

```
      "Better to be vaguely right than precisely wrong"
      But are we the guy in the truck bed?
```

Strongest case for corr(ad,sales)

Corr(ad,sales) contains some truth

```
      - If ads cause sales, then corr(ad,sales)>0
```

Some products/channels just don't sell without ads

```
      - E.g., Direct response TV ads for 1800 #s
      - Career professionals tell me those #s get 0 calls until a TV ad
      - Then they get 1-5 calls per 1k viewers, lasting up to ~30 minutes
      - Then calls drop back to 0 ; so here we actually know the
counterfactual
      - We can calculate exact profits if we know call profit and ad cost
      - What are some digital analogues to this?
```

However, this argument gets pushed too far

```
      - For example, when search advertisers disregard organic link clicks
when calculating search ad click profits
```

Problem 1 with corr(ad,sales)

Advertisers try hard to maximize ad effects

We select messages, media, times, contexts, target audiences, publishers (etc.) to maximize potential impact

Sometimes, we use ML algos that max corr(ad,sales)

So, if you assume that past was random, it's functionally equivalent to assuming that the advertising team is incompetent

```
- This type of selection/treatment problem is common in marketing
```

Problem 2 with corr(ad,sales)

Suppose you wisely advertise only in places where you expect a big response

    E.g. you advertise surfboards in coastal cities with big waves, but not in landlocked cities

You'll get a big correlation between ads and sales, partly because of differences in addressable market sizes

    More ads in san diego, more surfboard sales in san diego

    Corr(ad,sales) would overestimate the causal effect of ads on sales, and likely lead you to spend too much on ads in san diego

Many, many firms basically do this

Problem 3 with corr(ad,sales)

- Leaves marketers powerless vs ~~big~~ colossal ad platforms
- Google and Meta obfuscate ad placement algorithms

```
    - How many ad placements are incremental?
    - How many ad placements target likely converters?
    - How can advertisers react to adversarial ad price adjustments?
    - How can advertisers evaluate brand safety, targeting, other
contextual elements?
```

- Have ad platforms ever left ad budget unspent?

```
    - Would you, if you were them?
    - If not, why not? What does that imply about incrementality?
```

- To balance ad platform power, know your ad profits, vote with your feet

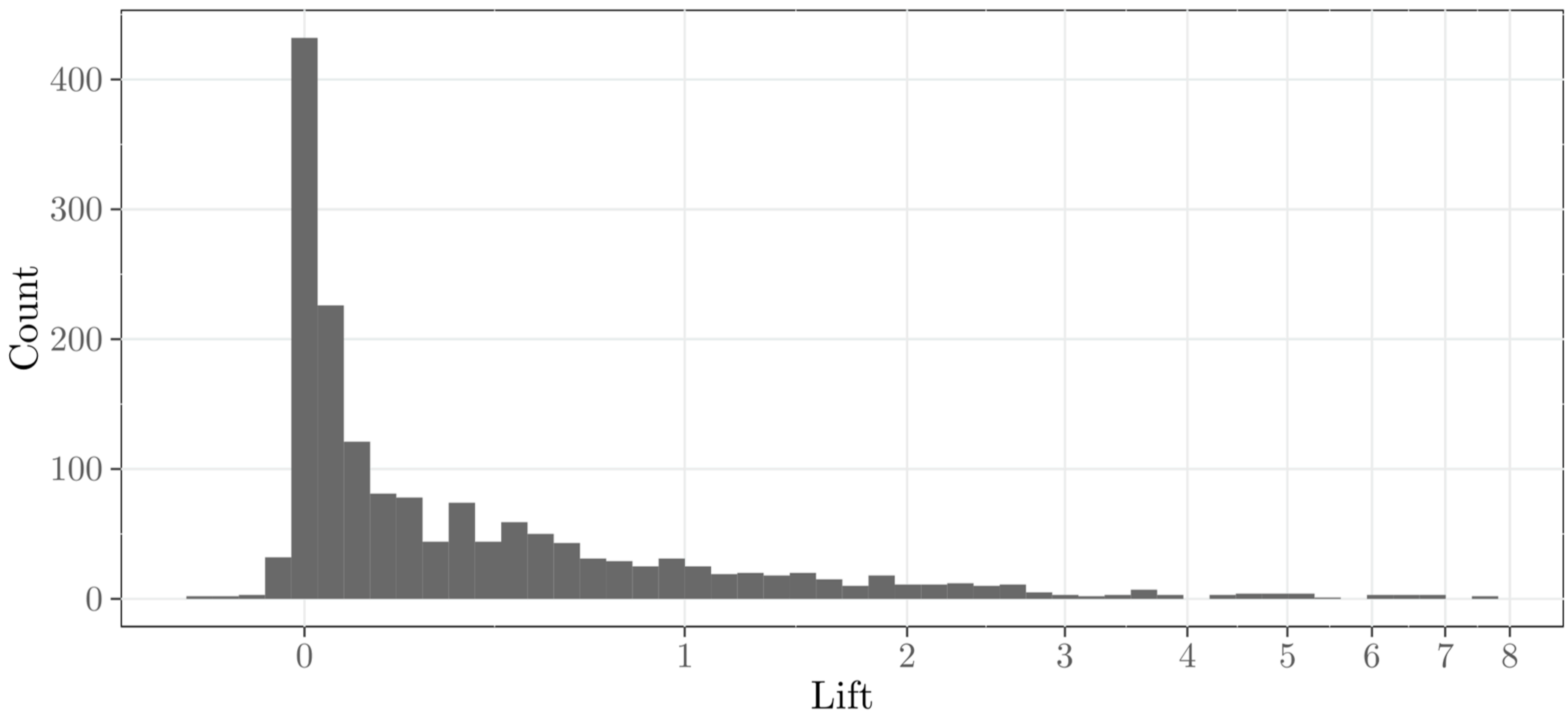
Close Enough? A Large-Scale Exploration of Non-Experimental Approaches to Advertising Measurement

