How to improve the timing of advertising: An empirical study

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Motivation

- Firms spend large amounts on advertising while relying largely on "industry practice" and "experience" for deciding on how to exactly spend the money.
- This paper:
  - relate online sales/site visits to TV and radio advertisements
  - do this using high frequency data (at the hourly level)
  - in a context that is much cleaner than usual: online sales of lottery tickets
  - use the data to estimate a model of ticket sales that predicts total sales per month as a function of the advertising schedule and can thus be used to improve the timing of TV advertisements.

Related results

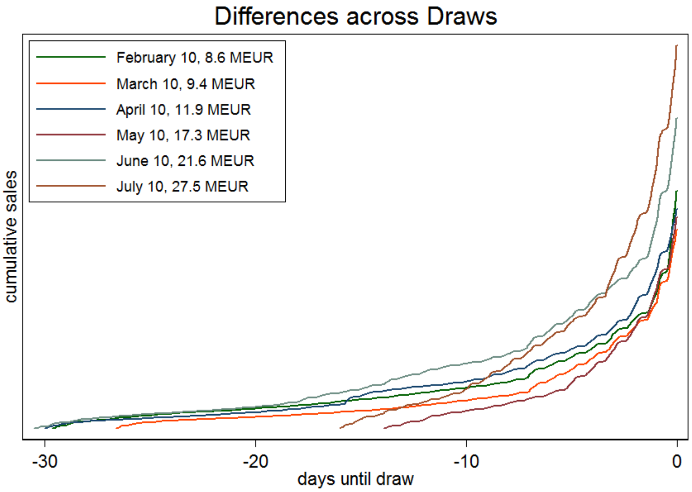
- Effectiveness of TV advertising:
  - Lodisch *et al.* (1995a,b): TV advertising works, but not always; Hu *et al.* (2007): effects for packaged goods significant and stronger after 1995
  - Ackerberg (2001, 2003): distinguishes between informative and image advertising, finds mainly support of former.
- TV advertising and online sales:
  - Joo *et al.* (2013): TV advertising and online search
  - Lewis and Reiley (2013): effect of Superbowl advertising on online search behavior
  - Stephens-Davidowitz *et al.* (2015): effects of Superbowl advertising on movie ticket sales.
- From a modeling perspective:
  - Dubé *et al.* (2005): model of sales response to advertising in a discrete choice framework.
  - adoption models: Melnikov (2013) for durable products, De Groote and Verboven (2015) for solar panels.

The market for lottery tickets in the Netherlands

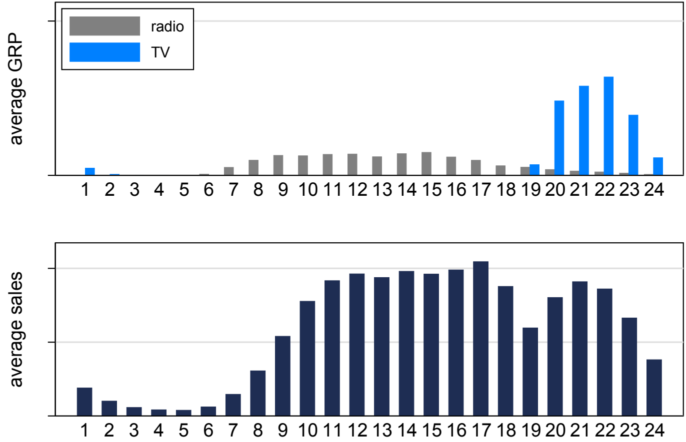
- Staatsloterij: biggest lottery in NL, turnover of 890 MEUR in 2009. Run by the government, goes back to 1726, merger of smaller lotteries.
- Numbers are drawn and the size of the prize depends on how many numbers match with the ticket number. There is a jackpot whose size varies over time.
- 1/5 Staatslot costs 3 EUR.
- Regular draws on the 10th of the month. Additional draws on King's day, on 1 July, 1 October, and on 31 December (biggest jackpot). Draws take place at 6pm.
- Only other big lottery, Postcodeloterij, works differently and its purpose is to donate money to charity.

