Social Advertising

Social Media and Web Analytics

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Learning Goals for this Week

- Explain the advantages of an RCT in estimating ad effectiveness
- Explain why observational studies cannot estimate casual effect of digital ads
- Summarise effects of digital ads on checkout, page views and registrations
- Discuss why company tweets may increase demand
- Evaluate the effectiveness of company tweets on demand for products
- Summarise the effects of advertising on word of mouth
- Critically evaluate research results in the existing literature

Today's Agenda

Three papers:

- A Comparison of Approaches to Advertising Measurement: Evidence from Big Field Experiments at Facebook
  - Gordon, Zettelmeyer, Bhargava and Chapsky (2019, Marketing Science)
- Tweeting as a Marketing Tool – Field Experiment in the TV Industry
  - Gong, Zhang, Zhao and Jiang (2017, Journal of Marketing Research)
- Can Your Advertising Really Buy Earned Impressions? The Effect of Brand Advertising on Word of Mouth
  - Lovett, Peres and Xu (2019, Quantitative Marketing and Economics)

Approaches to Advertising Measurement

Measuring Ad Effectiveness

Motivation: Measuring the causal effect of digital advertising

Specific Questions:

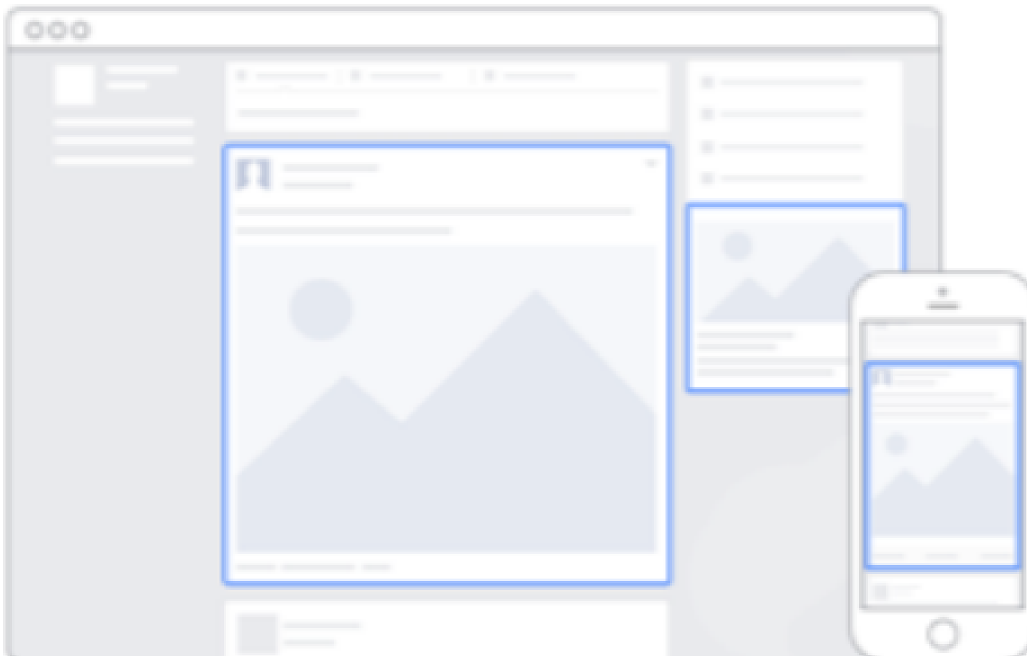
- What **is** the effect?
- Can we reliably estimate the effect without RCTs?

How?: Large scale experiments (15) at Facebook

- Note: This paper is **very** cool
- The authors are *extremely* careful in their explanations

Advertising on Facebook

- Ads appear in the News Feed



Source: https://www.facebook.com/business/ads-guide

- Advertiser chooses target demographic(s), users then exposed to treatment / control

Endogeneity Abounds Us (Them)

Concern: Sources of selection bias (Why?)

