Leveraging Promotions for Social Good: Insights from COVID-19 Vaccine Distribution

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Overview

Motivation

- The role of advertisement in influencing consumers' uptake of private goods and services is well studied
- Promotions can have opposite effect – it can reduce the perceived quality of goods and services
- Promotions range from free tickets to a national park and free beer at a local bar to chance to win a lottery and cash payments

Motivation

- Why is our set-up novel?
  - Government reacted quickly to boost vaccine uptake
  - Promotions are introduced at the state level
  - exploit heterogeneity at the county level– various policy experiments
- What is the average effect of promotion on vaccine adoption?
- Also explore heterogeneity– across income, race?

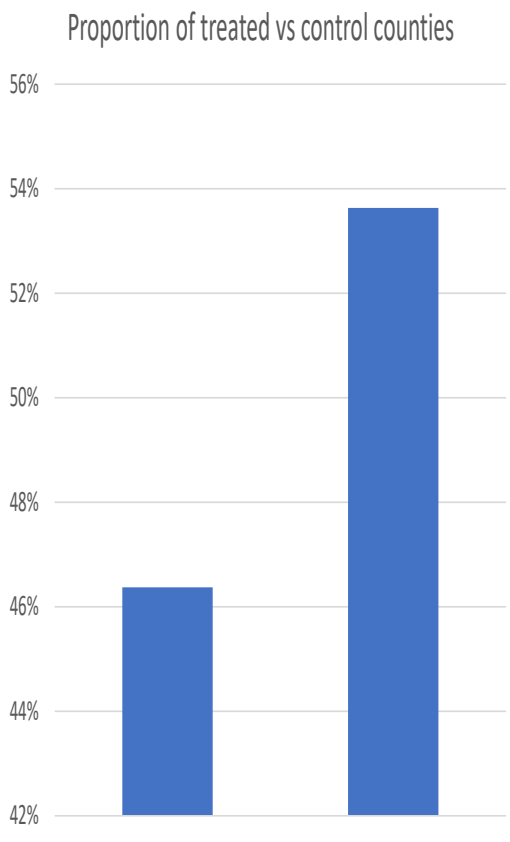
Literature

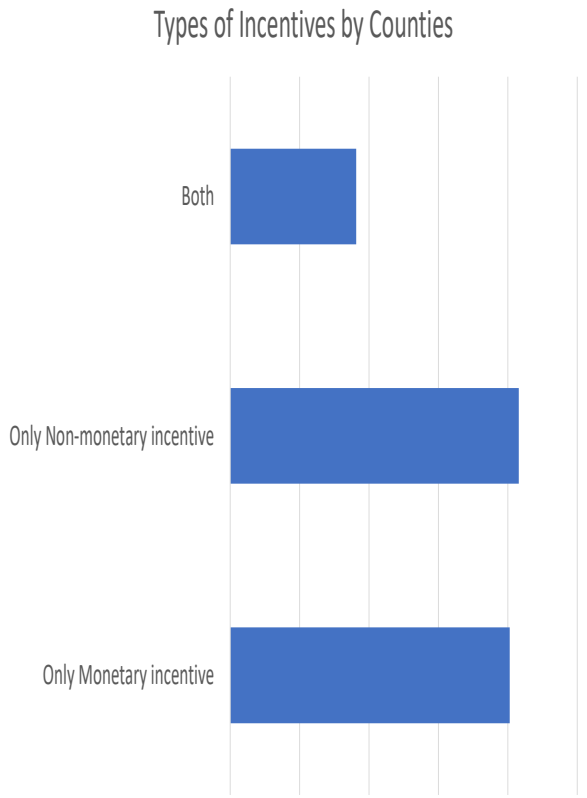
- Allan J. Walkey et al (2021): Lottery-Based incentive in Ohio and COVID-19 vaccination rates
- Thiess Buettner (2006): The incentive effect of fiscal equalization transfers on tax policy
- Shuming Ren and Ziyu Song (2020): Intellectual capital and firm innovation: incentive effect and selection
- Maryke et al (2020): Using Social Media for Vaccination Promotion: Practice and Challenges

