Program Evaluation with Remotely Sensed Variables

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Problem description

- Growing availability of experiments in social science and industry
- But... analysis often challenging due to limited access to outcomes
  - Ex1 Anti-poverty programs require measuring consumption
  - Ex2 Anti-deforestation/land-use programs requiring observing deforestation

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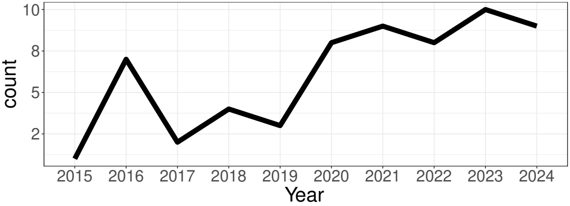
- How (and when) should we use such data for program evaluation?

"Top-5" and AEJ Applied econ journals



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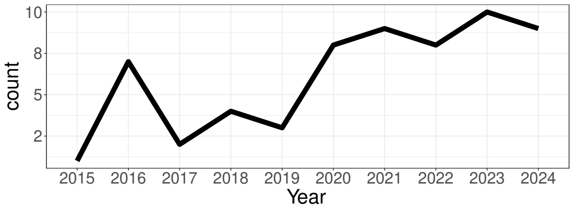

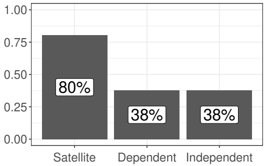

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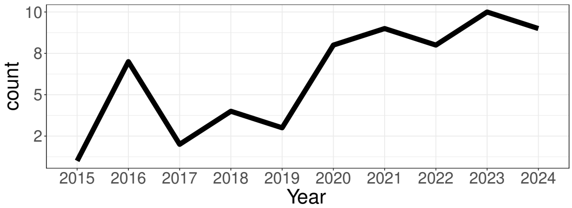

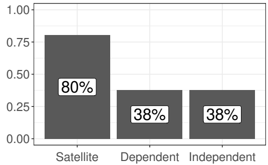

Other examples

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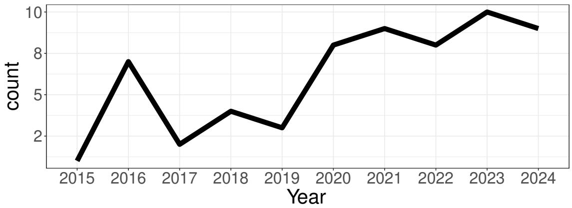

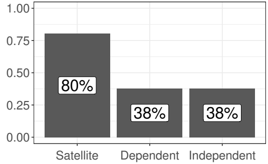

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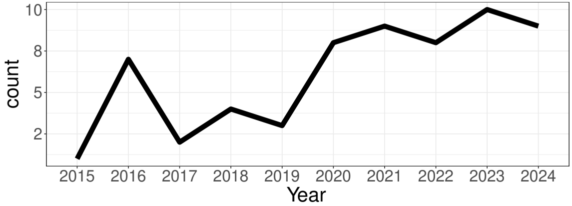

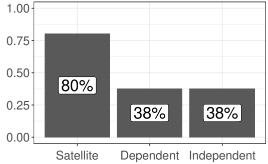

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- "Using Satellite Imagery and Deep Learning to Evaluate the Impact of Anti-Poverty Programs" (Huang et al., 2021)
- "Estimating Impact with Surveys versus Digital Traces: Evidence fro RCTs in Togo" (Aiken et al, 2023)

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  - Study large-scale public-policy (Smartcards) replicating results in Muralidharan et al., 2023 with satellite images

Related literature in econometrics and statistics

- Growing econometric literature on data fusion
  - Long and short regressions [Cross and Manski, 2002; Molinari and Peski, 2006; D'Haultfoeuille, Gaillac and Maurel, 2024; Bareinboim and Pearl, 2016]
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- Measurement error and ML imputations
  - Classic ME [Hasuman, 2001; Hu, 2008; Molinari, 2008; Schennach, 2020; ...]
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  ⇒ Here ME problem with missing data (data fusion)