Brett R. Gordon, Robert Moakler, Florian Zettelmeyer

Despite their popularity, randomized controlled trials (RCTs) are not always available for the purposes of advertising measurement. Non-experimental data are thus required. However, Facebook and other ad platforms use complex and evolving processes to select ads for users. Therefore, successful non-experimental approaches need to "undo" this selection. We analyze 663 large-scale experiments at Facebook to investigate whether this is possible with the data typically logged at large ad platforms. With access to over 5,000 user-level features, these data are richer than what most advertisers or their measurement partners can access. We investigate how accurately two non-experimental methods—double/debiased machine learning (DML) and stratified propensity score matching (SPSM)—can recover the experimental effects. Although DML performs better than SPSM, neither method performs well, even using flexible deep learning models to implement the propensity and outcome models. The median RCT lifts are 29%, 18%, and 5% for the upper, middle, and lower funnel outcomes, respectively. Using DML (SPSM), the median lift by funnel is 83% (173%), 58% (176%), and 24% (64%), respectively, indicating significant relative measurement errors. We further characterize the circumstances under which each method performs comparatively better. Overall, despite having access to large-scale experiments and rich user-level data, we are unable to reliably estimate an ad campaign's causal effect.

$$\ell = \frac{\text{Conversion rate due to ads in the treated group}}{\text{Conversion rate of the treated group if they had } \textit{not} \text{ been treated}}$$

