Advertising Measurement

Data Science for Marketing Decision Making
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Overview

1. Measuring advertising exposure
2. Does advertising work? — Split cable experiments
3. Estimating advertising effects using demand models
   - Dynamic advertising effects
   - Adstock model
   - Short-run and long-run advertising effects
4. Advertising and causality
   - Cross-sectional and time series confounds
   - Border estimation strategy
   - Example: Advertising effects in the pharmaceutical industry
5. Long-run ROI
6. Optimal advertising scheduling

U.S. leading national advertisers (2015)

Rank	Marketer	Total U.S. ad spending ($ mill.)
1	Procter & Gamble Co.	4,264.8
2	AT&T	3,865.5
3	General Motors Co.	3,495.3
4	Comcast Corp.	3,435.6
5	Verizon Communications	2,749.0
6	Ford Motor Co.	2,678.0
7	American Express Co.	2,348.6
8	Fiat Chrysler Automobiles	2,250.0
9	Amazon	2,197.5
10	Samsung Electronics Co.	2,122.5
11	Walmart Stores	2,090.3
12	JPMorgan Chase & Co.	2,063.0
13	Johnson & Johnson	2,008.6
14	L'Oreal	1,994.4
15	Pfizer	1,926.4
16	Toyota Motor Corp.	1,801.9
17	Walt Disney Co.	1,797.9
18	Time Warner	1,690.3
19	Berkshire Hathaway	1,683.0
20	Anheuser-Busch InBev	1,682.8
21	Capital One Financial Corp.	1,650.7
22	21st Century Fox	1,632.5
23	Deutsche Telekom (T-Mobile)	1,600.0
24	Macy's	1,587.0
25	Bank of America Corp.	1,572.9

Source: AdvertisingAge

Industry advertising/sales ratios (2016)

Industry Name	Ad/sales ratio
TRANSPORTATION SERVICES	27.9
PERFUME,COSMETIC,TOILET PREP	21.2
MOTION PIC, VIDEOTAPE PRODTN	20.5
MAILING,REPRO,COMML ART SVCS	18.3
MEDICINAL CHEMS,BOTANICL PDS	17.7
SOAP,DETERGENT,TOILET PREPS	14.0
LOAN BROKERS	13.3
DOLLS AND STUFFED TOYS	11.2
DISTILLED AND BLENDED LIQUOR	10.9
WOMENS,MISSES,JRS OUTERWEAR	10.8
SPECIAL CLEAN,POLISH PREPS	10.3
VIDEO TAPE RENTAL	10.3
RUBBER AND PLASTICS FOOTWEAR	9.7
EDUCATIONAL SERVICES	9.6
WATCHES, CLOCKS AND PARTS	8.8
HOUSEHOLD FURNITURE	8.4
WINE,BRANDY & BRANDY SPIRITS	8.3
OPHTHALMIC GOODS	7.6
PERSONAL SERVICES	7.5
DIVERSIFIED MULTI-MEDIA	7.2
SPORTING & ATHLETIC GDS, NEC	7.0

Source: AdvertisingAge

Does advertising (always) work?

- Central marketing question:
  - Does advertising (TV, newspaper/magazine, . . .) affect demand?
- Traditional advertising measurement (1970's -)
  - Small audiences
  - Recall, liking, stated purchase intent
- How are advertising messages targeted to customers?
- What answer do you expect if you ask an advertising agency if "advertising works"?

Measuring TV viewing behavior

- Nielsen
  - TV ad exposure measures since 1950's
- Nielsen TV families
  - Panel of U.S. households (more than 20,000)
    - Intended to be representative of U.S. population
- People Meter
  - Connected to TV set
  - Records what is watched on TV
  - Each household member has a personal viewing button

- Nielsen rating: Percent of households (TV homes) tuned in to a specific program
  - 3.8 rating for "Game of Thrones": 4.4 million households out of 115.6 million (live and same day DVR playback)

Commercial identification technology

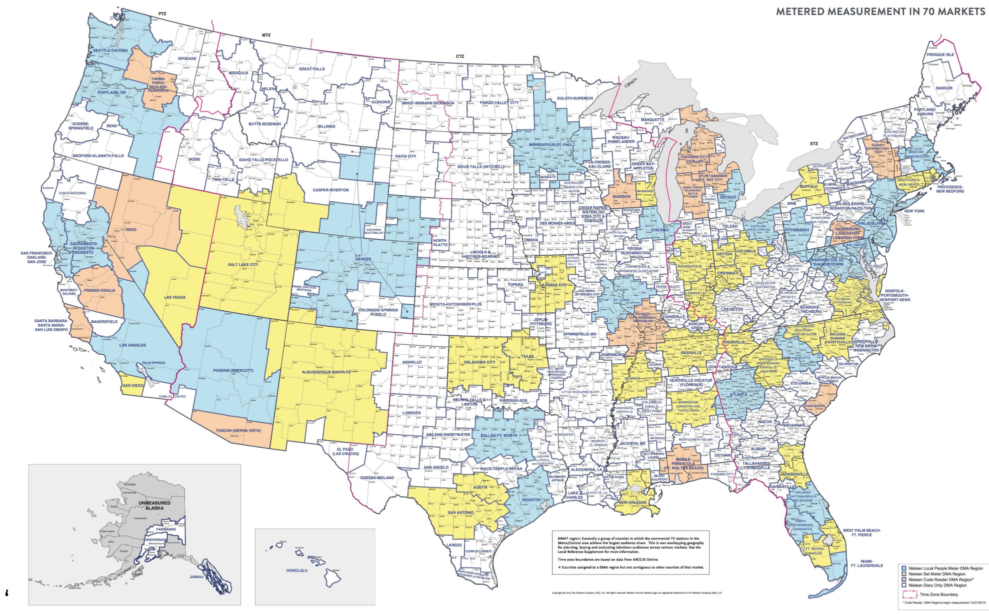
- Create a fingerprint of each commercial:
  - Pattern recognition software analyzes video and audio signal

- Software checks if fingerprint of ad that household watches matches a previously identified commercial