Content

Notation

- $D \in \{0, 1\}$: binary treatment
- $Y(1), Y(0)$ POs under treatment and control satisfy SUTVA
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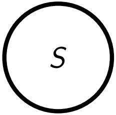
- Some extensions
  - Pre-treatment covariates X
  - Researchers observe *some* outcomes in the experiment

Causal model for RSV

- Goal: $\theta = \mathbb{E}[Y(1) - Y(0)|S = E]$ (ATE in experiment)



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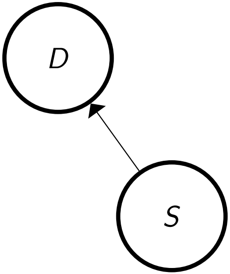

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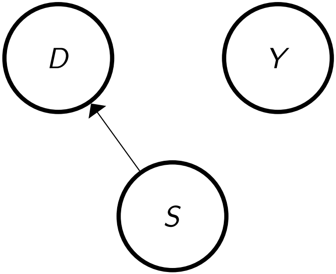

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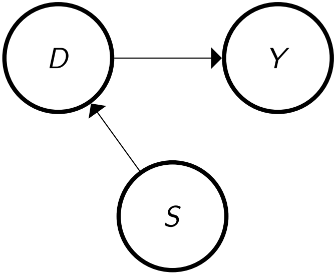

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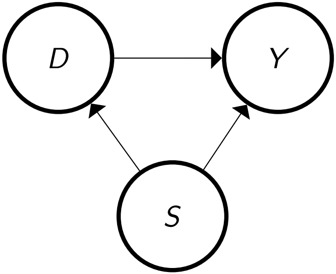

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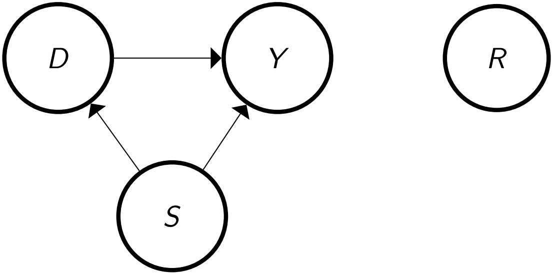

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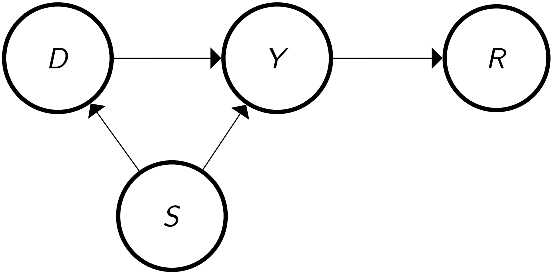

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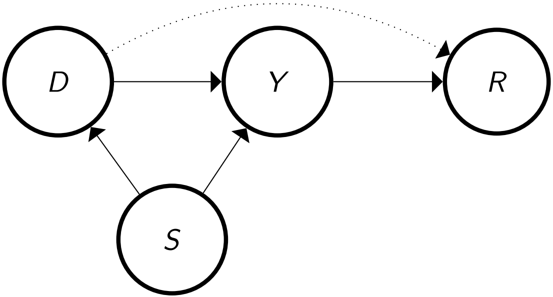

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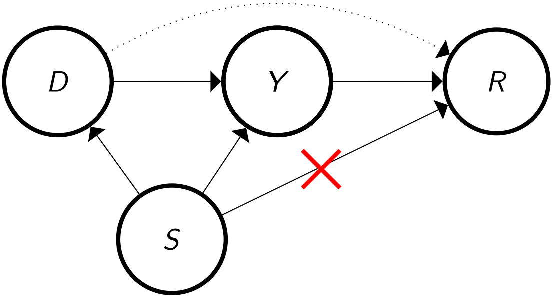