Figure 3: Lifts across all RCTs



Excludes the top 1% of lifts

Figure 4: Lifts by Purchase Funnel Position

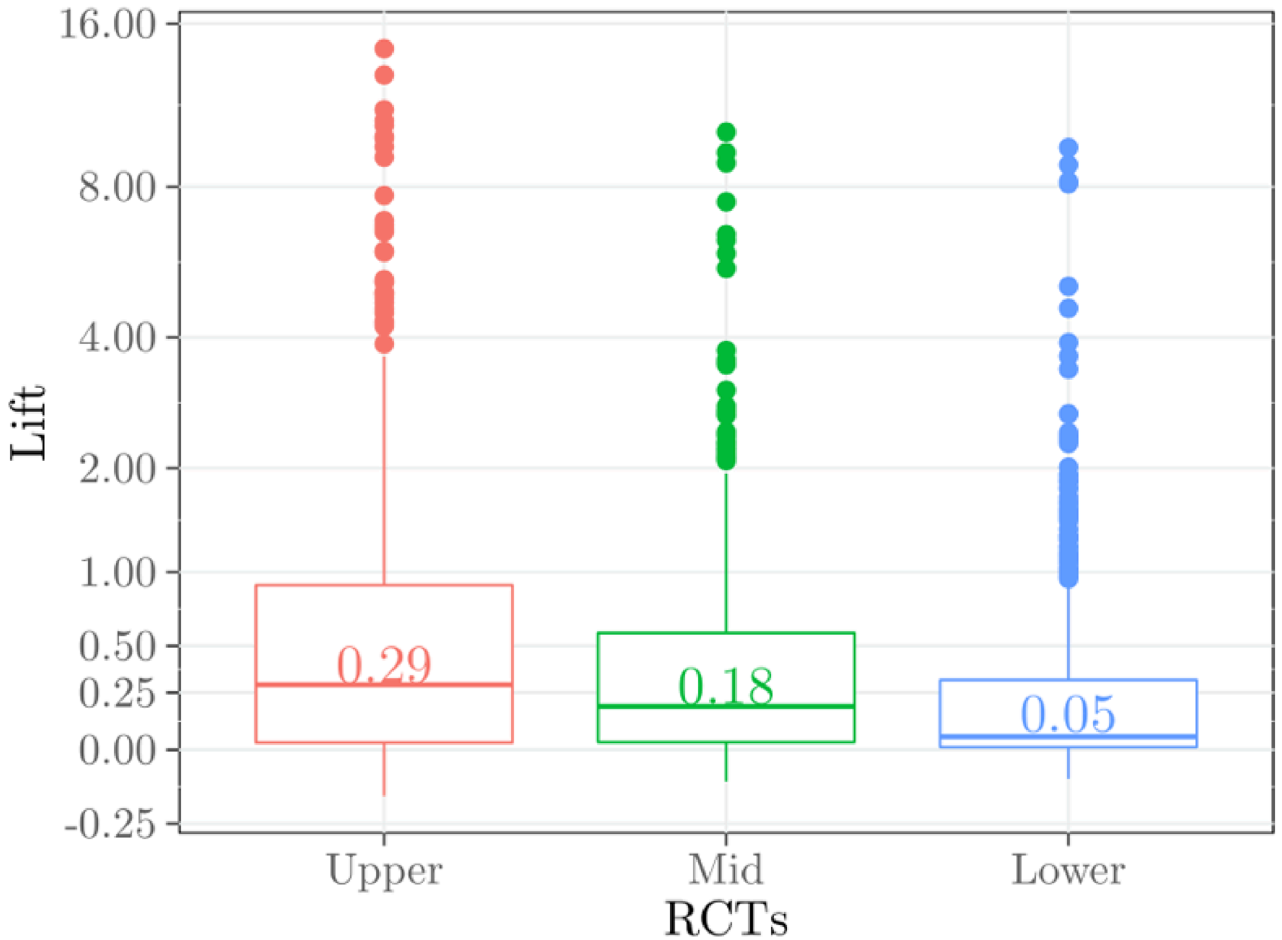