Data Source

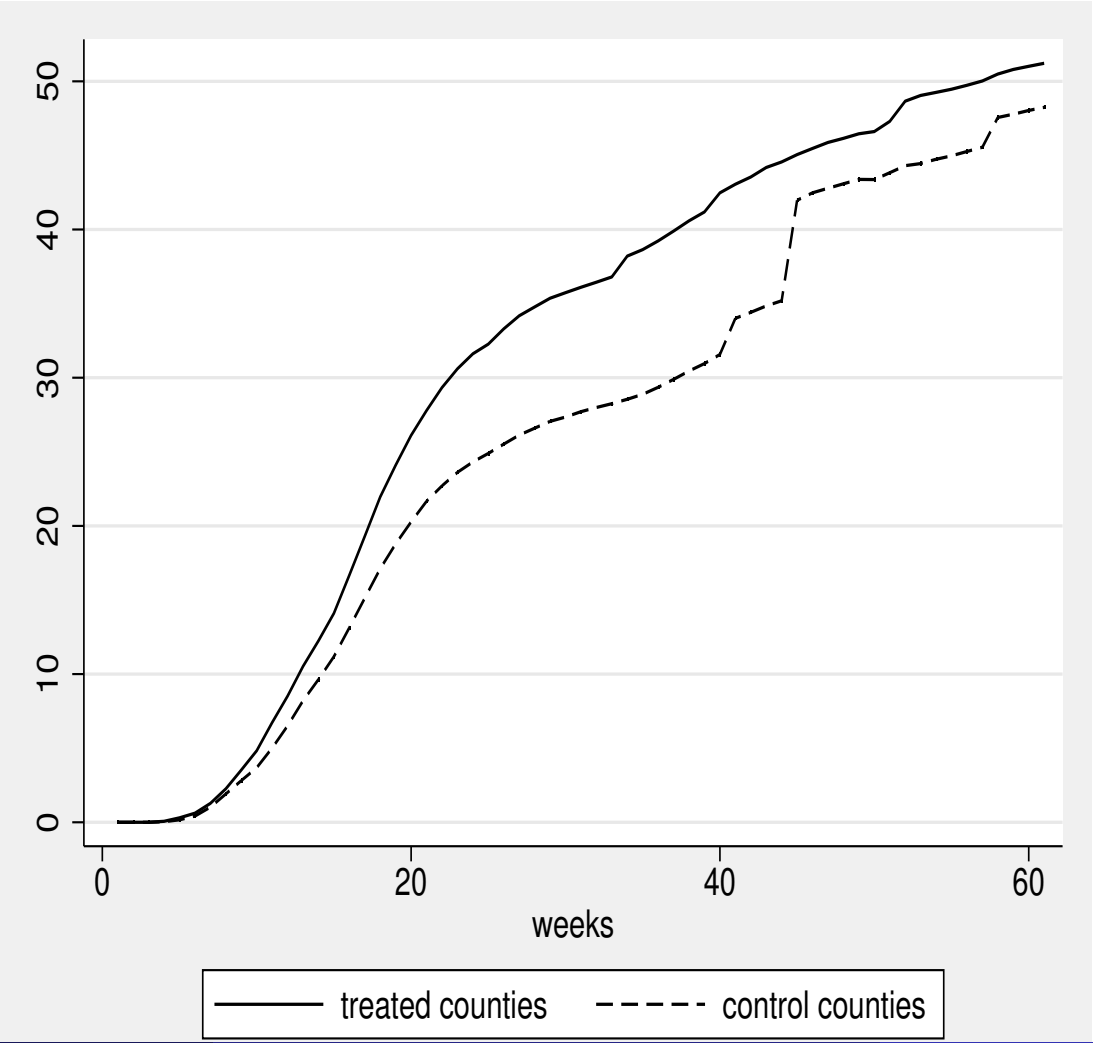
- We used vaccination data from Centers for Disease Control and Prevention (CDC)
- Further CDC Data: COVID Death Statistics and Vaccine Hesitancy/Health Access Measures at the county-level
- Collected Voting Differential in the 2020 election, county-level
- Demographic Information and Number of Hospitals within the county
- Exploring time-varying social distancing metrics (Safegraph/Apple/Google)

Breakdown of counties: treated vs control and treatment types





The average rate of vaccination: treatment vs control counties



How to recover the causal effect? Common Practice

$$Y_{i,t} = \alpha_i + \lambda_t + \beta^{TWFE} D_{i,t} + \beta X_{i,t} + \epsilon_{i,t} \quad (1)$$

where $Y_{i,t}$ represents percentage vaccinated in county i at period t.

controls	Model 1	Model 2
treatment	1.753*	2.6*
deaths	-.0415*	-0.042*
minority*treatment		-4.97*
constant	0.255	0.258
λ_t	Yes	Yes
α_i	Yes	Yes

TWFE estimates are biased!