User Induced Endogeneity

- 'Activity bias' - user must be on Facebook during campaign to be exposed

Targeting Induced Endogeneity

- Ad delivery system optimizes whom to show ads

Competition Induced Endogeneity

- Displaying ad $\implies$ won an auction $\implies$ exposed users are highly values (higher expected conversion probability)

$\implies$ estimating causal effects without an RCT will be tough!

What are they Measuring?

Average Treatment Effect on the Treated: effect of the ads on users who are actually exposed to ads

Lift

$$\begin{aligned}\tau_\ell &= \frac{\Delta\text{Conversion rate due to ads in the treated group}}{\text{Conversion rate of the treated group if they had } \textit{not} \text{ been treated}} \\ &= \frac{\tau}{\mathbb{E}[Y^{obs}|Z=1, W^{obs}=1] - \tau}\end{aligned}$$

Data

Study	Vertical	Observations	Test	Control	Impressions	Clicks	Conversions	Outcomes*
1	Retail	2,427,494	50%	50%	39,167,679	45,401	8,767	C, R
2	Finan. serv.	86,183,523	85%	15%	577,005,340	247,122	95,305	C, P
3	E-commerce	4,672,112	50%	50%	7,655,089	48,005	61,273	C
4	Retail	25,553,093	70%	30%	14,261,207	474,341	4,935	C
5	E-commerce	18,486,000	50%	50%	7,334,636	89,649	226,817	C, R, P
6	Telecom	141,254,650	75%	25%	590,377,329	5,914,424	867,033	P
7	Retail	67,398,350	17%	83%	61,248,021	139,471	127,976	C
8	E-commerce	8,333,319	50%	50%	2,250,984	204,688	4,102	C, R
9	E-commerce	71,068,955	75%	25%	35,197,874	222,050	113,531	C
10	Tech	1,955,375	60%	40%	2,943,890	22,390	7,625	C, R
11	E-commerce	13,339,044	50%	50%	11,633,187	106,534	225,241	C
12	Retail	5,566,367	50%	50%	10,070,742	54,423	215,227	C
13	E-commerce	3,716,015	77%	23%	2,121,967	22,305	7,518	C, R
14	E-commerce	86,766,019	80%	20%	36,814,315	471,501	15,722	C
15	Retail	9,753,847	50%	50%	8,750,270	19,365	76,177	C

* C = checkout, R = registration, P = page view

RCT Results

Table 4: ATT lift for all studies and measured outcomes

Study	Outcome	Pct Exposed	Conversion Prob. Exposed in Test	Conversion Prob. Unexposed in Test	RCT ATT	RCT ATT Lift	RCT ATT Lift Confidence Interval	
S1	Checkout	76%	0.151%	0.069%	**0.035%**	**30.0%**	[16%	46%]
S2	Checkout	48%	0.054%	0.014%	0.001%	1.3%	[-5%	8%]
S3	Checkout	66%	0.260%	0.131%	**0.021%**	**8.8%**	[1.1%	17%]
S4	Checkout	37%	0.079%	0.025%	**0.033%**	**72.8%**	[49%	103%]
S5	Checkout	30%	0.055%	0.008%	**0.045%**	**449.6%**	[306%	761%]
S7	Checkout	51%	0.284%	0.217%	0.007%	2.7%	[-0.3%	6%]
S8	Checkout	26%	0.069%	0.039%	-0.002%	-2.9%	[-21%	23%]
S9	Checkout	6.6%	2.105%	0.052%	**0.049%**	2.4%	[-0.1%	5%]
S10	Checkout	65%	0.127%	0.092%	0.003%	2.0%	[-11%	20%]
S11	Checkout	42%	0.488%	0.124%	**0.039%**	**8.6%**	[5%	13%]
S12	Checkout	77%	6.403%	2.810%	**0.078%**	**1.2%**	[0.2%	2%]
S13	Checkout	30%	0.187%	0.309%	-0.033%	-15.1%	[-35%	20%]
S14	Checkout	35%	0.068%	0.019%	**0.026%**	**62.0%**	[43%	86%]
S15	Checkout	81%	1.470%	1.175%	**0.034%**	**2.4%**	[0.4%	5%]
S1	Registration	76%	0.725%	0.064%	**0.643%**	**781.4%**	[694%	890%]
S5	Registration	30%	0.993%	0.068%	**0.893%**	**893.1%**	[797%	1010%]
S8	Registration	26%	0.025%	0.008%	**0.010%**	**63.2%**	[11%	176%]
S10	Registration	65%	0.423%	0.313%	0.033%	8.6%	[0%	19%]
S14	Registration	35%	0.642%	0.119%	**0.393%**	**158.1%**	[145%	173%]
S2	Page View	48%	0.249%	0.007%	**0.233%**	**1517.1%**	[1357%	1733%]
S5	Page View	30%	0.753%	0.075%	**0.647%**	**608.8%**	[541%	692%]
S6	Page View	61%	0.557%	0.152%	**0.069%**	**14.0%**	[13%	15%]