Figure 10: Comparison of RCT Lifts with Lifts Estimated using SPSM and DML

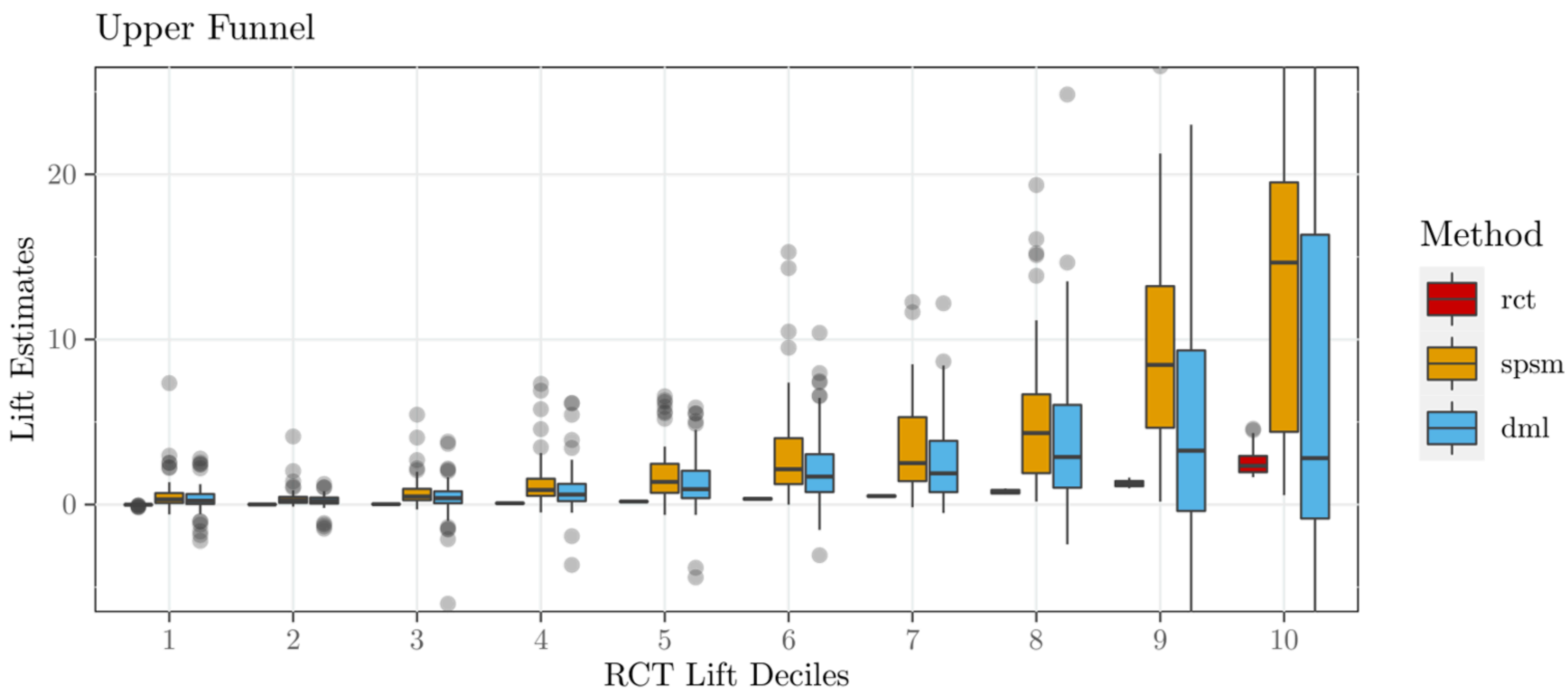
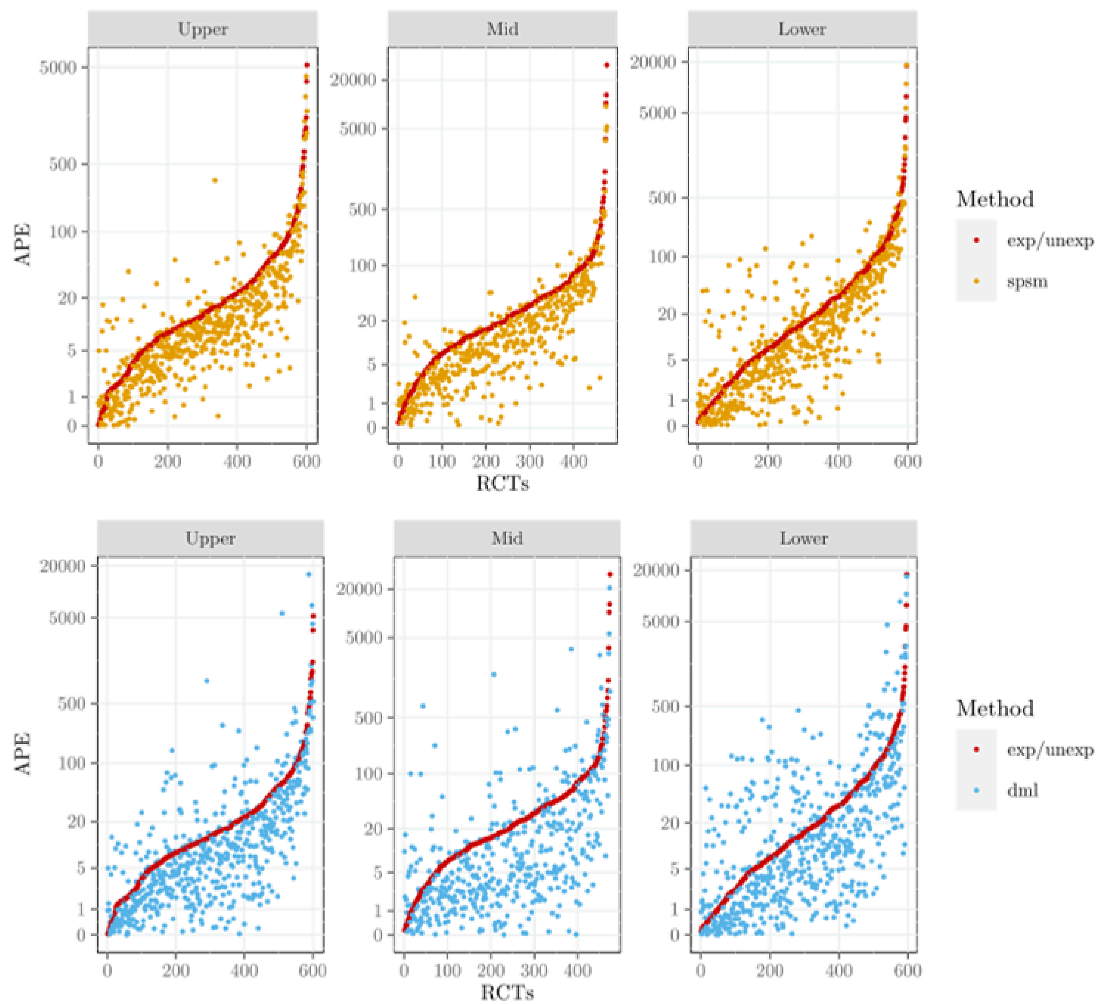