Measuring advertising exposure

- Use TV viewing behavior and commercial identification technology to measure the percent of households exposed to an ad
  - *Reach*: Percent of households exposed to an ad
  - *Frequency*: Number of ad exposures in time period (e.g. week)
- Key measure: *Gross rating points* (GRP's)
  - Defined as reach $\times$ frequency
    - 80% reach and 2 ad exposures on average $\longrightarrow$ 160 GRP's
- TRP's: Target rating points
  - GRP's for specific segments = demographic breaks
- GRP's can be measured in local markets
  - 210 *DMA's* (Designated Market Areas)
  - Regions with identical (or similar) TV and radio signal

Designated Market Areas



DMA map colors

- Blue: Local People Meter (LPM) region
  - Captures TV viewing at panelist-level, measures tuning and viewership by demographic
- Yellow: Set Meter region
  - Captures household tuning, but demographic data available only in "sweeps" months
- Brown: Code Reader region
  - New box that listens for encoded audio watermark (currently being introduced)
- White: Diary region
  - TV viewing reported by households in "sweeps" months or rating periods (February, May, July, November)
  - Need to extrapolate viewership to the other months

Measuring advertising exposure based on dollar advertising spending

- Easier to measure than impressions
  - Confound of variation in exposure and advertising cost over time or across markets

Media coverage (TV and radio)

1. NETWORK TV	
Number of Networks	8 (ABC, NBC, CBS, FOX since 1/93; UPN & WB 1/95-9/06; PAX/ION since 2/99; MNT 9/5/06-10/28/09; CW since 9/18/06, ME-TV & Bounce-TV 4/1/13)
Data Source	Nielsen
2. CABLE TV	
Number of Networks	97 networks
Data Source	Nielsen
3. SYNDICATION TV	
Barter Programs per month	200+ (since 1/93)
Data Source	Nielsen
4. SPANISH LANGUAGE NETWORK TV	
Number of Networks	6 Networks
Data Source	Nielsen
5. SPANISH LANGUAGE CABLE TV	
Number of Networks	8 Networks
Data Source	Nielsen
6. SPOT TV	
Number of Markets	All 210 DMAs (since 9/25/00) registered commercials; 27 Hispanic Markets) Top 75 DMAs (since 1/97); 50 Top DMAs (since 1/93)
Data Source	Nielsen
7. LOCAL REGIONAL/CABLE TV	
Number of Markets	51 DMAs
Data Source	Nielsen
8. NETWORK RADIO	
Number of Networks	3 Networks (Cumulus Media, Premier, Westwoodone)
Data Source	Radio Networks
9. LOCAL RADIO	
Number of Markets	43 DMAs
Data Source	MMI
Rating Source	Nielsen Audio

Key distinction: National vs. local advertising

Process: Raw data to GRP's

Occurrence data — at individual ad level

- Occurrence date, time, and length
- Brand code
- Ad code and creative ID
- Program code
- Media types: Network TV, Syndicated TV, Cable TV, ...

Impression data

- Estimates of households (or people) exposed to a media type (National TV, Syndicated TV, ...)
- Monthly or for specific time slots
- Demographic groups

Universe estimates

- Total number of household (or individuals) with access to specific media type
- Yearly

GRP for an individual ad for a brand j at a specific date d and time slot t in DMA m:

$$\text{GRP}_{jdtm} = \frac{\text{impressions}}{\text{universe estimate}}$$

Aggregate to day, week, month level by summing up over all individual occurrences

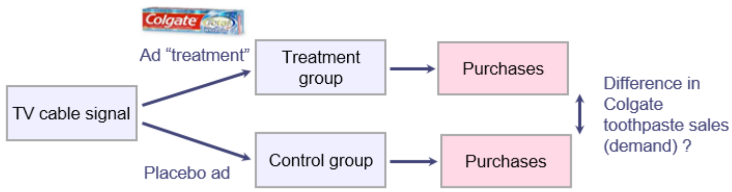
Measurement error?

Testing if advertising works: Split cable experiments

- Lodish et al. (1995) and Abraham and Lodish (1990) report results from split cable experiments
  - Reported results from tests conducted in 1980's
  - Most credible available evidence on the effect of TV advertising
  - Direct link between cause (advertising) and effect (purchases)
- Uses IRI's BehaviorScan household panel
  - Small, isolated markets (Eau Claire (WI), Pittsfield (MA), ...)
  - Data captures household purchases at (almost) all stores
  - Data captures the whole marketing environment — prices, promotions, coupons
  - Only one major newspaper in each market
  - TV viewing behavior of households recorded

Design of split cable experiments

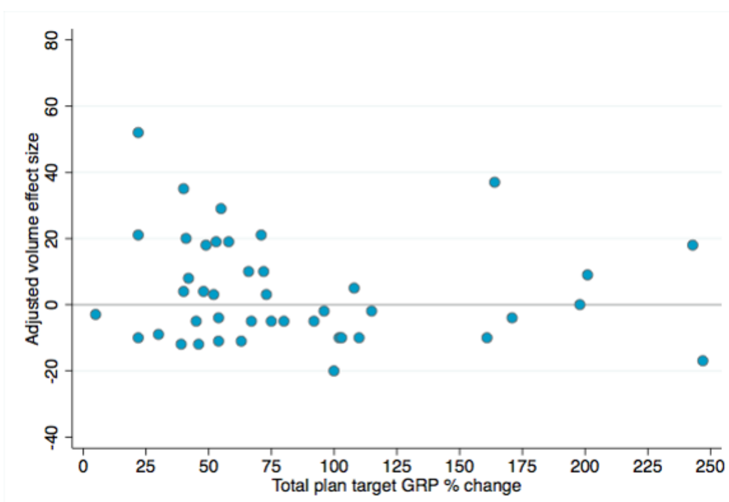
- Key:
  - Ability to intercept cable signal and substitute ads for specific households



- Randomized controlled trial
  - Random assignment of households to treatment and control groups
  - Allows to infer causal effect (average treatment effect) of advertising
- Focus on weight tests
  - Increase in number of ads for product in a specific period for treatment group

Visual evidence for ad effects

- Sales volume increase for percent target GRP increase
  - Established products



Split cable experiment results

- Increase in purchases/sales due to increase in advertising weight

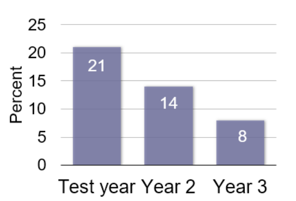
	Significant sales increase	Insignificant sales increase
New products	55%	45%
Established products	33%	67%

