How TV Advertising Influences Word of Mouth:

Evidence from Twitter

Lachlan Deer[1] Pradeep K. Chintagunta[2] Gregory S. Crawford[1]

[1]University of Zurich

[2]Chicago Booth School of Business

Ads and (online) Word of Mouth

- Consumers now spend more than 135 mins per day on social media
  - Social media sites contain a treasure-trove of decision relevant information
  - Twitter is the main platform for opinion exchange about brands and products
- Advertisers can potentially influence the volume and sentiment of online WoM through their advertising strategies
- Estimated that 20% of all WOM references TV ads (Keller and Fay, 2009)
  - Backed by industry reports
    - Graham and Havlena (2007), Nielsen (2016), Turner (2016)

Growing Importance of Social TV

- Multi-screen activity by television viewers is on the rise,
  - 80% of U.S. television viewers simultaneously using another device while watching television (Nielsen 2014, IAB 2015).
- Nearly 40% of multiscreen viewers engage in social TV activity (IAB 2015).
- $\Longrightarrow$ instantaneous discussion of ads a growing phenomena

What this Paper is About

Quantify the Impact of TV Ads on Online WoM

- How:
  - Estimate short run effects of TV ads on tweets
  - 5 minute window after TV ad airs ...
  - ... ads as good as random to viewers ...
  - ... use high dimensional fixed effects to control for non-ad driven tweeting & desirability of ad times for advertisers
- Application:
  - Movie Industry
  - Twitter

Part of a Bigger Research Agenda

- Marketing:
  - Impact of online WoM / Twitter on demand for new products
    - Deer, Chintagunta and Crawford (2019)
  - Jointly modelling tweet - demand relationship
    - Potential cinema goers may or may not tweet before- and after seeing a movie
  - Strategic Advertising Decisions and online WoM
- Tweet Classification / Computational Language:
  - Beyond positive/negative/neutral
    1. Notion of “buzz” vs review (vs. Corporate Tweets)
    2. Topics in the online conversation
  - Quantifying “Movie Buzz”

Why Should We Care?

- Online WoM influences demand
  - Godes and Mayzlin (2004), Chevalier and Mayzlin (2006), Liu (2006), Chintagunta et al (2010), Babic-Rosario (2016), Seiler et al (2017)
- For Advertisers:
  - Characteristics of products that generate larger spikes
  - Adjust timing of ads to increase WoM
- For TV channel owners:
  - Incorporate WoM channel into pricing strategies

The US Movie Industry & Twitter

- Twitter is main online platform for movies (Twitter, 2014)
  - Sixth most discussed topic on Twitter (Hu et al, 2017)
  - $\approx 200,000$ tweets per day (Suslak, 2014)
- Tweets influence movie demand
  - Deer, Chintagunta and Crawford (2019), Gelper et al (2019), Hennig-Thurau et al (2015)
  - Supported by industry evidence (Nielsen, 2014/2015)

Related Literature

- Advertising Spending and Word of Mouth
  - Lovett et al (2019), Trusov et al (2009); Pauwels et al (2016), Gopinath et al (2014), Hewett et al (2016)
- TV ads and Social Media
  - Fossen and Schweidel (2017), Tirunillai and Tellis (2017), Fossen and Schweidel (2019)
- Immediate Effects of Ads on Online Behaviour
  - Lewis and Reiley (2013), Joo et al (2014), Liaukonyte et al (2015), Du et al (2019)

Data: Movie Advertising

- TV Ads from Nielsen Ad Intel
  - Focus on National TV Ads
    - $\approx$ 70% of Share and $\approx$ 95% Spending
  - We extract
    1. Time of an Ad
    2. Estimated Viewership
    3. Channel
    4. Ad Spot Characteristics
  - $\approx$ 1 million ad spots over all commercial networks

Focus on East Coast Viewership

Data: Movie Tweets

Individual tweets about each wide-release movie from Twitter's Historical Powertrack