Figure 11: Absolute Percentage Error by Event Funnel



Why are some teams OK with corr(ad,sales)?

1. Some worry that if ads go to zero -> sales go to zero

```
 - For small firms or new products, this may be good logic
 - However, claim may imply a customer satisfaction problem. Happy
customers usually share their experiences with others. If you really
believe this, try a referral program
 - Plus, we can run experiments without setting ads to zero, e.g. weight
tests
```

2. Some firms assume that correlations indicate direction of causal results

```
 - The guy in the truck bed is not pushing backwards right?
 - But what is this assumption based on?
 - Direction is only part of the picture; what about effect size?
 - Unfortunately, if it's hard to get a causal estimate, then this
assumption is probably ill founded
```

Why are some teams OK with corr(ad,sales)?

3. CFO and CMO negotiate ad budget

```
- CFO asks for proof that ads work
- CMO asks ad agencies, platforms & marketing team for proof
- CMO sends proof to CFO ; We all carry on
- Things may change if ad effects team reports to CFO
```

4. Few rigorous analytics cultures or ex-post checks

```
- Downside of lost sales may exceed downside of foregone profits
```

5.Estimating causal effects of ads can be pretty difficult

```
- Many firms lack expertise, patience, execution skill
- Ad/sales tests may be statistically inconclusive, especially if small
- Tests are often designed without subsequent actions in mind
```

Why are some teams OK with corr(ad,sales)?

6. Platforms often provide correlational ad/sales estimates

```
 - Which one do you think is larger, correlational or experimental ad
effect estimates?
 - Which one would most client marketers prefer?
 - Platform estimates are typically "black box" without neutral auditors
 - Sometimes platforms respond to marketing executive demand for good
numbers
 - "Nobody ever got fired for buying [famous platform brand here]"
```