- Advertising elasticities

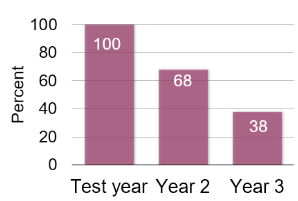
	No. of obs.	Avg. elasticity	St. dev.
All tests	141	0.13	0.4
New products	52	0.26	0.49
Established products	89	0.05	0.32

- How long does it take until advertising affects demand?
  - If advertising works: Effects show within six months
  - If no effects show within the first six months, then further advertising (i.e. increased advertising beyond six months) also has no impact

- Are there long-run effects of advertising?
  - Experimental design
    - In test year, households in treatment group received more ads
    - In second and third year, no differences in advertising weights between treatment and control groups
    - Results (based on 42 tests that showed any advertising effect)



Percent sales increase in treatment group



Persistence of sales effect

Estimating advertising effects using demand models

- Goal: Estimate advertising effects or elasticities using a demand model
  - Extend log-linear demand model
- Scope: What advertising effects on consumer behavior will the analysis capture?
  - Information effects
    - New products
  - Branding, image, or persuasion effects
    - Established products
  - Often there are not enough observations to estimate a demand model for a new product
- Advertising effects are harder to measure than price effects
  - Why? — Consider:
    - How does price influence purchase decisions?
    - How does ad exposure influence purchase decisions?

Allowing for dynamic advertising effects

- Allowing for dynamics: Current advertising may affect sales in future periods
  - Split cable experiments provide evidence for dynamic ad effects
  - Dynamics of lesser importance when measuring price elasticities
- Capturing dynamics in a statistical model
  - t is a time-index (day, week, year, ...)
  - Data: $x_t, x_{t+1}, \dots$
  - Fix a time period t. Then:
    - x_{t-l} is the lth lag — observation l periods in the past
    - x_{t+l} is the $l$the lead — observation l periods in the future

Adstock (goodwill) model

- *Adstock* or *goodwill*
  - Combined effect of current and past advertising on current consumer knowledge and attitudes toward the product
  - Idea: Advertising creates *brand capital* that increases demand for the product in future

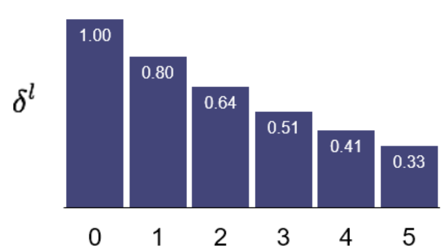
- Adstock (goodwill) model with geometrically distributed (declining) lags

$$
\begin{aligned}
g_t &= \log(a_t) + \delta \log(a_{t-1}) + \delta^2 \log(a_{t-2}) + \cdots + \delta^L \log(a_{t-L}) \\
&= \sum_{l=0}^{L} \delta^l \log(a_{t-l})
\end{aligned}
$$

  - δ is the *advertising carry-over* between periods
  - $1 - \delta$ is the *depreciation factor*

- Consumers remember advertising messages for at most L time periods

- Carry-over measures how consumers remember advertising messages
  - Example: $\delta = 0.8$
  - Consumers remember 80% of last period's advertising and forget 20%
  - Goodwill consists of current advertising, 80% of last period's advertising, 64% (80% of 80%) of advertising two periods ago, ...



Impact of advertising on demand

- Demand is affected by adstock/goodwill

$$\log(Q_t) = \alpha + \gamma g_t - \eta \log(P_t) + \beta \mathtt{promo}_t + \cdots + \epsilon_t$$

  - Current and past advertising influence demand
  - Competitor variables to be included

- Estimation
  - Fix number of lags L and carry-over parameter δ
  - Calculate adstock
  - Estimate the regression model above

Estimating the carry-over parameter

- Estimate model with different carry-over values, δ
  - Select final model based on a goodness-of-fit measure, in-sample or out-of-sample
    - RMSD — root-mean-square-deviation between predicted and observed volume
- Example:
  - Choose $\delta = 0.5, 0.6, \ldots, 0.9$
  - Estimate and choose model with smallest RMSD
- Choose L using a similar approach or (recommended) choose L large enough such that δ^L is small

- Alternative
  - Estimate all parameters jointly using maximum-likelihood (ML) or non-linear least squares (NLLS)
  - More difficult especially if we have a large number of fixed effects in the model

Model specifications

- Alternative parametric form

$$\log(Q_t) = \alpha + \gamma \log(g_t) + \dots,$$
$$g_t = \sum_{l=0}^{L} \delta^l a_{t-l}$$

- Infinite distributed lags are also used:

$$g_t = \sum_{l=0}^{\infty} \delta^l \log(a_{t-l})$$

  - Goodwill then follows the simple recursive formula

$$g_t = \delta g_{t-1} + \log(a_t)$$

Generally, we know little about the "true" functional form by which advertising affects demand. Flexible models such as the model below are hard to estimate in practice

$$g_t = \sum_{l=0}^{L} \omega_l \texttt{poly}(a_{t-l}; \theta)$$

- Largely unexplored area, both in marketing academia and the industry

Advertising effects: Short and long run

Advertising model:

$$\begin{aligned}\log(Q_t) &= \alpha + \gamma g_t + \cdots + \epsilon_t \\ &= \alpha + \gamma \sum_{l=0}^{L} \delta^l \log(a_{t-l}) + \cdots + \epsilon_t\end{aligned}$$

Advertising has short-run and long-run effects on demand through goodwill

Effect of an increase in advertising at time t on demand in period $t+k$

$$\Delta \log(Q_{t+k}) = \gamma \delta^k \Delta \log(a_t)$$

Effect on demand if we increase advertising permanently for at least L (number of lags) periods:

$$\begin{aligned}\Delta \log(Q) &= \gamma \sum_{l=0}^{L} \delta^l \Delta \log(a) \\ &= \gamma \cdot \frac{1-\delta^{L+1}}{1-\delta} \Delta \log(a) \\ &\approx \gamma \cdot \frac{1}{1-\delta} \Delta \log(a)\end{aligned}$$