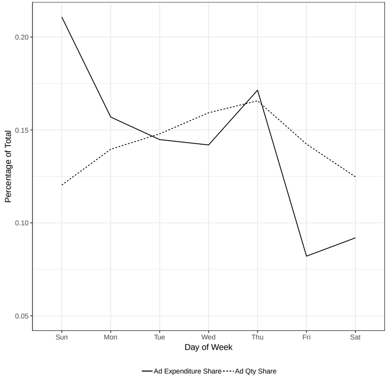
- Search for tweets about each movie using
  1. Movie name
  2. Relevant hashtags
  3. Movie franchise + Sequel indicators
- Baseline data: ± 6 months from release date
  - Restrict to 60 days pre-release to 40 days post-release
  - 60 million movie relevant tweets
    - approx 300K per movie
- Agggregate to volume per movie-minute
  - 222 movies
  - $\approx$ 13.1 million movie-minutes

Data: Movie Industry

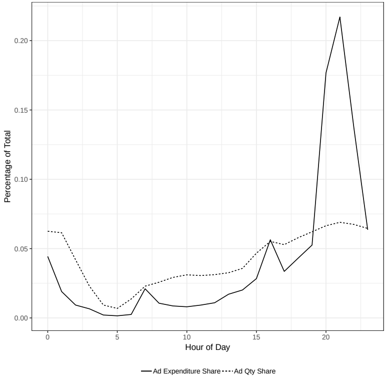
Dimensions of Heterogeneity ...

- Box Office Mojo
  - Movie Characteristics (Sequel / Genre)
- Hollywood Stock Exchange
  - Expected Box Office Success
    - ... measured through 'trading prices'