7. Historically, most advertising work was done by agency professionals

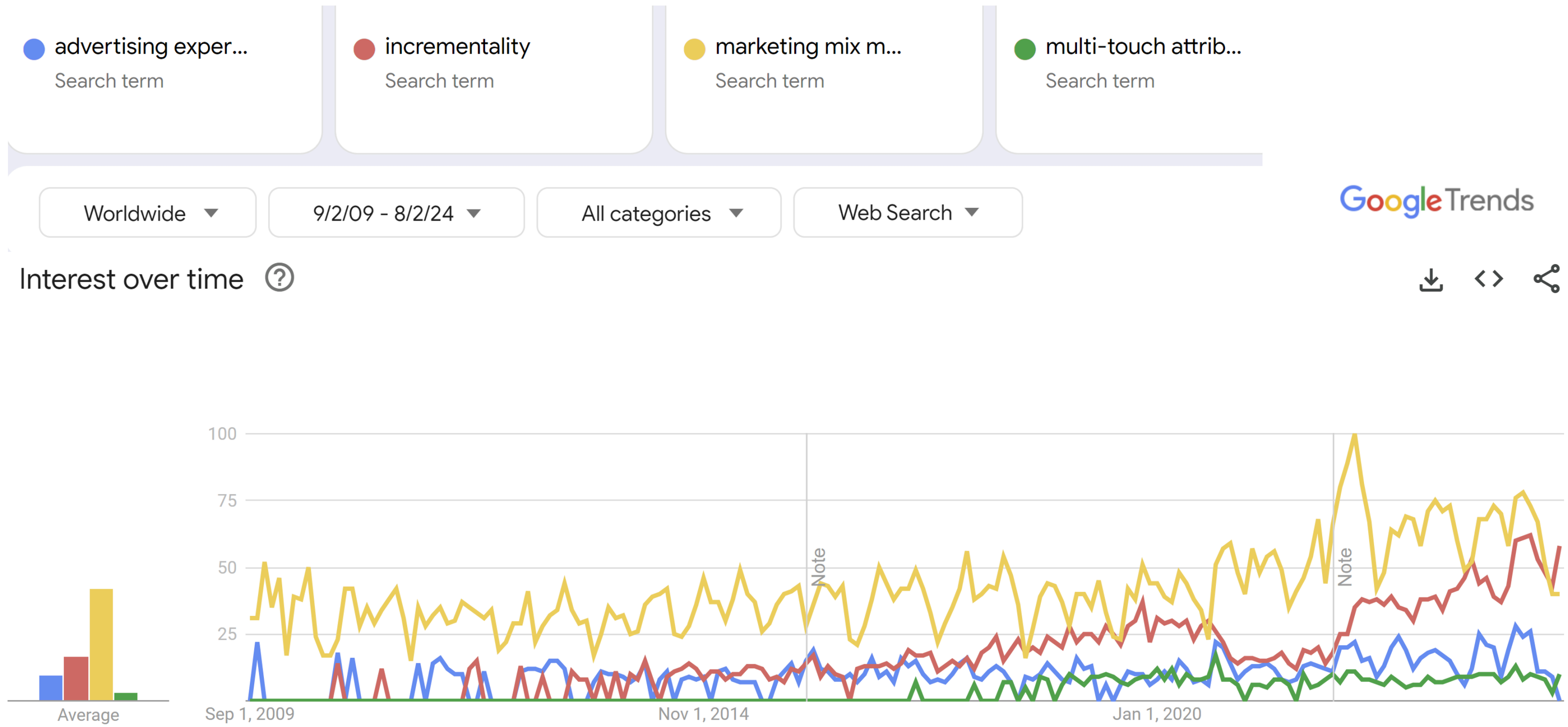
```
 - Agency compensation usually relies on spending, not incremental sales
 - Principal/agent problems are common
 - "Advertising attribution" is all about maximizing credit to ads
 - These days, most marketers have in-house agencies, and split work
```

What is incrementality?

Incrementality refers to the measure of the additional impact or value generated by a specific action, campaign, or intervention beyond what would have occurred naturally without it. In marketing and advertising, incrementality is often used to determine the effectiveness of campaigns by comparing the results of those exposed to the campaign versus a control group that was not exposed. This helps in understanding the true value and ROI of marketing efforts.

Key Points of Incrementality

1. **Causal Inference**: Incrementality is rooted in causal inference, aiming to isolate the effect of a specific action from other factors.
2. **Control Groups**: A key methodology involves using control groups to measure what would have happened in the absence of the intervention.
3. **Lift**: Incrementality is often expressed as "lift," representing the increase in desired outcomes (sales, conversions, engagement, etc.) due to the campaign.
4. **A/B Testing**: Commonly used techniques to measure incrementality include A/B testing, where one group is exposed to the treatment, and the other is not.
5. **Attribution Models**: Incrementality is crucial for accurate attribution models, ensuring that credit is assigned correctly to the actions that tr drive results.