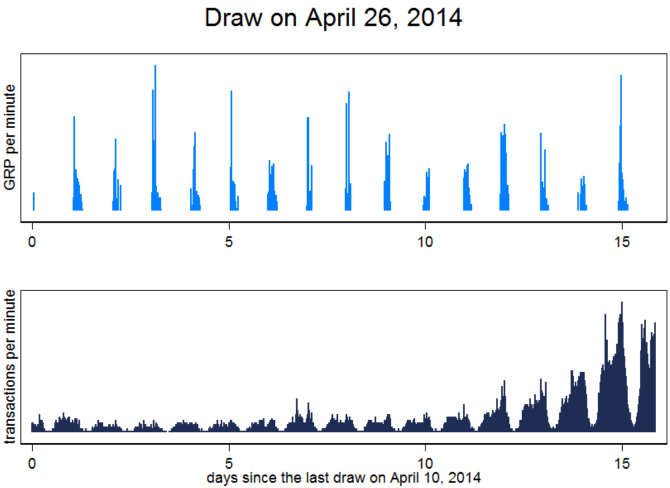
Data

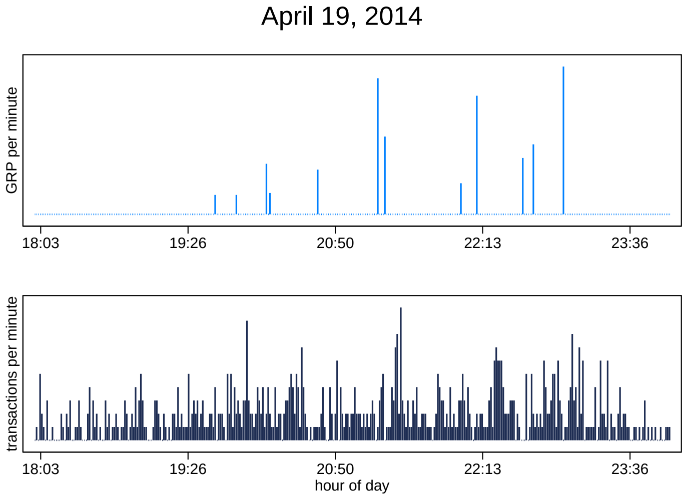
- Online sales and gross rating points (GRP) for TV and radio advertising at the minute level.
- 1 complete year of data, 16 draws.


Differences across Draws
February 10, 8.6 MEUR
March 10, 9.4 MEUR
April 10, 11.9 MEUR
May 10, 17.3 MEUR
June 10, 21.6 MEUR
July 10, 27.5 MEUR
cumulative sales
-30
-20
-10
0
days until draw

Pattern During the Day



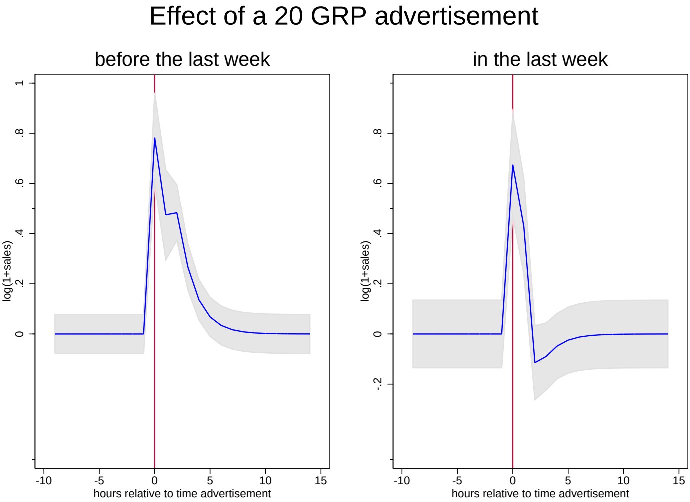

Draw on April 26, 2014
GRP per minute
0
5
10
15
transactions per minute
0
5
10
15
days since the last draw on April 10, 2014

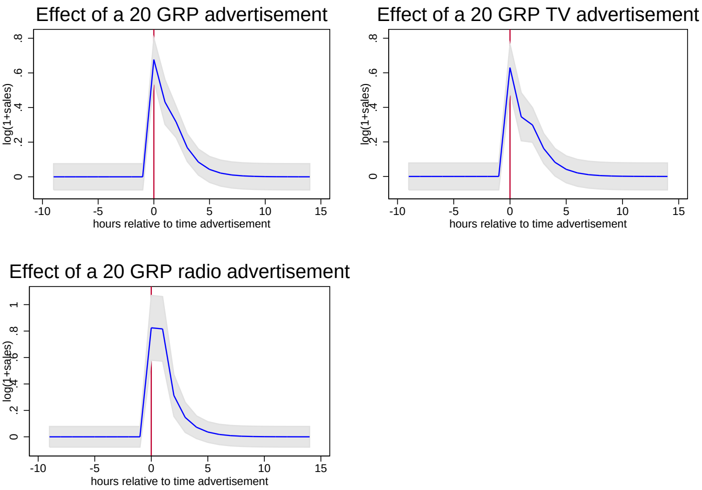


April 19, 2014
GRP per minute
18:03
19:26
20:50
22:13
23:36
transactions per minute
18:03
19:26
20:50
22:13
23:36
hour of day