When Movies are Advertised

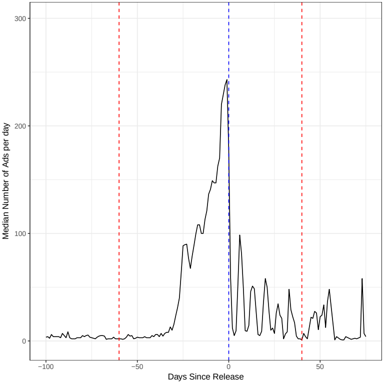


(a) Advertising per Weekday

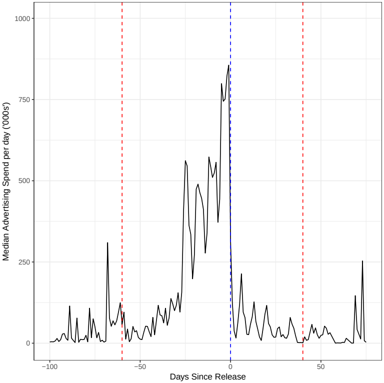


(b) Advertising per Hour of Day

Movie Ads Around Release Date

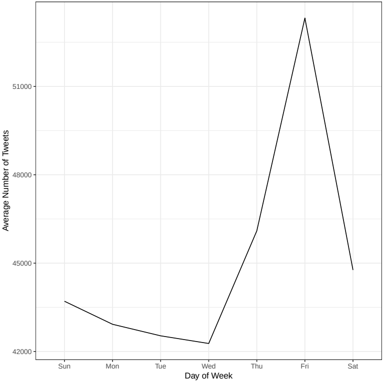


(a) Number of Ads per day

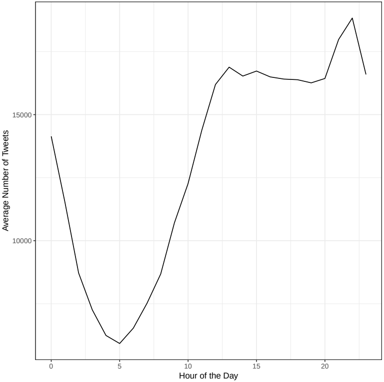


(b) Ad Spending per day

When Movies are Tweeted About



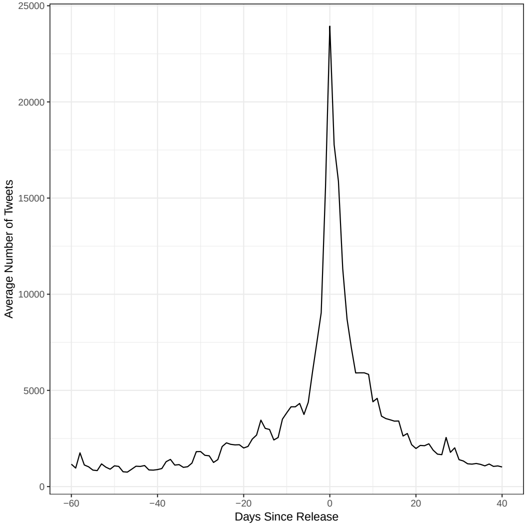
(a) Average Number of Tweets per Day



(b) Average Number of Tweets per Hour

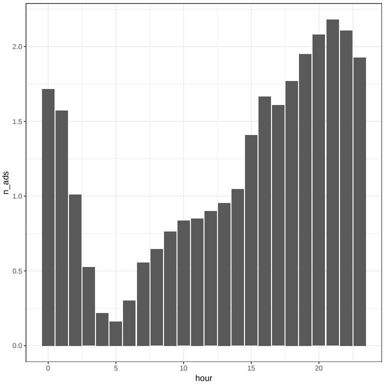
Movie Tweets Around Release Date

Figure 4: Average Movie Tweets Around Release Date

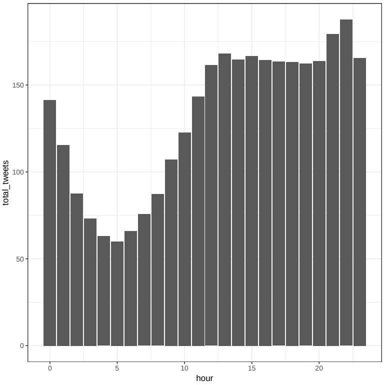


Suggestive Evidence

Figure 5: Hourly Variation averaged across movies



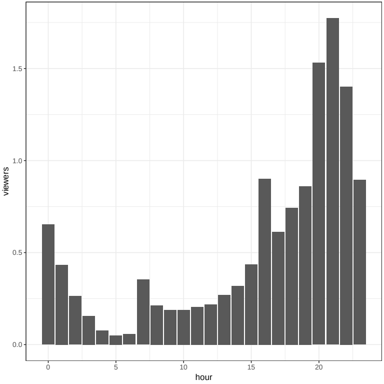
(a) Number of Ads per hour



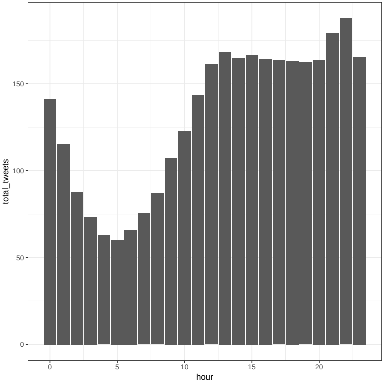
(b) Average Tweets Per hour

Suggestive Evidence

Figure 7: Hourly Variation averaged across movies



(a) Number of Viewers per hour



(b) Average Tweets Per hour

Regression Framework

$$\text{Volume}_{jdhm} = \sum_{\ell=0}^{\overline{T}} \rho_\ell X_{jdh(m-\ell)} + \theta_j \times \lambda_{(d-r_j)} + \tau_{dh} + u_{jdhm}$$

where

- j is a movie
- d is a date
- h is a time interval, i.e hour, half-hour, quarter-hour
- m is a minute

Regression Framework

$$\text{Volume}_{jdhm} = \sum_{\ell=0}^{\overline{T}} \rho_\ell X_{jdh(m-\ell)} + \theta_j \times \lambda_{(d-r_j)} + \tau_{dh} + u_{jdhm}$$

- $X_{jdh(m-\ell)}$
  - Either:
    1. Number of Ads aired $m - \ell$ minutes ago
    2. Number of Viewers of Ads $m - \ell$ minutes ago
- ρ_ℓ
  - Effect of $X_{jdh(m-\ell)}$ on Volume in minute m
    - Sum from Ad airing to $\overline{T}$ is causal effect of an ad
- We set $\overline{T} = 5 \rightarrow 5$ minute window after and ad airs

Regression Framework

$$\text{Volume}_{jdhm} = \sum_{\ell=0}^{\overline{T}} \rho_\ell X_{jdh(m-\ell)} + \theta_j \times \lambda_{(d-r_j)} + \tau_{dh} + u_{jdhm}$$

- Movie $\times$ days since release FE
  - 222 movies $\times$ 100 days $\rightarrow$ 22,200 Fixed Effects
  - Absorbs:
    1. Consumers: tendency to tweet about a movie on a given day
    2. Advertisers: attractiveness of advertising a given number of days pre-/post-release