Preliminary conditions on experiment and obs/ study

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Condition 3: Stability $S \perp R | Y, D$

Remarks and desiderata

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! Bonus: efficient choice of R

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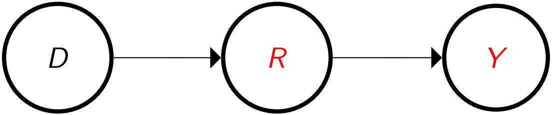
  - Exercise mimics surrogates in data fusion lit (Athey et al., 2018)



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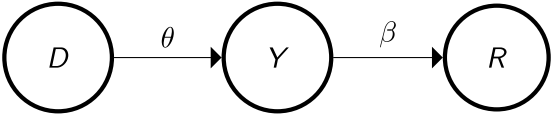
$\Rightarrow$ Bias can be significant in applications (E.g., in a cash transfer program to reduce crop burning by farmers, estimated effects using satellite images under-estimate ATE by at least 50%)

Surrogate method: intuition



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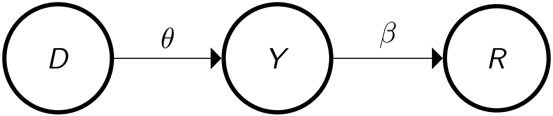

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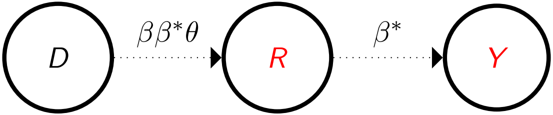

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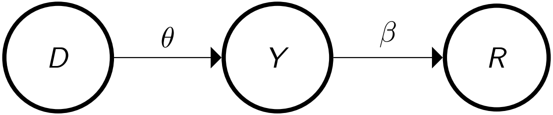

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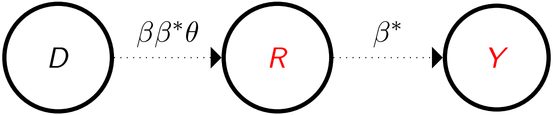

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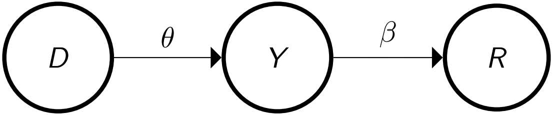

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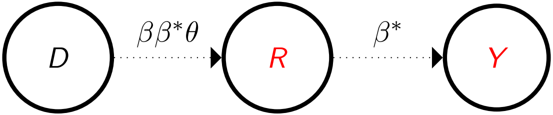

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Prop There exist at least two DGPs satisfying $(D, S) \perp R | Y$ and Conditions 1-3 hold, so that (formula)

$$\underbrace{\theta}_{\text{estimand}} - \underbrace{\tilde{\theta}}_{\text{surrogate prediction}}$$

can have arbitrary sign reversals under RSV assumptions.

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$\Rightarrow$ The probability of what we observe in experiment is a mixture of probabilities of what we would have observed in the obs study

Identification: second step

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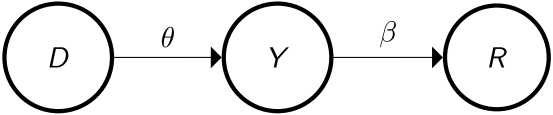

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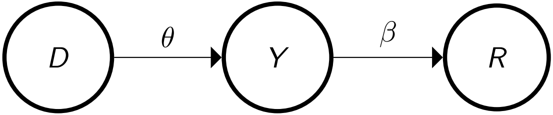

$\Rightarrow$ Challenge: such probabilities are difficult to predict.

Identification: obtaining simple moment conditions

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Conditional moments that do not depend on $P(R)$

Can we circunvent correct specification of $D|R$, $Y|R$?