- researchers routinely interpret β^{TWFE} as "a causal parameter of interest"
- States adopted incentives at different periods– the treatments are also heterogeneous
- Two Way Fixed Effect (TWFE) might result in under-identification and spurious identification of long-run treatments

There must be a better way?

Reduced Form Model

Difference-in-Differences (DiD) with staggered treatment adoption and variation in treatment timing (Borusyak, Jaravel and Spiess (2021), Callaway and Sant'Anna (2020), Sun and Abraham (2020), de Chaisemartin and D'Haultfoeuille(2017))

Structural Form Model

Estimate utility-based Diffusion Model (Cosguner and Seetharaman (2022))

Reduced Form: Treatment grouping-based estimation

Here we explain the method by Callaway and Sant'Anna (hereafter CS(2020)). They consider identification and inference with:

- multiple time periods
- variation in treatment timing, and
- when the "parallel trends assumption" holds potentially only after conditioning on observed covariates

Reduced Form: Treatment grouping-based estimation

We are interested in the causal effect:

$$ATT(g,t) = \mathbb{E}[Y_t(g) - Y_t(0)|G_g = 1] \quad for \quad t \geq g \tag{2}$$

Taking weighted average of the ATT(g,t):

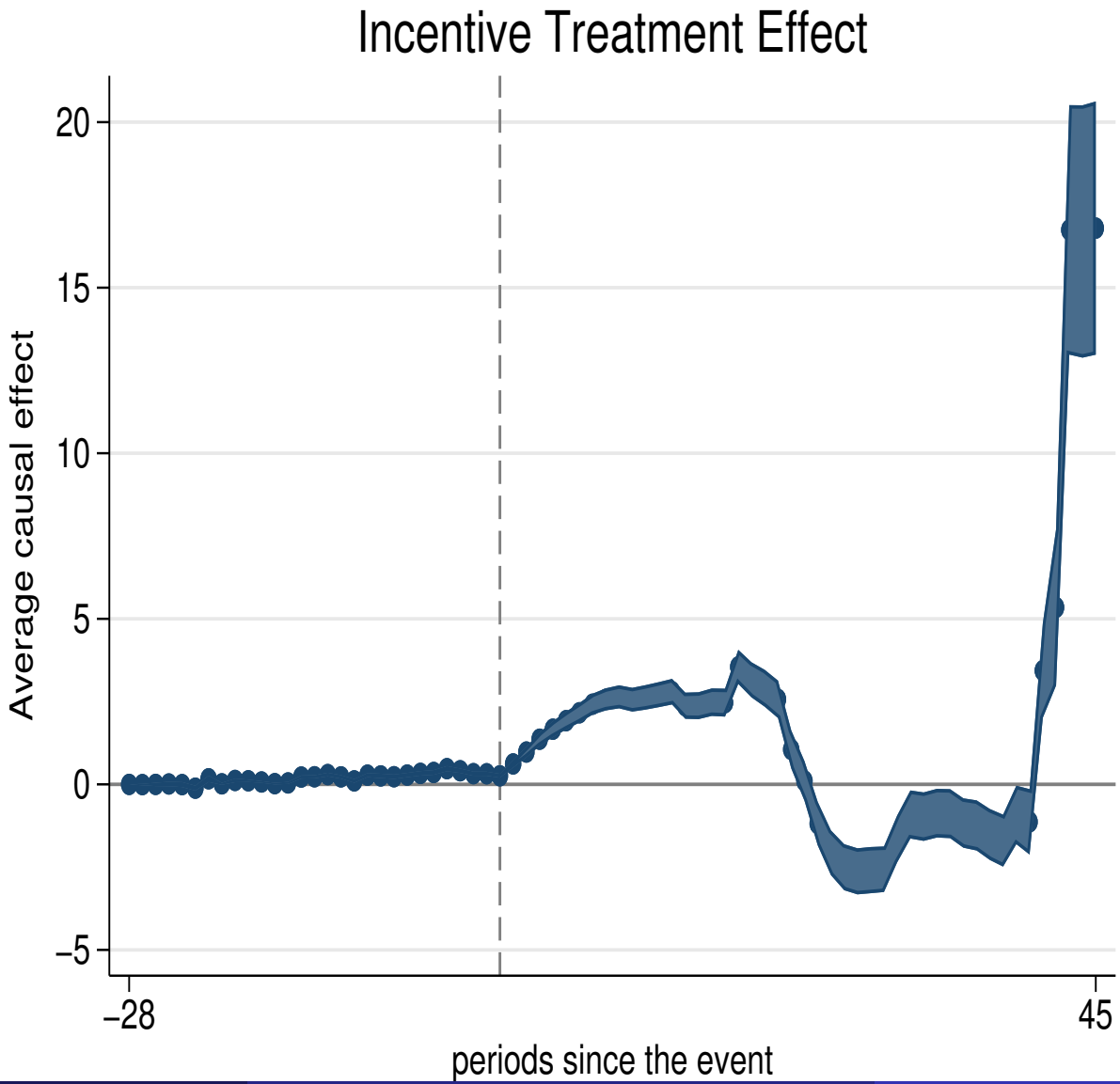
$$\tau_{CS} = \sum_{g=2}^{K} \sum_{t=2}^{T} \mathbb{1}(g \leq t)\, \omega_{gt} ATT(g,t) \tag{3}$$