RCT ATT and RCT ATT Lift in **bold**: statistically different from zero at 5% level. 95% confidence intervals for RCT ATT Lift obtained via bootstrap.

Observational Approaches

Study	RCT Lift	E-U	EM: Age, Gender	Stratification: Age, Gender +FB	Stratification: Age, Gender +FB +Census	Stratification: Age, Gender +FB +Census +Activity	Stratification: Age, Gender +FB +Census +Activity +FB Match	Propensity Score Matching: Age, Gender +FB	Propensity Score Matching: Age, Gender +FB +Census	Propensity Score Matching: Age, Gender +FB +Census +Activity	Propensity Score Matching: Age, Gender +FB +Census +Activity +FB Match	Regression: Age, Gender +FB	Regression: Age, Gender +FB +Census	Regression: Age, Gender +FB +Census +Activity	Regression: Age, Gender +FB +Census +Activity +FB Match	Inv. Prob. Weighted Regression Adjustment: Age, Gender +FB	Inv. Prob. Weighted Regression Adjustment: Age, Gender +FB +Census	Inv. Prob. Weighted Regression Adjustment: Age, Gender +FB +Census +Activity	Inv. Prob. Weighted Regression Adjustment: Age, Gender +FB +Census +Activity +FB Match	Stratified Regression: Age, Gender +FB	Stratified Regression: Age, Gender +FB +Census	Stratified Regression: Age, Gender +FB +Census +Activity	Stratified Regression: Age, Gender +FB +Census +Activity +FB Match
Checkout																							
1	30%	217%	116%	105%	100%	105%	94%	109%	107%	89%	93%	99%	94%	59%	49%	104%	99%	88%	76%	101%	94%	69%	51%
2	1.5%	577%	452%	156%	148%	59%	57%	161%	149%	57%	56%	114%	103%	55%	30%	149%	140%	43%	35%	97%	98%	54%	40%
3	8.8%	198%	69%	22%	25%	46%	18%	20%	24%	41%	17%	6%	9%	21%	5%	21%	25%	38%	5%	18%	19%	30%	2%
4	73%	316%	222%	140%	136%	145%	99%	145%	131%	145%	95%	63%	61%	64%	37%	126%	122%	134%	100%	98%	87%	96%	74%
5	450%	678%	511%	427%	452%	448%	306%	418%	445%	465%	316%	409%	415%	429%	299%	428%	452%	457%	305%	447%	451%	455%	301%
7	2.7%	151%	57%	19%	20%	-34%	-35%	20%	18%	-35%	-36%	22%	23%	-19%	-21%	19%	20%	-33%	-35%	19%	19%	-31%	-33%
8	-2.9%	179%	48%	34%	39%	52%	33%	31%	36%	50%	27%	39%	45%	60%	33%	36%	41%	54%	29%	32%	37%	52%	28%
9	2.4%	4074%	3414%	1994%	1995%	2519%	1724%	2062%	1970%	2514%	1710%	1925%	1960%	2069%	1506%	1994%	1999%	2519%	1716%	1962%	1962%	2210%	1656%
10	2.0%	158%	58%	20%	20%	56%	-15%	23%	16%	45%	-7%	10%	10%	25%	-5%	20%	20%	54%	-15%	21%	21%	55%	-11%
11	9%	392%	275%	30%	30%	59%	7%	29%	31%	58%	7%	16%	16%	11%	-5%	30%	31%	55%	5%	30%	31%	54%	2%