Identification: conditional moments

- Write
$$\Delta_i(e) = \frac{1\{D=1, S=e\}}{P(D=1, S=e)} - \frac{1\{D=0, S=e\}}{P(D=0, S=e)}$$
and similarly $\Delta_i(o) = \frac{1\{Y=1,S=o\}}{P(Y=1,S=o)} - \frac{1\{Y=0,S=o\}}{P(Y=0,S=o)}$

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Thm (Informal) Identification simplifies to

$$\mathbb{E}[\Delta_i(e) - \theta\Delta_i(o)|R] = 0$$

$\Rightarrow$ No need to know data generating process for $R|Y$

A simple Wald estimand

- Take any representation of R, call it $H(R)$ [e.g. average luminosity]
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- Testable implication:
  - θ is constant as we vary $H(\cdot)$
  - Can change representation $H(\cdot)$ to test if estimate changes

Content

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- How to choose $H(R)$ to maximize precision?
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- Representation as an optimal instrument [Chamberlain, 1987; Newey, 1993]

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- Intuition:
  - use a function of the predicted outcome as an instrument
  - Heteroskedasticity depending on treatment and outcome predictions

Algorithm in a nutschell

- Use a high-dim estimator with regularization to estimate

$$\underbrace{P(Y=1|R,S=o)}_{\text{outcome prediction}},\quad \underbrace{P(D=1|R,S=e)}_{\text{treatment prediction}},\quad \underbrace{P(S=e|R)}_{\text{assignment prediction}}$$

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$\Rightarrow$ Methods of moments with estimated "optimal instrument" [e.g., Newey, 1993]:

- standard $n^{-1/2}$-inference if $\hat{H} \to H^*$ for some arbitrary H^*, with $\mathbb{E}[\Delta_i(o)H^*(R_i)] \neq 0$ and regularity conditions or cross-fitting

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Step 4: estimation and inference as for standard methods of moments

Content

Experimental background

- Can we use remote sensed data to evaluate anti-poverty programs?
- Focus here on the Smartcards experiment [Muralidharan et al., 2016; 2023]
  - How to deliver payments securely to targeted beneficiaries?
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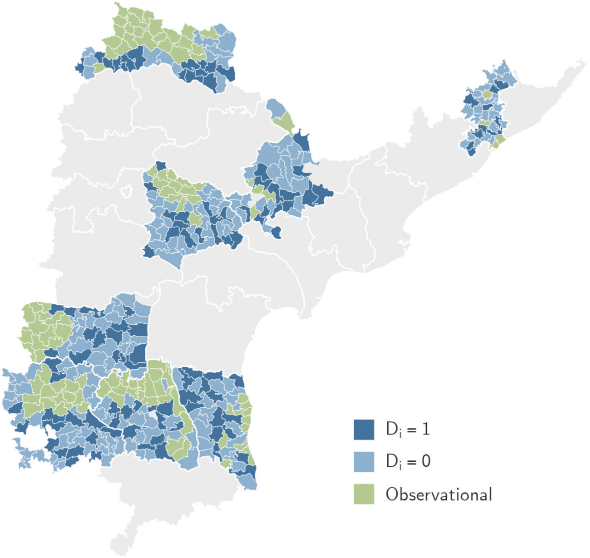
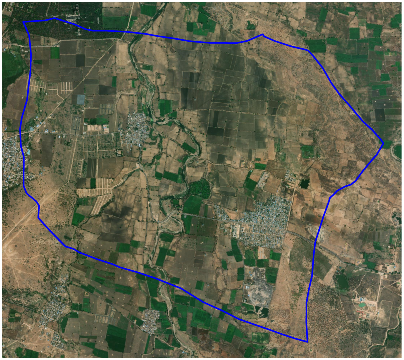
- Use village-level information and satellite images to estimate ITT
  - ⇒ We compare point estimates using limited outcome info, with regression that have access to outcome data from the experiment

Map from the original experiment



Feature extraction (MOSAIKS features)