- The approximation ($\approx$) is good if δ^{L+1} is small, which will be true if L is large or δ is small

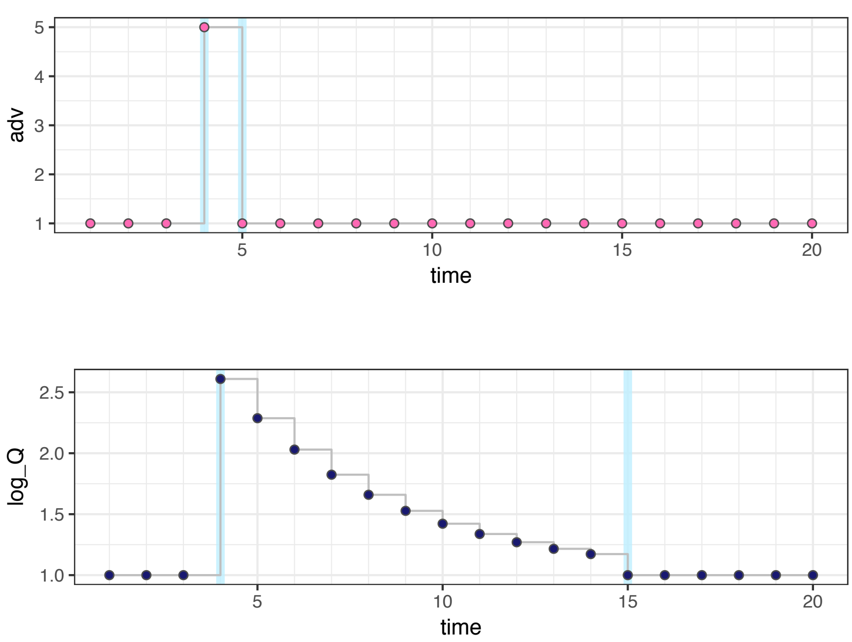
Example: $\delta = 0.8$

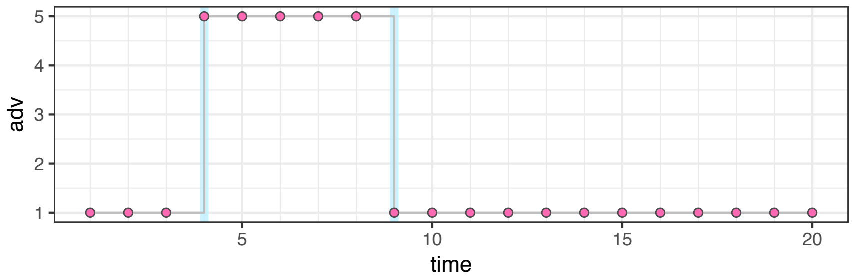
- Long-run elasticity: $1/(1-0.8) = 5$ times larger than the short run elasticity

advertisingResponse

Model predictions best explored using a simple function that predicts the response of sales to a change in the advertising policy

See `Advertising-Simulator.Rmd`

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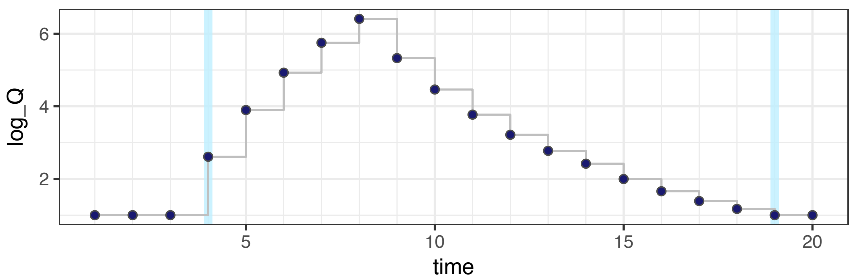
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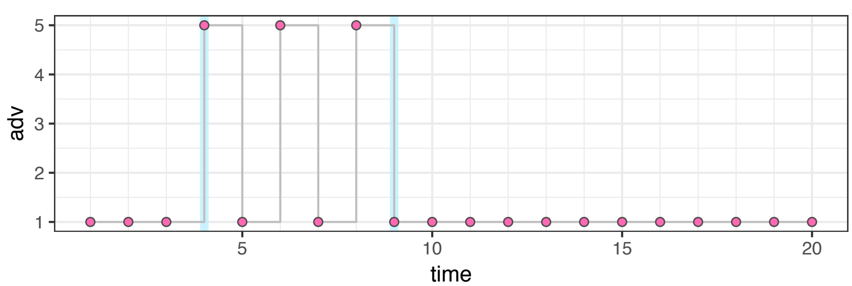
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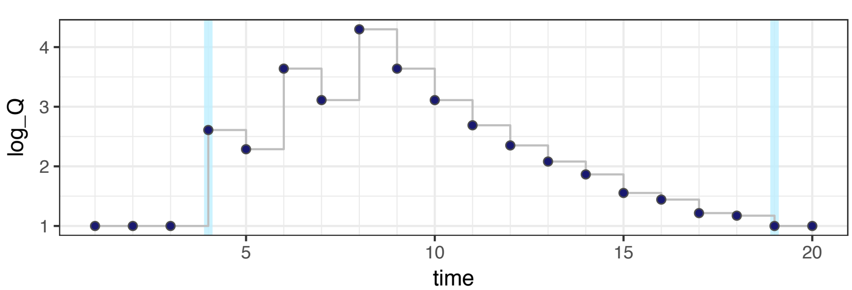
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Survey of advertising elasticity and carry-over estimates

Surveys of many published results in the marketing literature:

- Average elasticity: 0.221, average carry-over: 0.468
  - Implies that the average long-run advertising elasticity is over twice the size of the current period elasticity
  - At the weekly level: Advertising carry-over typically in the 0.5 - 0.9 range

Note: Advertising elasticities are typically much smaller than price elasticities

- Does not imply that advertising is generally unprofitable!
- Cannot directly compare price and advertising elasticities

Sources:

- Assmus et al. (1984): "How Advertising Affects Sales: A Meta-Analysis of Econometric Results," *Journal of Marketing Research*, 21(1), 65-74
- Leone (1995): "Generalizing What is Known About Temporal Aggregation and Advertising Carryover," *Marketing Science*, 14(3), G141-G150

Advertising and causality

Our goal is to estimate *causal* advertising effects to evaluate the *incremental* volume due to advertising

What are the potential confounds when using the advertising model?

$$\begin{aligned}\log(Q_t) &= \alpha + \gamma g_t + \cdots + \epsilon_t \\ &= \alpha + \gamma \sum_{l=0}^{L} \delta^l \log(a_{t-l}) + \cdots + \epsilon_t\end{aligned}$$

Think of confounds when using these two sources of variation in the data:

- Cross-sectional variation in advertising levels across markets (DMA's)
- Time-series variation in advertising levels over the course of the sample period

Cross-sectional confounds

Many advertisers set advertising budgets in part as a percentage of sales,

$$A_m \approx \rho P_m Q_m$$

- ρ is a target percentage (e.g. 5 percent)
- m is an index for a local DMA/media market

We then have reverse causality ("correlation does not imply ...")

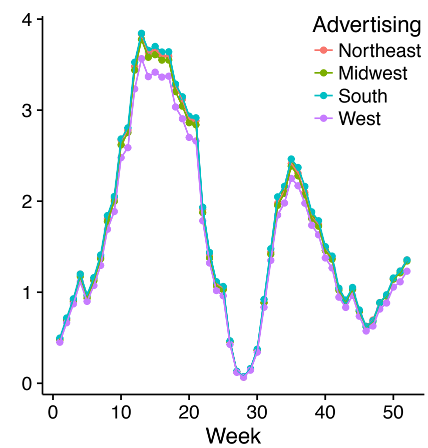
Solution:

- Within-estimator — market fixed effects

Time-series confounds

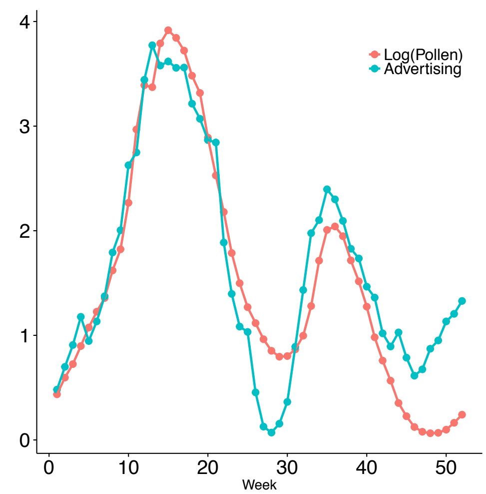
Example: Market for antihistamines

Regional average advertising levels by week:



High variance in advertising is good—but can we interpret the ad effect as causal?

Antihistamine advertising and pollen data (national average)



Confound: Time-series variation in organic demand vs. advertising

Thomas (2016): *Targeting Demand Forecasts with Advertising*

Source of the problem:

$$\log(Q_t) = \alpha + \gamma \log(a_t) + \tau_t + \cdots + \epsilon_t$$

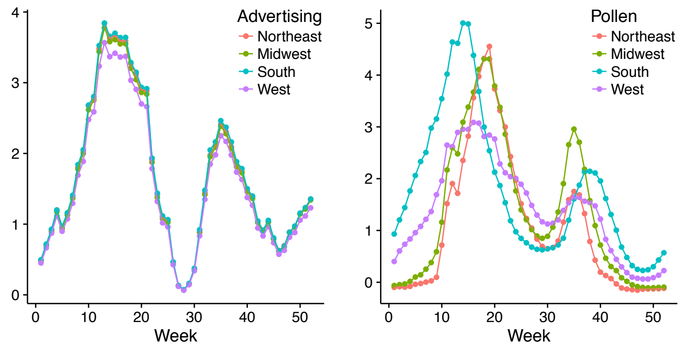
- Pollen level τ_t is an *organic* source of time-series variation in demand
- Pollen levels and advertising are correlated, $\mathbb{E}(\tau_t | a_t) \neq 0$

How can we solve this problem?

The empirical strategy in Thomas (2016) relies on *observable* variation in a *variable that is correlated with organic demand* — pollen levels

- Pollen levels, τ_t, can be measured

Strategy requires independent variation in pollen levels versus advertising across markets m: a_{mt} and τ_{mt} must not be perfectly correlated



Satisfied because advertising planned in advance based on national pollen/demand forecasts

Estimation results:

	OLS No D_{it}	OLS Pollen	IV Pollen	OLS GTrend	IV GTrend
Ad. Elast.	.38	.132	.141	.194	.263
	(.030)	(.018)	(.30)	(.016)	(.019)
Price	-.404	-.544	-.545	-.488	-.503
	(.025)	(.022)	(.023)	(.017)	(.016)
Pollen	–	.287	.274	1.17	1.01
	–	(.017)	(.002)	(.074)	(.078)
Year FE	X	X	X	X	X
Store FE	X	X	X	X	X
N Obs.	1,380,002	1,380,002	1,379,761	1,380,002	1,379,761
N Clust. (DMAs)	87	87	87	87	87
N Stores	30,931	30,931	30,931	28,959	30,931

Advertising effects are overestimated if the correlation between advertising and organic demand is ignored

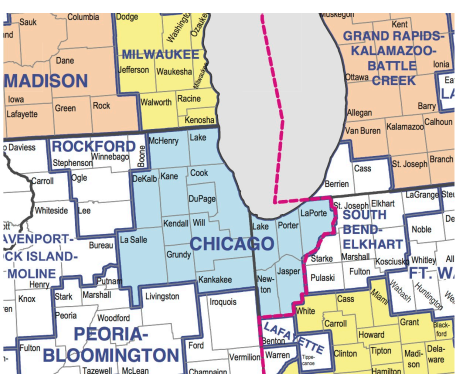
DMA border estimation strategy

In many industries it may be hard to control for organic variation in demand that is correlated with within-market changes in advertising

- In particular if advertiser has access to market research that yields demand information that later cannot be replicated using available data sources

Solution proposed in work by Shapiro (2016): Exploit the discontinuity in advertising at the common border between two neighboring DMA's

Central idea: Cross-border differences in advertising exposure



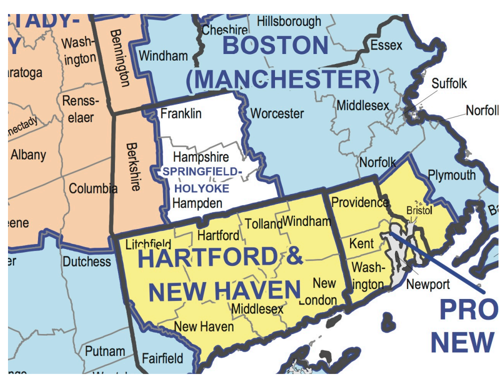


Illustration of central idea

Let m and n be two markets, for example counties, that are in separate DMA's. m and n share a common DMA border.