12	1%	235%	129%	112%	110%	81%	81%	111%	110%	82%	82%	109%	107%	73%	74%	112%	111%	82%	81%	112%	111%	84%	82%
13	-15%	61%	-39%	-35%	-35%	-31%	-30%	-35%	-36%	-30%	-31%	-36%	-36%	-31%	-30%	-35%	-35%	-31%	-30%	-35%	-35%	-31%	-30%
14	62%	365%	119%	81%	86%	99%	99%	80%	85%	95%	101%	80%	83%	93%	92%	80%	83%	92%	90%	74%	77%	82%	84%
15	2%	126%	26%	-9%	-9%	-10%	-13%	-10%	-9%	-10%	-13%	-6%	-6%	-10%	-12%	-9%	-9%	-11%	-14%	-9%	-9%	-12%	-14%
Registration																							
1	781%	1152%	1024%	976%	962%	1126%	1025%	978%	944%	1060%	977%	625%	595%	205%	155%	968%	960%	1087%	985%	824%	800%	452%	348%
5	895%	1456%	1270%	1064%	1065%	1074%	744%	1071%	1095%	1070%	765%	1204%	1189%	1196%	681%	1067%	1067%	1063%	728%	1112%	1104%	1081%	772%
8	63%	351%	180%	154%	156%	161%	135%	162%	159%	175%	167%	124%	126%	139%	99%	150%	155%	158%	114%	157%	161%	160%	125%
10	9%	136%	34%	19%	19%	32%	0%	19%	18%	34%	-5%	16%	16%	27%	5%	18%	18%	31%	0%	19%	18%	31%	2%
14	158.1%	540%	275%	219%	221%	245%	241%	215%	219%	244%	241%	234%	234%	277%	281%	219%	219%	238%	234%	219%	218%	240%	239%
Page View																							
2	1517%	3363%	4261%	2481%	2479%	1147%	1185%	2495%	2416%	1150%	1177%	744%	747%	202%	209%	2408%	2422%	1175%	1187%	1162%	1181%	1722%	1268%
5	609%	1010%	846%	749%	747%	711%	480%	771%	751%	719%	484%	809%	805%	828%	490%	751%	748%	710%	477%	776%	769%	717%	498%
6	14%	360%	227%	103%	106%	262%	254%	103%	105%	265%	255%	66%	68%	222%	250%	103%	106%	250%	246%	111%	115%	255%	270%

* Red: RCT Lift is statistically different from 0 at 5% significance level

Red: Observational method overestimates lift

Blue: Observational method underestimates lift

Color proportional to overestimation factor; darkest color reached at 3-times over- or underestimation

Main Takeaways

RCTs are the gold standard for measuring ad effectiveness

- Insignificant differences for checkout conversion in 6/15 experiments
- Significant for registration and page views almost always

Observational models generally overestimate lift

- Can be wrong by a factor of 3
- 'Better' for registrations and page views than checkout

Tweeting as a Marketing Tool

Do Firm Tweets Matter?

Motivation: Does tweeting increase demand for their products

Specific Questions:

- What is the causal effect of company tweets on demand?
- Do retweets by influential users help?