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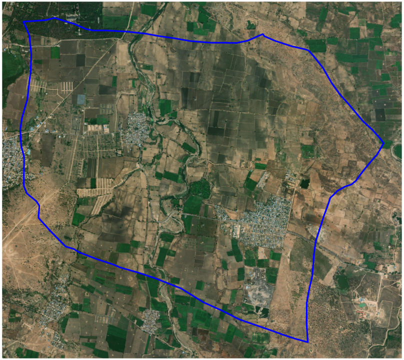
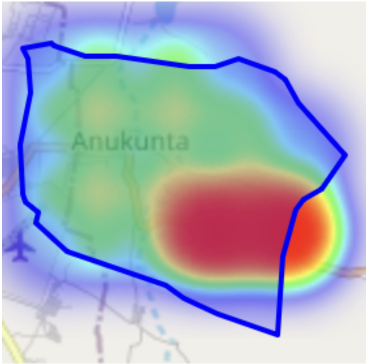




Validation exercise

Metrics:

- Whether consumption is below its first quartile
- whether no individual in the village has income above Rs. 5,000
- whether no individual in the village has income above Rs 10,000

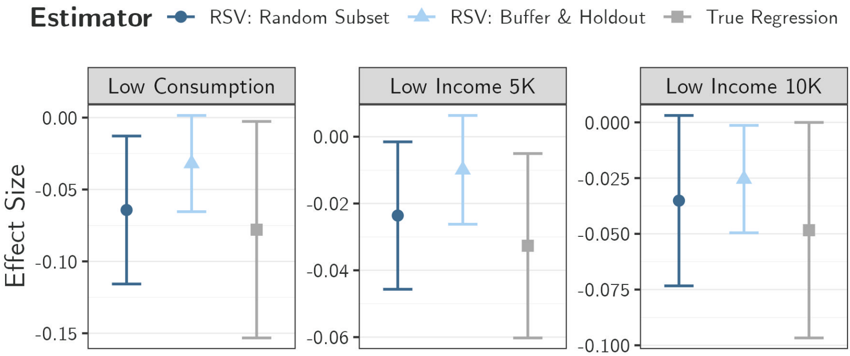
⇒ We can observe outcome metrics for each village using census data

⇒ Compare to regression that uses outcomes of all villages

Two validation exercise implementing our method that

- Uses outcomes for **first half** of the experimental mandals **only**
- Uses outcomes of **buffer** control and **holdout** sample **only**
  - ⇒ Not require outcome info for $\sim$ 3,000 villages

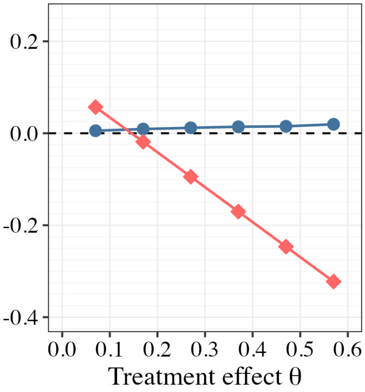
Results



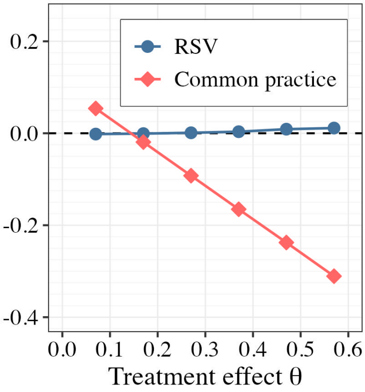
Estimator
RSV: Random Subset
RSV: Buffer & Holdout
True Regression
Low Consumption
Low Income 5K
Low Income 10K
Effect Size
0.00
-0.05
-0.10
-0.15
0.00
-0.02
-0.04
-0.06
0.000
-0.025
-0.050
-0.075
-0.100

Simulations using satellites and consumption data in India

(a) Bias ($n = 2000$)