(i) Demand levels may be different across market m and n
(ii) Advertising levels may be different across market m and n
(iii) Demand or advertising may have a trend that is common to m and n

In a regression model (i is an index for either market m or n):

$$\log(Q_{it}) = \alpha_i + \gamma \log(a_{it}) + \tau_t + \epsilon_{it}$$

- α_i accommodates different demand and advertising levels (i) and (ii)
- τ_t is a time fixed effect that is *common* to market m and n (iii)

The common time fixed effect may be correlated with the advertising levels in markets m and n. Nonetheless we can consistently estimate the advertising effects. This is easily seen when we take the difference between the regression equations across the two markets:

$$\log(Q_{mt}) - \log(Q_{nt}) = (\alpha_m - \alpha_n) + \gamma (\log(a_{mt}) - \log(a_{nt})) + \tilde{\epsilon}_t$$

- Common time fixed effect drops out!

For the strategy to work we need:

1. Variation in $\log(a_{mt}) - \log(a_{nt})$ over time
2. $\log(a_{mt}) - \log(a_{nt})$ and the error term $\tilde{\epsilon}_t$ are uncorrelated

1. can be checked from the data

2. means that there are no differential trends in organic demand in market m versus n that are correlated with *differences* in advertising in m versus n. This is plausible because we use two relatively small *adjacent* markets.

Border strategy

Key advantage: The strategy is very conservative and relies on plausible assumptions

Possible disadvantages:

1. Due to the inclusion of the local time trends we are left with little variation in the data to estimate the model parameters
   - Lack of statistical power and high standard errors
   - Possibly exacerbates measurement error in advertising
2. Advertising effects in border counties (markets) may not be entirely representative of the overall advertising effects

Because of 1. we may want to use time fixed effects for somewhat longer time periods than the data

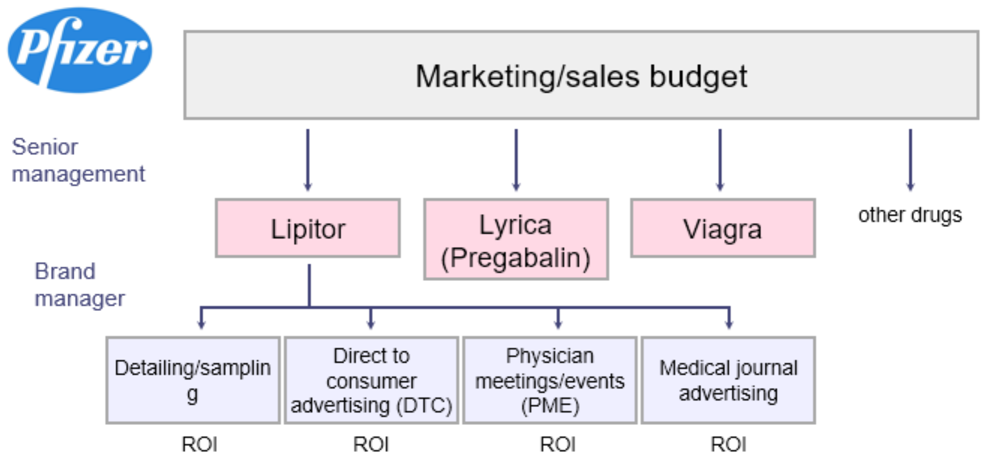
- For example, use month or quarter fixed effects with weekly data

Long-run ROI

$$\text{ROI} = \frac{\Delta(\text{PDV of profits}) - I}{I}$$
$$= \frac{\sum_{t=0}^{T} \left(\frac{1}{1+r}\right)^t (P-c)\Delta Q_t - I}{I}$$

- T is the planning horizon, r is the firm's discount rate
- We sometimes do not discount when looking at short time horizons (say 1-3 months)
- Calculation of long-run ROI
  - Consider a *current period investment* (e.g. additional advertising today)
  - Calculate increase in sales volume now and in future from the current period investment
    $$\Delta Q_0, \Delta Q_1, \ldots, \Delta Q_T$$
  - Use formula above

Application: Marketing mix modeling and funds allocation in the pharmaceutical industry

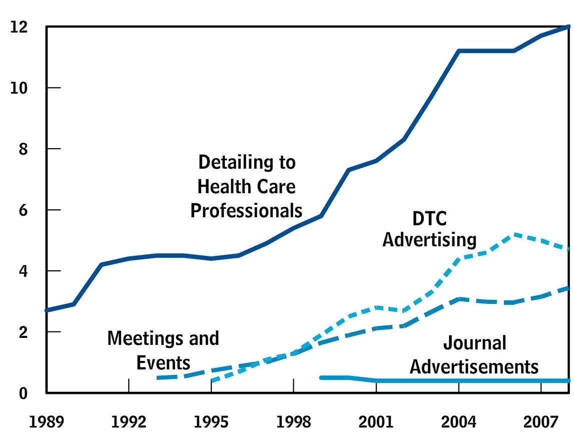


Industry background

Pharmaceutical marketing is a politically sensitive topic

- Detailing
- DTC only legal in the U.S., Brazil, and New Zealand
- DTC growth in U.S. driven by relaxation of regulation by the FDA in 1997

Spending in billions of dollars:



ARPP study

- *Analysis of ROI for Pharmaceutical Promotion* (2001/2002)
- Commissioned by the Association of Medical Publications
  - Conducted by two marketing professors
- Goal:
  - Provide insights on the effectiveness (long-run ROI) of different types of pharmaceutical promotions
    - Based on long-run advertising effects
- Results revealed serious mis-allocation of marketing budget across promotion types
  - DTC frequently ineffective during 1994-2000, negative ROI's for many drug classes

Shapiro's (2016) border strategy

- Focus on advertising effects in the antidepressants industry ($9 billion industry, 16 million long-term patients)
- Data
  - Prescription data from IMS Health
  - Detailing data: AlphaImpactRx and IMS Health
- Results reveal why DTC dollars may be easily misallocated in the pharmaceutical industry

Small own-advertising elasticity, cross-advertising elasticity only somewhat smaller ⇒ positive category spillovers

Table 2: The Effect of Own and Rival Advertisements on Sales

VARIABLES	(1) $log(Q)$
lagged $log(Q)$	0.334***
	(0.00746)
DTC	0.0240***
	(0.00621)
DTC^2	-0.00216*
	(0.00113)
DTC_{rival}	0.0164***
	(0.00266)
DTC^2_{rival}	-0.000938***
	(0.000252)
$DTCxDTC_{rival}$	-0.00134**
	(0.000631)
Product-Border-Time	yes
Product-Border-DMA	yes
Observations	316,428
R-squared	0.955

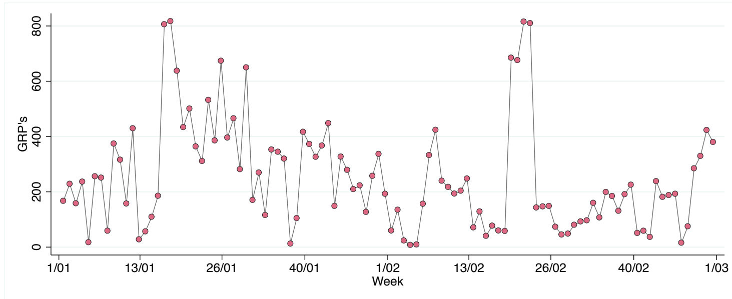
*** p<0.01, ** p<0.05, * p<0.1

Product-DMA clustered standard errors in parentheses

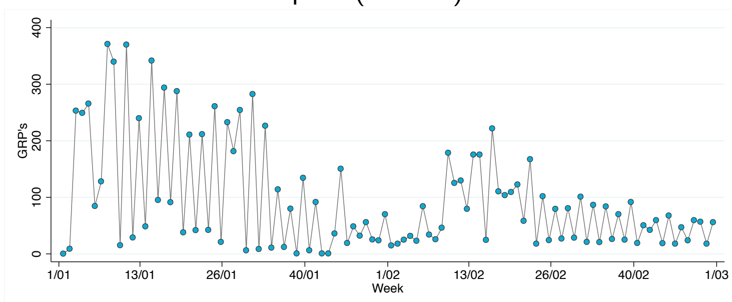
Advertising scheduling

- Advertising planning decisions
  - Size of advertising budget
  - How to spend the budget over the planning horizon
- Scheduling:
  - Spend evenly?
  - Concentrate spending in certain periods (week, months, etc.)?
- Practice observed in many industries and for many brands:
  - Advertising pulsing
  - See examples on next slide

Coca Cola Classic (Atlanta)



Sprite (Atlanta)

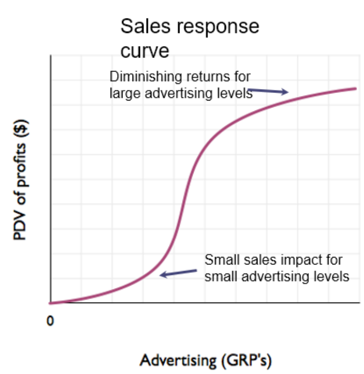


Why not spend the advertising budget evenly?

Some facts on consumer behavior

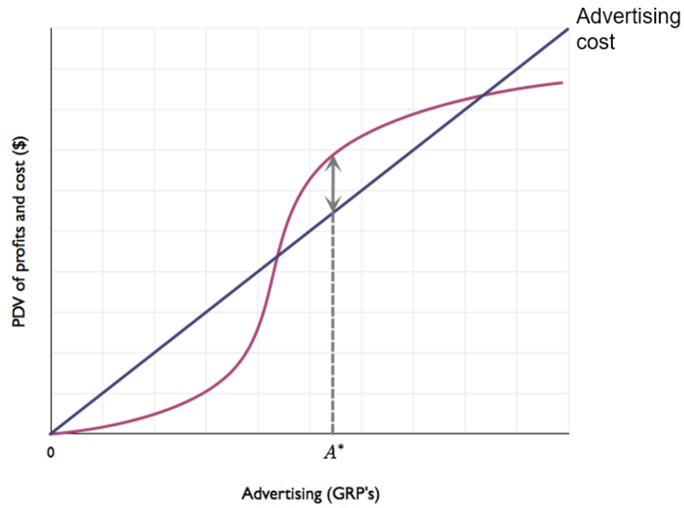
- Research in psychology: People often need more than one stimulus to act
  - Lab tests
- Once people have been exposed to an ad multiple times, additional exposures have little or no additional impact on purchase behavior

- Implications:
  - May need a minimum number of exposures before advertising increases sales
  - At high levels of advertising additional exposures have a small and diminishing sales impact
  - $\Rightarrow$ S-shaped sales response curve (present value of profits due to advertising)