How?: Large scale experiment on Weibo w/ a media company

- Note: (again) This paper is **very** cool

The Experiment

Weibo ≈ Chinese Twitter

Industry: documentary TV shows

- One show broadcast per day across seven local channels

Table 1 Summary of Experimental Conditions

Condition	Description	Number of TV Shows
Control	Each show is neither tweeted by the company nor retweeted by an influential	14
Tweet	Each show is tweeted by the company	42
Tweet & Retweet	Each show is tweeted by the company and retweeted by an influential	42

Notes. The company tweets at 11:00 am of the day of the show. Influentials retweet company tweets at noon.

Results

Table 7 Main Results – Effect of Tweeting on Show Viewing (Treated Channels)

	(1)	(2)	(3)	(4)	**(5) "Main Model"**
Tweet (α_1)	.0500	.0514	.0514	.0492	**.0576**
	(.0133)***	(.0138)***	(.0138)***	(.0145)***	**(.0161)*** **
Tweet & Retweet (α_2)	.0694	.0698	.0698	.0707	**.0824**
	(.0144)***	(.0148)***	(.0149)***	(.0156)***	**(.0169)*** **
#Noncommercial tweets		.0035	.0035	.0007	**-.0022**
		(.0030)	(.0031)	(.0050)	**(.0056)**
Channel dummies	No	No	Yes	Yes	**Yes**
Week dummies	No	No	No	Yes	**Yes**
Day-of-week dummies	No	No	No	Yes	**Yes**
Series dummies	No	No	No	No	**Yes**
Episode dummies	No	No	No	No	**Yes**
Genre dummies	No	No	No	No	**Yes**
$\alpha_2 - \alpha_1$	.0194	.0184	.0184	.0215	**.0248**
p-value of $\alpha_2 - \alpha_1$	.069	.080	.081	.052	**.039**
#Observations	490	490	490	490	**490**
R-squared	.033	.035	.347	.372	**.389**

Notes. An observation is a show-channel combination. The dependent variable is the percentage of a channel's audience viewing a show. The sample consists of all 98 shows on the five treated channels (i.e., channels that broadcast the shows after the time of company tweets and influential retweets). The *p*-values for the difference between α_2 and α_1 are based on one-tailed tests. OLS estimates with robust standard errors clustered at the show level. * $p<.10$, ** $p<.05$, *** $p<.01$.

Results II

Table 16 Effect Magnitude by Experimental Condition

	Show Viewing Percentage		Daily Growth in Company followers	
	Mean	Change	Mean	Change
Current effects				
Control	.0749	0%	259	0%
Tweet	**.1325**	**77%**	244	-6%
Tweet & Retweet	**.1573**	**110%**	**349**	**35%**
Display	**.1755**	**134%**	N/A	N/A
Not display	.1300	74%	N/A	N/A

Main Takeaways

Effects:

- Tweeting: positive & significant effect
- Tweeting + Influential retweet: retweet gives a significant boost

What's the mechanism? (subtle)

- Influential tweets with broadcast time info attract new viewers
  - Table 8 and 9
- Informative tweets (broadcast time) also attract new followers to company page

Advertising and Word of Mouth

Can Ads Generate WoM?

Motivation: 20% of WoM references TV Ads

Specific Questions:

- Does advertising effect WoM (online and offline)?
- What about during large events (Superbowl)?

How?: Observational data on WoM and advertising

Data and Model

536 brands, 16 product categories

Advertising Data: monthly ad expenditure from Ad$pender

Word of Mouth:

- TalkTrack from Keller-Fay group ('Engagement Labs' / 'TotalSocial')
- Nielsen's UGC search engine ('Nielsen McKinsey Incite')

$$\log(WOM)_{jt} = \alpha_j + \alpha_{cq} + \beta_{1j} log(AdTV)_{jt} + \beta_{2j} \log(AdInternet)_{jt} + \gamma_{1j} \log(WOM)_{jt-1} + \gamma_{2j} \log(WOM)_{jt-2} + X_{jt}\beta_{0j} + \varepsilon_{jt}$$