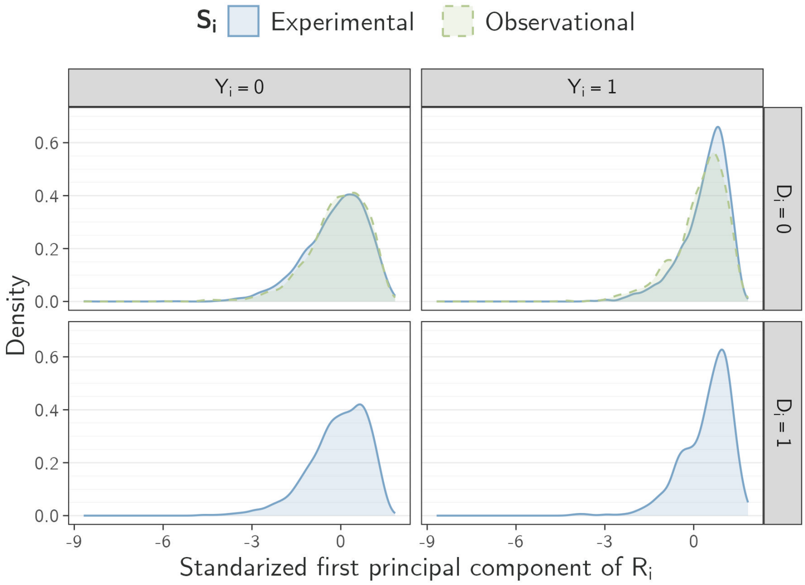


(b) Bias ($n = 3000$)



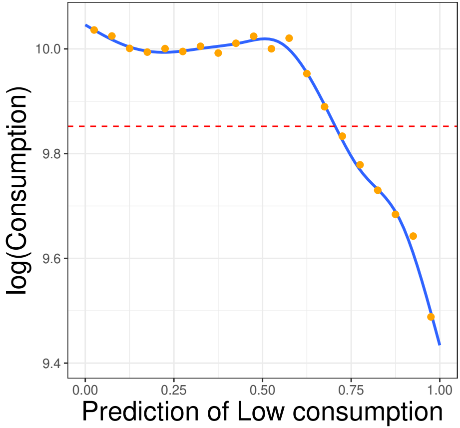
(similar behavior for mean-squared error) (more)

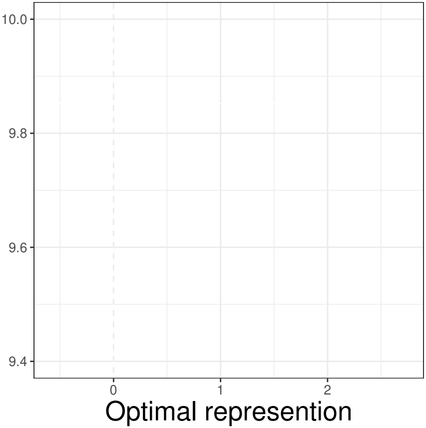
Checking for our assumptions using the full data



Binary outcome prediction using ML

⇒ Per-capita average consumption below 1st quartile





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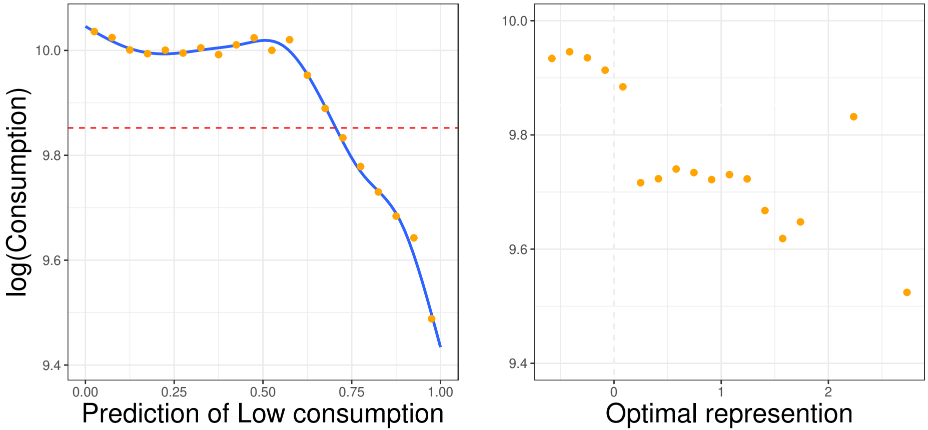