Regression Framework

$$\text{Volume}_{jdhm} = \sum_{\ell=0}^{\overline{T}} \rho_\ell X_{jdh(m-\ell)} + \theta_j \times \lambda_{(d-r_j)} + \tau_{dh} + u_{jdhm}$$

- Time of day Fixed Effects
  - $\approx$ 17,500 unique day-hours
  - $\approx$ 70,000 unique day-quarter-hours
  - Absorbs:
    1. Consumers - tendency to tweet in a given time interval
    2. Advertisers - attractiveness of that time for advertisers

Regression Framework

$$\text{Volume}_{jdhm} = \sum_{\ell=0}^{\overline{T}} \rho_\ell X_{jdh(m-\ell)} + \theta_j \times \lambda_{(d-r_j)} + \tau_{dh} + u_{jdhm}$$

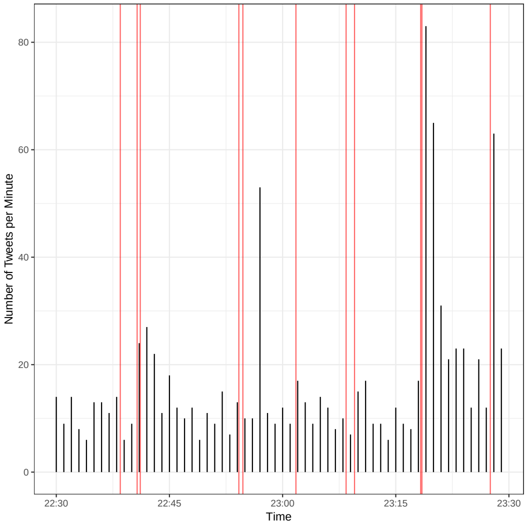
- Error term, $$
  - 2-way clustering
    - Each movie
    - Each date-hour
  - Allows correlated errors for each movie, and within an hour

Estimation

- Estimate by partialling out high dimensional fixed effects
  - Gaure (2013) and Guimaraes and Portugal (2010)
  - Between 40K and 90K fixed effects
- Identification
  - ‘quasi-experimental’
  - In US, advertisers choose exact time that ad airs ...
  - Advertising contracts require slots to be allocated on an equitable basis
    - Wilbur et al (2013), McGranaghan et al (2018)
  - Distributed Lag Model equiv. to panel event study ...
  - ... and handles multiple events
    - Schmidheiny & Siegloch (2019)

Identification: Graphical Intuition

Figure 9: Twitter Volume Spikes After Ads, Jurassic Park Lost World



Contextualizing Effects

- Tweets:
  - Median tweets per min: 2
- Advertising Spots
  - Median ads per min: 1
  - … conditional on any ad airing
- Advertising Viewers
  - Median viewers: 0.267 million
  - Mean viewers: 0.48 million

Results - Number of Ads

Table 1: Estimates of The Impact Of An Ad

	(1)	(2)	(3)	(4)
n_ads	0.67***	0.43***	0.43***	0.43***
	(0.24)	(0.10)	(0.10)	(0.10)
lag(n_ads, 1:5)1	1.28***	1.04***	1.04***	1.05***
	(0.28)	(0.16)	(0.16)	(0.16)
lag(n_ads, 1:5)2	0.99***	0.75***	0.76***	0.77***
	(0.27)	(0.15)	(0.15)	(0.15)
lag(n_ads, 1:5)3	0.79***	0.55***	0.55***	0.56***
	(0.25)	(0.12)	(0.12)	(0.13)
lag(n_ads, 1:5)4	0.72***	0.48***	0.48***	0.49***
	(0.25)	(0.11)	(0.11)	(0.11)
lag(n_ads, 1:5)5	0.64***	0.40***	0.40***	0.41***
	(0.24)	(0.11)	(0.11)	(0.11)
Time FE	Hour	Hour	Half Hour	Quarter Hour
Movie FE	Yes	No	No	No
Days Since Release	Yes	No	No	No
Movie $\times$ Days Since Release	No	Yes	Yes	Yes
N	13,131,818	13,131,818	13,131,818	13,131,818
Adjusted R^2	0.22	0.45	0.45	0.45