Results

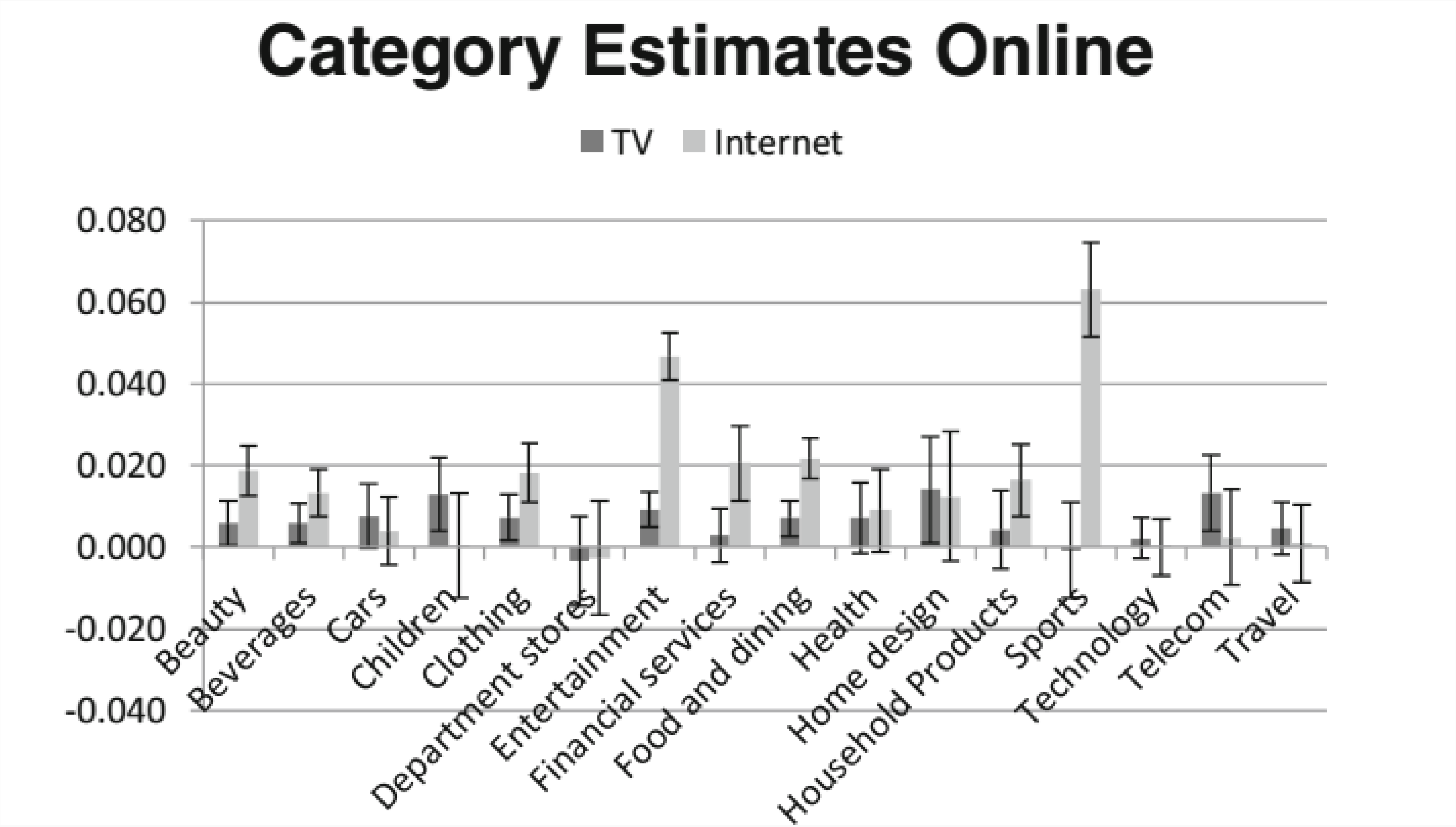
Table 2 Main model with dependent variable Ln(WOM)