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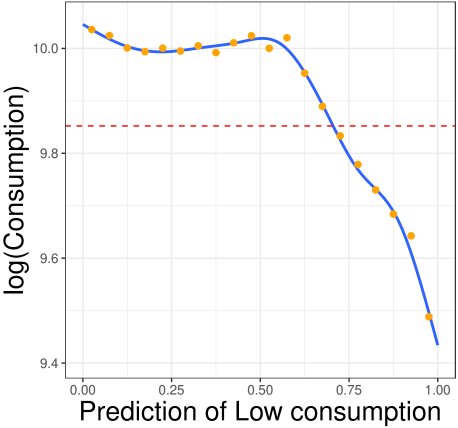

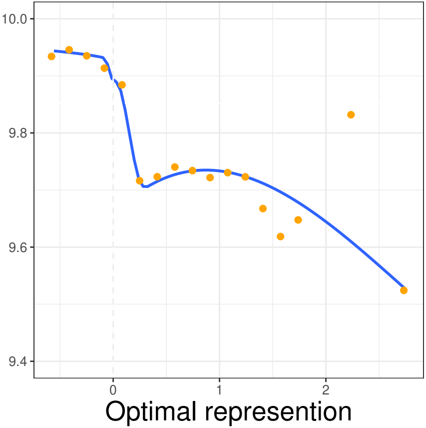

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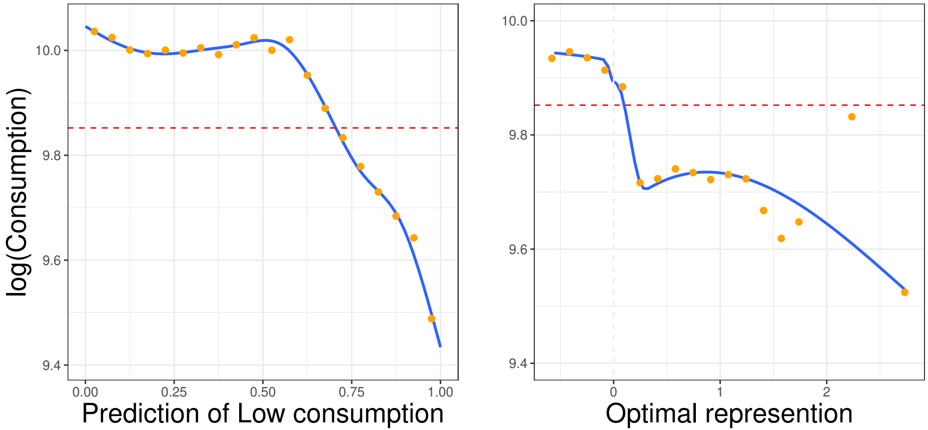

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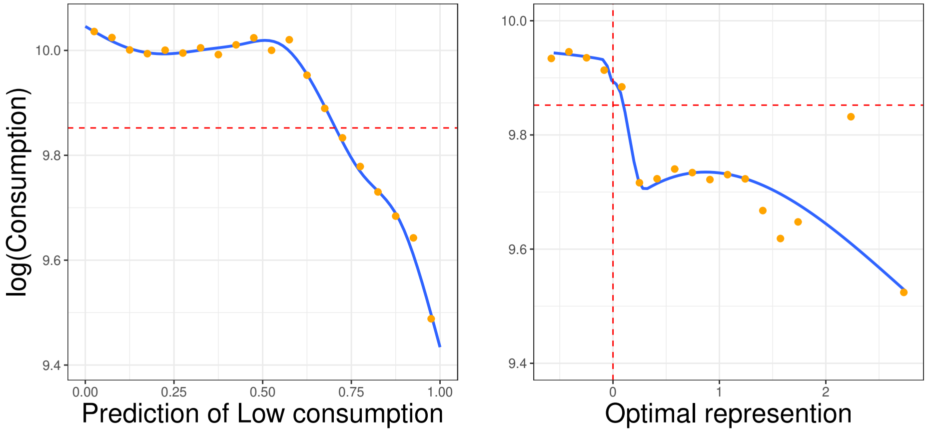