Reduced-form evidence on the effect of advertising

- Collapse data to the hourly level.
- Construct set of advertising goodwill stocks with different rates of depreciation.
- Regress log of 1 plus online sales on hour dummies, the numer of days left until draw, and all goodwill stocks.
- Underlying idea: form of model averaging.
- NB: This is not used for estimating the structural model.
- Graphs show that impact of advertisement is roughly **proportional** to baseline number of sales. First evidence that late advertisements are more effective, because baseline sales are higher.
- Also evidence in favor of one 20 GRP of radio advertising similarly effective as 20 GRP of TV advertising.


Effect of a 20 GRP advertisement
before the last week
in the last week
log(1+sales)
0
.2
.4
.6
.8
1
-.2
-10
-5
5
10
15
hours relative to time advertisement



Effect of a 20 GRP advertisement
Effect of a 20 GRP TV advertisement
Effect of a 20 GRP radio advertisement
log(1+sales)
hours relative to time advertisement
0
.2
.4
.6
.8
1
-10
-5
0
5
10
15

Motivation for estimating a structural model

- The goal of an advertising strategy can be split up in two sub-goals
  - maximize the number of sold tickets for a given number of total GRP in a month
  - in light of this allocate more or less GRP.
- For now we focus on the first sub-goal.
- Data are informative about the immediate impact of advertisements, model helps us to also understand the cannibalization effect:
  - if, due to a lot of advertising pressure, many individuals buy early, they are out of the market and will not buy late. Moreover, it may be more costly to reach them early, since they plan to buy later (which they may never do)
  - at the same time, only advertising later could be a suboptimal strategy because then one does not get multiple shots at reaching some people.

Model: Overview

- Adoption model in discrete, finite time $t = 1, 2, \ldots, T$.
- At any point in time, consumer decides whether or not to buy a lottery ticket. Can buy at most one ticket.
- Buying a ticket yields flow utiltiy $u_{it} = -p + \delta^{T-t} a + \Gamma(g_{it}^a) + \sigma\varepsilon_{i1t}$, where p is the price of the ticket, δ is the hourly discount factor, a is the value to holding a ticket at the time of the draw, g_{it}^a is an advertising goodwill stock (see below), and ε_{it} is a type 1 extreme value distributed taste shock.
- Not buying a ticket is associated with continuation value $\delta\mathbb{E}[V(g_{it+1}^a)|g_{it}^a] + \varepsilon_{i0t}$, where again ε_{i0t} is a type 1 extreme value distributed taste shock.
- Users take into account that the probability to see an advertisement, which serves as a reminder, changes over time. Form expectations consistent with the actual data.

Model: The effect of advertising

- Flow utility of buying a ticket depends on advertising goodwill stock g_{it}^a.
- Following Dubé *et al.* (2005), we specify

$$\begin{aligned} \Gamma(g_{it}^a) &= \gamma log(1 + g_{it}^a) \\ g_{it}^a &= \begin{cases} g_{it} & \text{if } i \text{ did not see advertisement} \\ g_{it} + log(2) & \text{if } i \text{ saw advertisement} \end{cases} \\ g_{it+1} &= \lambda g_{it}^a. \end{aligned}$$

- (Aside: we use log(2) for now because in Dubé *et al.* (2005) the specification is $\log(1 + A_t)$, where A_t is the number of advertisements; they do not allow for the fact that some individuals are reached multiple times and others are not reached; we instead model this but then assume that advertisements have a maximal impact when a consumer is reached at lest once in a given hour; reaching consumers multiple times in a row increases the advertising goodwill stock.)