Reduced Form: Treatment grouping-based estimation

	coefficient	std. err.	z
τ_{CS}	0.74	.21	3.57**

The causal effect of incentives on vaccine uptake is 0.74 %. This is the weighted average treatment on the treated (ATT) estimate.

Event study plots: Grouping Based Results



No more identification treat?

Does the latest DiD address all identification concerns? Not exactly!

- One potential identification threat is self-selection into treatment (at State level)
- Solution: estimate a structural model!
  - For the treatment counties we estimate the vaccine diffusion pattern when they are in and out of treatment
  - We use Random Forest to build the counterfactual (i.e. out of treatment diffusion pattern) using the features of non-treated counties

Structural Model: Bass Diffusion Model

- Given a market size of M consumers for a new product, the likelihood that a consumer will adopt a new product at time t, given that the consumer has not yet adopted, is given by:

$$\frac{f(t)}{1-F(t)} = p + qF(t) \tag{4}$$

where p and q represents the coefficients of innovation and imitation, respectively. $F(t)$ is cumulative distribution function and $f(t)$ is the probability density function.

Structural Model: Bass Diffusion Model

- Assuming $F(0) = 0$ and solving the differential equation (4), we get:

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} \tag{5}$$

- Given N(t), the observed vaccine data, the predicted vaccination is given by:

$$\hat{N(t)} = M[F(t) - F(t-1)] \tag{6}$$

Structural Model: Deriving Bass Model as a Utility-Based Diffusion Model

- Given a market size of M consumers, assume the utility of a consumer for the new product at time t is given by:

$$U_t = ln\left[ln[\frac{1-F(t-1)}{1-F(t)}]\right] + \boldsymbol{X_t}\boldsymbol{\beta} + \epsilon_t \tag{7}$$

where ϵ_t follows a logistic distribution with location parameter 0 and scale parameter 1.

Structural Model: Deriving Bass Model as a Utility-Based Diffusion Model

- Now, the discrete hazard function characterizing the consumer's time to adoption for the new product is given by:

$$pr_t = \frac{e^{w_t}}{1 + e^{w_t}} \tag{8}$$

where

$$w_t = ln\left[ln[\frac{1 - F(t-1)}{1 - F(t)}]\right] + \boldsymbol{X_t}\beta$$

- The consumer's unconditional likelihood of buying the new product at time t will be:

$$L_t = \left[\prod_{s=1}^{t-1} 1 - pr(s)\right] pr(t) \tag{9}$$

Structural Model: Constructing Counterfactual

- We use Random Forest to predict the diffusion parameters p, q and m for the treated counties based on untreated counties
- Nonparametric approach
- Similar to synthetic controls
- We compare the vaccine diffusion for treated counties against the respective counterfactual