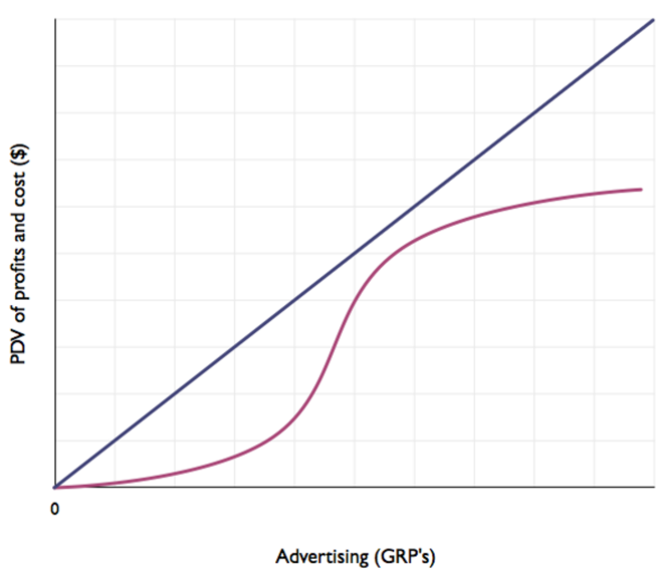


Optimal advertising level

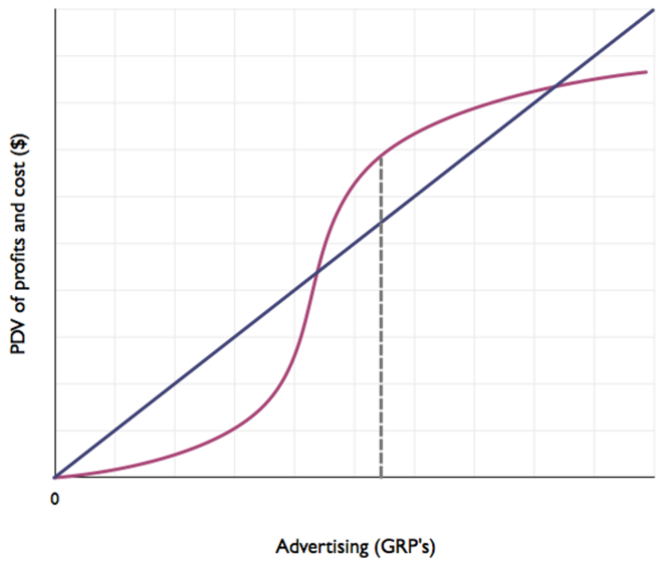
- Maximize difference between PDV of profits and total cost of advertising



- Next period the return to advertising is lower:
  - Advertising has long-run effects
  - $\rightarrow$ some of the additional adstock from the previous period remains



- No advertising in the previous period:
  - Adstock depreciates
  - $\rightarrow$ return to advertising increases



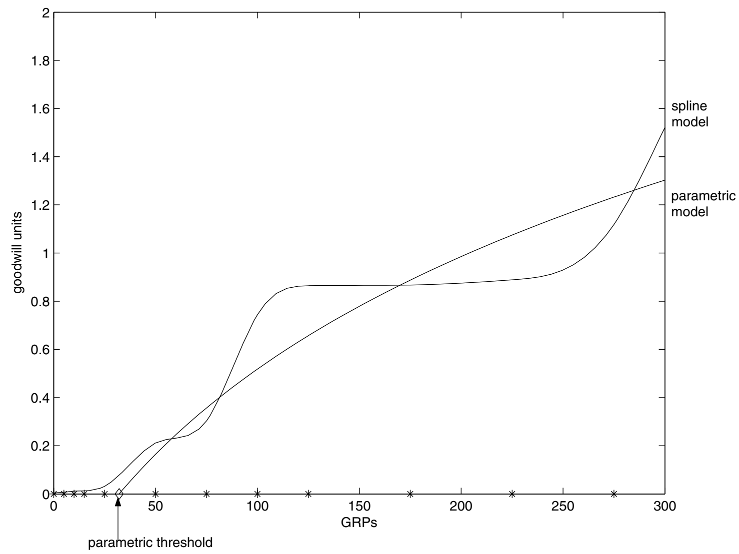
Optimality of pulsing

- Main intuition:
  - Because small advertising levels have a small impact on sales only large advertising levels are profitable
  - Because of long-run advertising effects advertising today decreases the return to advertising during the next periods

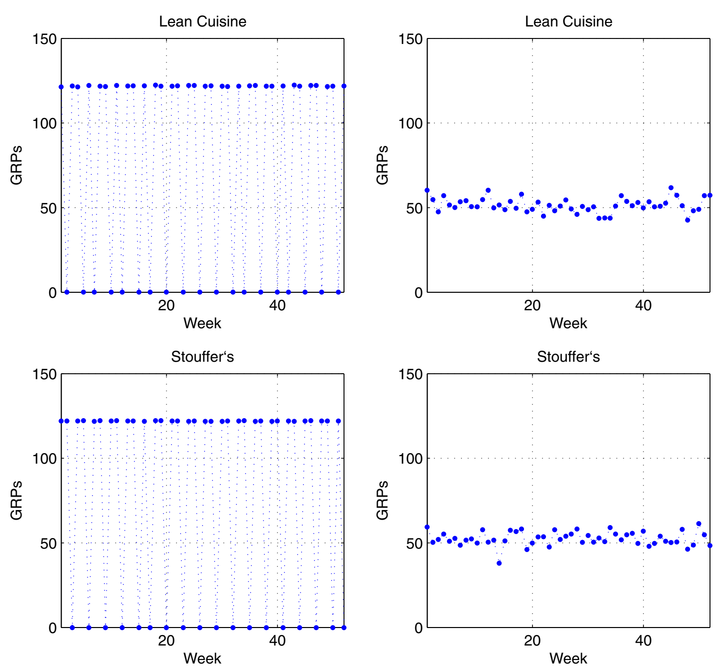
  $\Rightarrow$ optimal to concentrate advertising in a small number of periods

  Background: Dubé, Hitsch, and Manchanda (2005): "An Empirical Model of Advertising Dynamics," *Quantitative Marketing and Economics*, 3, 107-144
  - Estimation allowing for flexible response of goodwill to advertising
  - Prediction of optimal advertising based on optimal dynamic programming

Estimated goodwill production function



Predicted, optimal advertising levels



Left column uses S-shape, right column uses standard response curve

Summary

1. Measuring advertising exposure
2. Split cable experiments
   - Cleanest test to assess if advertising has a causal sales impact
   - Advertising need not always work
   - Evidence for long-run sales impact of advertising
3. Allowing for dynamic advertising effects
   - Adstock model
   - Allows to predict short-run and long-run advertising elasticities
4. Advertising and causality
   - Beware of cross-sectional and time series confounds
   - Border estimation strategy
5. Use dynamic advertising models to calculate long-run ROI
6. Advertising scheduling
   - Uneven spending (pulsing) can be optimal