Solving the model

- One time unit is equal to one hour. Compromise between computational burden and how realistic the model is.
- Numerically solve dynamic decision problem on a grid.
- State variables: time, whether or not a consumer has bought, g^a_{it}.
- Decision depends on the expectation of the decision maker on whether he will see an advertisement in the future. Use GRP data to estimate this probability using specification

$$grp_t = x_t \beta + \varepsilon_t,$$

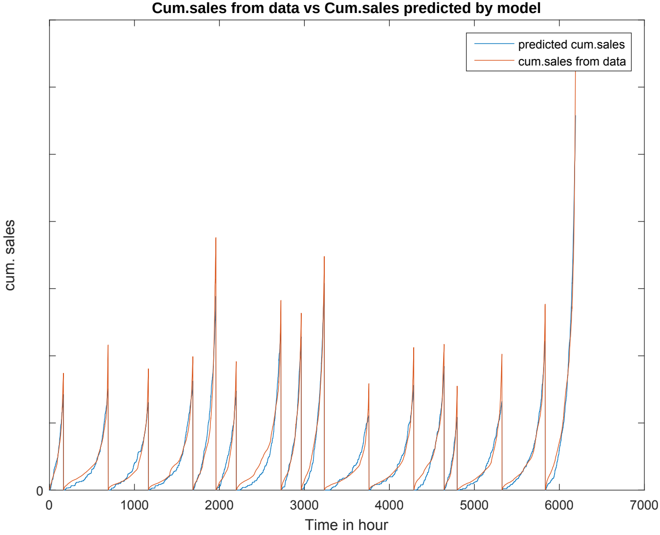
where x_t has constant term, full set of hour, day, and month dummies.
- Collapse time during the night (count time between Midnight and 8am as 1 hour).

Estimation

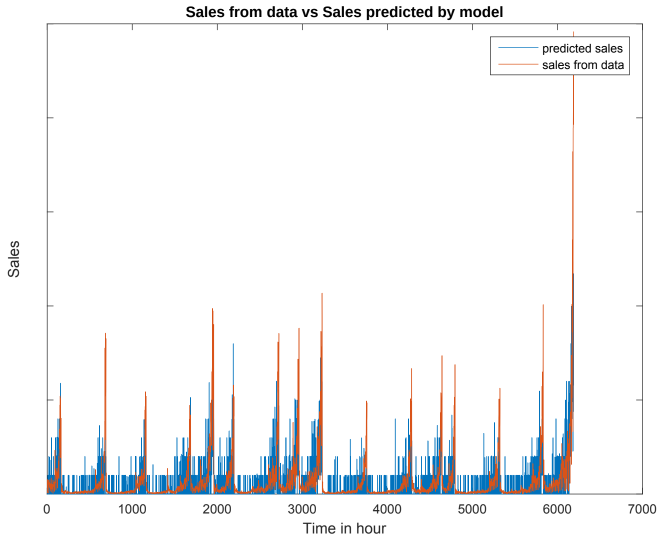
- Assume market size of 250,000.
- 1000 simulated consumers, with smoothing so that the function is smooth in the parameters.
- Simulated method of moments estimation.
- Moments: cumulative sales and sales at a given point in time, with equal weight.
- Our estimation procedure allows for "waste": some consumers are reached multiple times by advertisements, possibly even in spite of having already bought, while others are not reached repeatedly. Achieved through simulation with smoothing. This makes the estimation problem more complex.
- One function evaluation takes less than 1 minute.

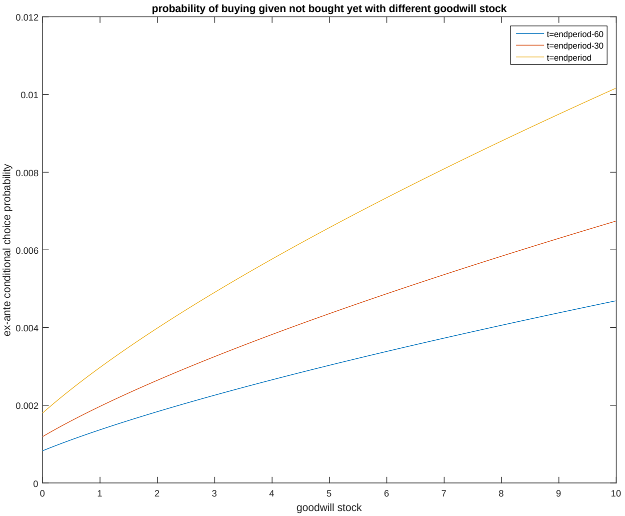
Parameter estimates

parameter	estimate
depreciation rate goodwill stock (λ)	0.269
effect of goodwill stock on flow utitliy (γ)	0.199
hourly discount factor (δ)	0.998
standard deviation taste shock (σ)	0.281
value to having a ticket on the day of the draw	
10 January, 2014	1.315
10 February, 2014	1.200
10 March, 2014	1.257
10 April, 2014	1.265
26 April, 2014 (King's Day)	1.596
10 May, 2014	1.270
10 June, 2014	1.422
24 June, 2014 (Oranjetrekking)	1.432
10 July, 2014	1.524
10 August, 2014	1.087
10 September, 2014	1.231
1 October, 2014	1.365
10 October, 2014	1.244
10 November, 2014	1.286
10 December, 2014	1.382
31 December, 2014 (Oudejaarstrekking)	1.860