Variables	Total WOM		Online WOM	
	Population Means		Population Means	
	Estimate	Std.Err.	Estimate	Std.Err.
Ln (Advertising $ TV)+	0.019	0.0017 **	0.009	0.001 **
Ln (Advertising $ Internet) +	0.014	0.0021 **	0.010	0.002 **
Ln (Advertising $ Other) +	0.013	0.0018 **	0.004	0.002 **
Ln (No of news mentions)	0.103	0.0049 **	0.138	0.009 **
Ln (WOM(t-1))	0.167	0.0087 **	0.429	0.009 **
Ln (WOM(t-2))	0.075	0.0064 **	0.039	0.007 **
Brand Fixed Effects?	Yes		Yes	
Brand Random Coefficients?	Yes		Yes	
Time Effects?	Category-Year-Quarter fixed effects and cubic functions of month of year		Category-Year-Quarter fixed effects and cubic functions of month of year	
	Heterogeneity Variances		Heterogeneity Variances	
	Estimate	Std.Err.	Estimate	Std.Err.
Ln (Advertising $ TV) +	0.0004	0.0001 **	0.0002	0.0000 **
Ln (Advertising $ Internet) +	0.0008	0.0001 **	0.0004	0.0001 **
Ln (Advertising $ Other) +	0.0003	0.0001 **	0.0002	0.0001 **
Ln (No of news mentions)			0.0272	0.0026 **
Ln (WOM(t-1))	0.0250	0.0021 **	0.0162	0.0016 **
Ln (WOM(t-2))	0.0078	0.0010 **	0.0054	0.0008 **
Sample size	40,888		21,689	

All log variables add 1 prior to logging

+ Spending is the log of $1000's dollars per brand per month. * indicates p value<.05; ** indicates p value<.01

Category Heterogeneity



Superbowl, Super Effect?

Table 4 Average Treatment Effect on the Treated (ATT) for total WOM and for online WOM, in various time resolutions

Type of WOM Data	Data Frequency	Effect size (ATT.avg)	Std.Err.	*p*.value	#Factors	#Pre Periods	#Treatment Periods
Overall WOM on a representative sample	week	0.1181	0.0335	0.0005	0	16	4
Overall WOM on a representative sample	week	0.1047	0.0444	0.0113	1	16	4
Overall WOM on a representative sample	month	0.1076	0.0431	0.0124	0	6	2
Overall WOM on a representative sample	month	0.1029	0.0505	0.0354	1	6	2
Online Posts	week	0.1405	0.0383	0.0003	3	16	4
Online Posts	month	0.1574	0.0370	0.0000	1	6	2
Online Posts	day	0.1511	0.0875	0.1789	10	60	31
Online Posts	day	0.2660	0.0638	0.0000	9	60	8

Main Takeaways

- **Small**, positive, statistically significant effect of advertising spending on WoM
  - Question: Is ad spend the *right* variable of interest?
- Heterogeneity across categories
  - Larger for Sports & Hobbies, Media & Entertainment, and Telecom
- Large events have larger effects that are short-lived

Recap

Recap

- Measuring (digital) Ad effects is **hard**, endogeneity is everywhere
  - RCTs/experiments are our the best way forward
- Company tweets (these are ads) can generate demand, influential retweets even more
  - mechanism: attracting a new audience
- Ads can spillover to generate (small) WoM effects
  - Question: can we quantify the effect on demand?

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Suggested Citation:

```
@misc{smwa_lecture_07,
      title={"Social Media and Web Analytics: Lecture 07"},
      author={Lachlan Deer},
      year={2021},
      url = "https://github.com/tisem-digital-marketing/smwa-lecture-07"
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