- I believe we're a few years into a generational shift
- However, corr(ad,sales) is not going away
- More like podcasts v AM radio than like streaming v CDs

2023 Advertising To Sales Ratios by Industry Sector

Industry Sector	Ad to Sales Ratio %	Ad Growth %	Sales Growth %
Agriculture, Forestry, Fishing	0.40	-17.79	17.64
Mining, Extraction	0.07	13.28	-3.45
Construction	0.35	26.94	0.53
Manufacturing	2.70	10.47	0.69
Transportation, Communications, Utilities	3.60	4.26	5.31
Wholesale Trade	1.27	7.81	0.70
Retail Trade	2.42	11.69	4.09
Finance, Insurance, Real Estate	2.31	-0.05	8.57
Services	4.06	11.27	11.86
All sectors combined	2.83	9.01	4.77

Advertising Ratios & Budgets is the source for the above data. This detailed report covers over 2,500 companies and 315 industries with fiscal 2023 and 2022 advertising budgets and revenue, 2023 ad-to-sales ratio and ad-to-profit ratio, as well as 2023 annual growth rates in ad spending and sales. Use it to track competition, win new ad agency clients, set and justify ad budgets, sell space and time or plan new media ventures and new products. Includes industry and advertiser ad spending rankings and data on over 350 non-U.S. headquartered companies. Bought by major advertising agencies, media companies, advertisers and libraries. Published May 2024.

Advertising Sales Ratios - SAI Books

- Typical net margin: 8-10% (see Damodaran)
- Ads finance information production

HAWKSEM
DIGITAL MARKETING AGENCY

Free Consultation

Here, Sam Yadegar, CEO of HawkSEM, delivers expert advice on marketing budget estimates and how to balance your profit margin with your marketing goals for ultimate return on investment (ROI).

How much revenue should I spend on marketing?

Your marketing budget needs anywhere from 5-20% of your revenue to thrive. Generally, 5-10% is enough to sustain, but you'll need 11-20% into data-driven marketing campaigns to grow.

Campaigns can span digital marketing, traditional advertising, outreach events, tools, technology, in-house marketing team salaries, and agency services.

That said, arbitrary spending reaps minimal rewards, if any. To truly drive results, you've gotta spend *wisely*.

Marketing Mix Model

- The "marketing mix" consists of quantifiable marketing efforts, such as product line, length and features; price and price promotions; advertising, PR, social media and other communication efforts; retail distribution intensity and quality; etc.
- A "marketing mix model" quantifies the relationship between marketing mix variables and outcomes

```
- Idea goes back to the 1950s
- E.g., suppose we increase price & ads at the same time
- Or, suppose ads increased demand, and then inventory-based systems raised prices
```

- A "media mix model" quantifies numerous advertising efforts and relates them to sales

```
- For example, suppose the brand bought ads from 000s of publishers
- Confusingly, both abbreviated MMM and often feature similar structures
```

- MMM goal is to quantify past marketing mix effects, to better inform future efforts

MMM elements

Typically, MMM uses geo/time data

```
      - Outcome: usually sales. Could include more funnel metrics (visits, leads, ...)
      - Predictors: Marketing mix factors under our control, plus competitor variables, seasonality,
macroeconomic factors, + any other demand shifters
```

Model structure is usually some type of panel regression, vector autoregression, or bayesian model

```
      - Often includes lags, interactions, and other nonlinear terms
      - Regressions typically estimate marginal effects, not average effects
      - Nonlinearities built into the model, such as Inc or Dec returns to ad spend, can drive key results
```

MMM often used to retrospectively evaluate advertising media and copy, advertising interactions, and inform future ad budgets

```
      - MMM can be used for prediction but should be calibrated appropriately
```

MMM Challenges

- Without experimental data, MMM results are correlational
- Data availability, accuracy and granularity are all critical
- MMM requires sufficient variation in predictors, else it cannot estimate coefficients
- “Model uncertainty” : Results can be strongly sensitive to modeling choices
- For much more, see this MSI White Paper or the MMM Wikipedia article

Other Popular Ad/Sales Approaches

```
Remember, model <> identification strategy
```

- Lift Tests
- Multi-touch attribution (MTA)

```
- Seeks to allocate "credit" for sales across advertising touchpoints
- Related: First-touch attribution, last-touch attribution
```

- Cookie-based approaches vs. Google's Privacy Sandbox
- Ghost ads
- Other platform-provided experimentation tools

Kenneth Wilbur • You
Professor of Marketing and Analytics at University of California, San Diego...
4d • Edited •

MSBA student asked a great question. How would you answer?