Cum.sales from data vs Cum.sales predicted by model
predicted cum.sales
cum.sales from data
cum. sales
0
0
1000
2000
3000
4000
5000
6000
7000
Time in hour


Sales from data vs Sales predicted by model
predicted sales
sales from data
Sales
0
1000
2000
3000
4000
5000
6000
7000
Time in hour



Notes: Figure shows probabilty of buying a ticket as a function of the advertising goodwill stock.

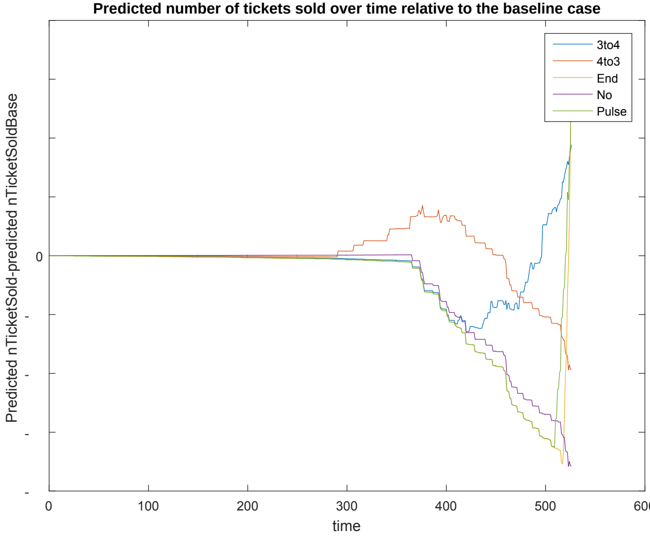
Counterfactuals

- Use the model to evaluate different advertising strategies for February 2014.
- Do this for two cases (to see whether expectations matter):
    - expectations on the probability to see an advertisement in the future consistent with the actual data
    - expectations adapt to the counterfactual strategy.
- Hold total number of GRP fixed and focus on the total number of tickets sold.

Counterfactuals

	expectations consistent with	
situation	data	counterfactual
data (reference point)	100%	100%
no advertising at all	97%	97%
all advertising in the last hours before the draw	103%	103%
pulsing strategy in the last days before draw	103%	103%
shift advertising from third week before draw to last week	102%	101%
shift advertising from fourth week before draw to third week	99%	99%

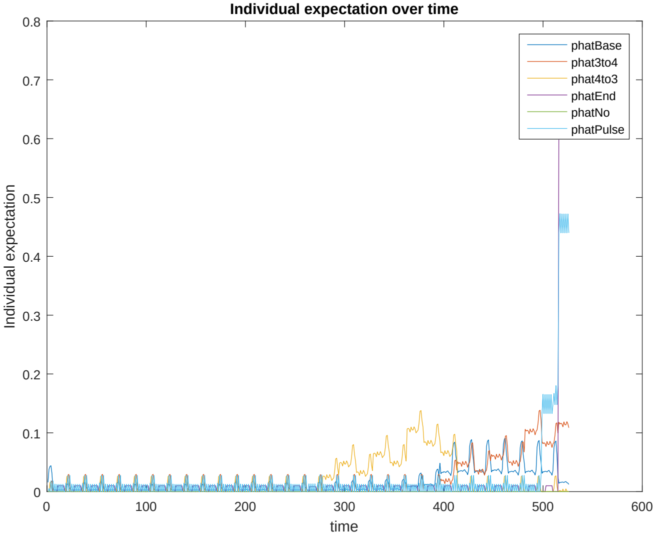
Notes: In the column labeled "data" consumer expectations are consistent with the actual advertising data. In the last column, we adjust expectations to reflect the change in the policy.



Notes: Number of individuals relative to the baseline case in the data. Consumer expectations are consistent witht the GRP schedule.

Summary and concluding remarks

- Look at online sales of lottery tickets. Allows us to measure the short term effect of advertising.
- Find strong effects of advertising that last up to about 5 hours.
- Build a model of long term effects that allows us to simulate sales for counterfactual advertising strategies.
- Find that shifting advertisements to later times may increase overall sales.



Notes: Figure shows the expected probabillity to see an advertisement, from the individual perspective. Obtained from regression of GRP's on time, day, month and draw dummies.