Results - Number of Viewers

Table 2: Estimates of The Impact Of An Ad

	(1)	(2)	(3)	(4)
viewers	0.52^{***}	0.43^{***}	0.44^{***}	0.44^{***}
	(0.13)	(0.08)	(0.08)	(0.08)
lag(viewers, 1:5)1	2.32^{***}	2.24^{***}	2.24^{***}	2.24^{***}
	(0.35)	(0.33)	(0.33)	(0.33)
lag(viewers, 1:5)2	1.52^{***}	1.44^{***}	1.44^{***}	1.45^{***}
	(0.26)	(0.23)	(0.23)	(0.23)
lag(viewers, 1:5)3	0.87^{***}	0.78^{***}	0.79^{***}	0.79^{***}
	(0.17)	(0.13)	(0.13)	(0.13)
lag(viewers, 1:5)4	0.61^{***}	0.53^{***}	0.53^{***}	0.53^{***}
	(0.15)	(0.09)	(0.10)	(0.09)
lag(viewers, 1:5)5	0.48^{***}	0.40^{***}	0.40^{***}	0.40^{***}
	(0.13)	(0.07)	(0.07)	(0.07)
Time FE	Hour	Hour	Half Hour	Quarter Hour
Movie FE	Yes	No	No	No
Days Since Release	Yes	No	No	No
Movie $\times$ Days Since Release	No	Yes	Yes	Yes
N	13,131,818	13,131,818	13,131,818	13,131,818
Adjusted R^2	0.22	0.45	0.45	0.45

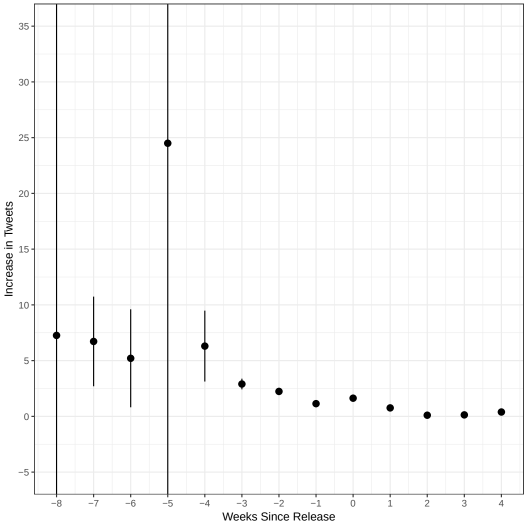
Heterogeneity?

How does the tweet responses differ across:

1. Ad Characteristics
   - Time to release, time of day, program type, network
2. Movie Characteristics
   - Sequels, expected performance, genre

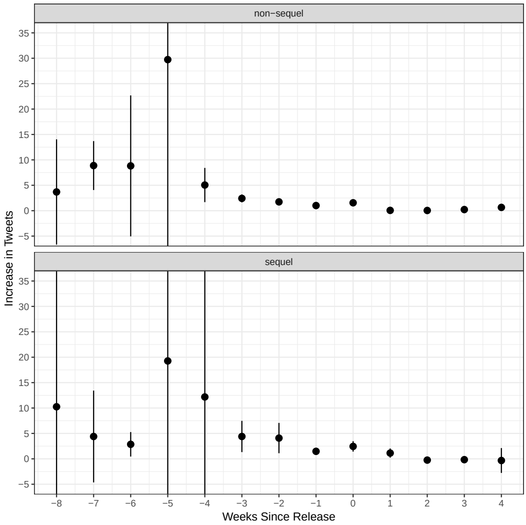
Heterogeneity - Weeks Before/Since Release

Figure 10: Tweet Response Around Release Date



Heterogeneity - Movie Sequels

Figure 11: Tweet Response Around Release Date



Main Takeaways (so far)

- RQ: Do TV ads lead to increases in online conversation
- What we find:
  - Yes ...
    - but the effects of individual ads are small
  - Average ad $\rightarrow$ extra 3.5 tweets
    - equiv. an extra 1.5 mins of ‘usual activity’
  - Heterogeneity
    - Effect concentrated pre-release, and further out

Where next?

1. Get a better handle of heterogeneity
2. Shifts in the Sentiment / Topics of conversation
3. Map Estimates into bigger units of advertising, effect on demand
    - Using elasticities from our demand paper
4. ...

Thanks!

Questions & comments welcome

lachlandeer.github.io

lachlan.deer@gmail.com

@lachlandeer