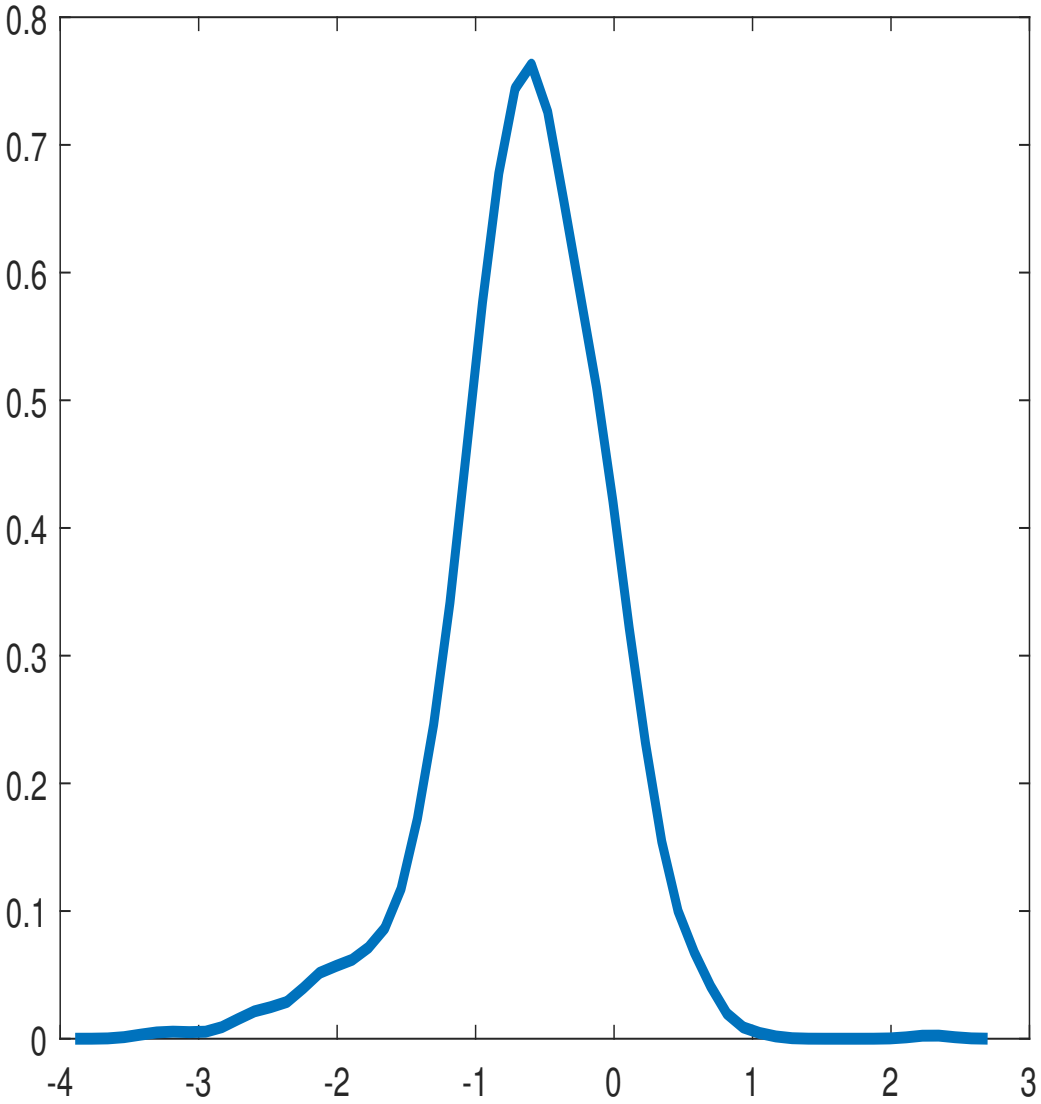
Structural Model: Deriving Bass Model as a Utility-Based Diffusion Model

- The probability of vaccine adoption in and out of treatment will be given by p and $\hat{p}$, respectively
- Treatment effect on contemporaneous correlation will be given by the difference in the log odds ratios

$$\tau = log\left(\frac{p}{1-p}\right) - log\left(\frac{\hat{p}}{1-\hat{p}}\right) \tag{10}$$

- To measure heterogeneity, the treatment effects will be projected onto covariates

Bass Treatment Effects– median τ=−0.5948



Bass Treatment Effects– exploring heterogeneity!

$$\tau_i^{bass} = \beta_0 + \beta_1 novax_i + \beta_2 vote_i + \beta_3 income_i + \epsilon_i \quad (11)$$

where vote = Trump's vote share - Biden's vote share

treatment effect	Coefficient	std. err.	t-stat
constant	-0.629	0.172	-3.65***
vaccine hesitant	-5.13	0.811	-6.33***
vote	-0.217	0.095	-2.27**
log(income)	0.094	0.022	4.19***

‡ We used bootstrap standard errors.

Conclusion

- careful about the adverse effects of promotion on public good consumption
- estimates from the reduced form model differs from the Bass diffusion model results
- vaccine hesitants became more hesitant
- red states became more hesitant