Suppose you understand the importance of incrementality in advertising measurement, but everyone you work with prefers correlational measurements, and some actively discourage experiments. What should you do?

Robert Olinger 4d
Assistant Dean, Institutional Collaboration at Duke University - The Fuqu...

Ask the colleagues to teach you more about correlational measurements. Listen to them first, then ask what they have learned about incrementality. This is a psychological problem more than a preference, so use phsychology to address it.

Like 4 · Reply 3

Rachel Fagen 4d
COO | Co-Founder | Partner | Advisor

💯 🏆

Like · Reply

Kenneth Wilbur Author 4d
Professor of Marketing and Analytics at University of California, Sa...

Robert Olinger could you say more about what you mean by psychological problem?

Like · Reply

Robert Olinger 4d
Assistant Dean, Institutional Collaboration at Duke University - Th...

Kenneth Wilbur: I believe if experimentation is actively discouraged, this is due to aversion, a desire to feel comfortable, a desire to feel right, loss aversion, etc. The way you phrase the argument sounds like a lack of openness to listen--so my advice is you need to open up the colleagues--the best way to do that is by listening to them, understanding as best you can their expertise and approach--then engage their curiosity toward something new--the experimentation has to seem like it was their idea--so focus on engaging curiously with the colleagues, and when there is an openness ask questions related to the ideas you want included. Have them think about it... This is the way to shift preferences--persistent nudging.

Like 2 · Reply

Joel Persson 4d
Research Scientist at Spotify | Causal Inference, Machine Learning and D...

You could demonstrate the value of experimentation for the business use case, for instance by showing via simulation that correlational evidence can lead to incorrect decisions (product launches, rollouts, etc) but that causal estimates from experiments get it right. You could even attach a relevant business metric (dollar value, engagement, reach, etc) ...see more

Like 4 · Reply

Dean Eckles (edited) 4d
scientist & statistician; faculty at MIT

One option: Consider looking for a new job. The number of firms with people who get A/B testing has expanded a lot. Fits with avoiding being the smartest person in the room.
(Of course, there are other good options... but as a person in a junior role, this is one of the better ones.)

Like 5 · Reply

Brett Gordon 4d
Professor of Marketing at Kellogg School of Management | Amazon Sch...

Definitely bring in academics as outside consultants ;-)

Like 6 · Reply

Nirzar Bhaidkar 4d
Executive Paid Search @ GroupM | AI-Driven Marketing

Propose small scale pilot experiments to demonstrate the value of incremental measurement without significant resource investment.

Like 1 · Reply

Ayman Farahat 10h
Principal Scientist at Amazon

Like · Reply

Brad Shapiro 3d
Professor at The University of Chicago Booth School of Business

Generally agree with Dean Eckles. But depends on their reason for discouraging experimentation. If it is a genuine lack of understanding, I would try and be persuasive, show examples of how correlational assessments might lead you astray, etc. If it is an agency problem whereby they feel they need to mislead their management in order to keep their jobs, I'd say look for another job.

Like 1 · Reply

Michael Cohen 2d
Customer Centric Privacy Protecting Marketing AI

Change the way they are compensated or incentivized to be aligned with marginal economics of business aligned kpis.

Like 4 · Reply

Ken’s take

Takeaways

- Fundamental Problem of Causal Inference: We can’t observe all data needed to optimize actions. This is a missing-data problem
- Approaches: Experiments, Quasi-experiments, Correlations, Ignore
- Experiments are the gold standard, but are costly and difficult to design, implement and act on
- Ad effects are subtle but that does not necessarily imply unprofitability

Going deeper

- What is Incrementality? And How Do We Measure it in 2024?
- Inferno: A Guide to Field Experiments in Online Display Advertising: Covers frequent problems in online advertising experiments
- Inefficiencies in Digital Advertising Markets: Discusses digital RoAS estimation challenges and remedies
- The Power of Experiments: Goes deep on digital test-and-learn considerations
- New Developments in Experimental Design and Analysis (2024) by Athey & Imbens
- Mostly Harmless Econometrics: Covers quasi-experimental techniques