Content

Some extensions

Non-binary outcomes:

- assuming no direct effects for simplicity

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$\Rightarrow$ $H(R)$ of dimension $|\mathcal{Y}|$ where $\mathbb{E}[H(R)W(o)]$ is full rank (invertible)

Some extensions

Non-binary outcomes:

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Direct effect

- Identified if observe outcomes of some treated units (more)

Conclusions

- We study program evaluation with remote sensed variables
- We review pitfalls for practice and provide constructive identification
- No model specification for RSV is required and estimation/inference can use arbitrary ML algorithms
- We re-evaluate a large scale public policy program using satellite images and recover effects and SE with half of the sample

Conclusions

- We study program evaluation with remote sensed variables
- We review pitfalls for practice and provide constructive identification
- No model specification for RSV is required and estimation/inference can use arbitrary ML algorithms
- We re-evaluate a large scale public policy program using satellite images and recover effects and SE with half of the sample
- Many open questions for future research: spillover effects, high-dimensional outcomes, noisy measured treatment, ...

Thanks very much, questions?

Exact formula for bias of the surrogate

Specifically, we can write under the stated assumptions

$$\mathbb{E}[Y(d)|S=E] - \mathbb{E}[f(R)|S=E, D=d] =$$
$$\mathbb{E}[Y(d)|S=E] \cdot \int (1-w(d,r))P(R_i = r|Y_i = 1, S_i = e)dr$$

where

$$w(1,r) = \frac{P(Y(0)=1|S=E)P(R=r|D=1)}{P(Y(1)=1|S=E)P(R=r|D=0)}, \quad w(0,r) = \frac{1}{w(1,r)}$$

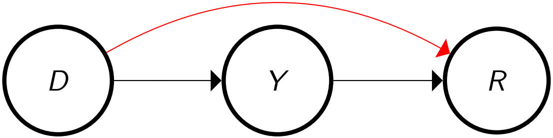
Taking differences, we obtain the bias for ATE of the form

$$\int \Big((1-w(1,r))\theta + \mu(0)(w(1,r)^{-1} - w(1,r))\Big)P(R_i = r|Y_i = 1, S_i = e)dr$$

where $\mu(d) = \mathbb{E}[Y(d)|S=E]$ (back)

Estimation with direct effects

What if we also expect direct treatment effects?



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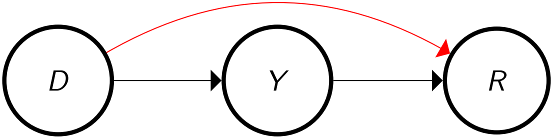

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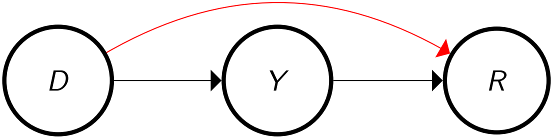

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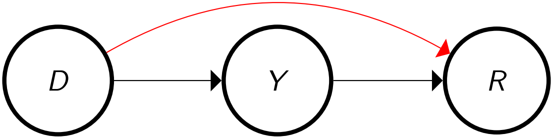

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$\Rightarrow$ Remove contribution of direct effect

Data description: Village (Shrid) level information

- Village boundaries through SHRUG project [Asher et al., 2021]
- Village per-capita consumption and poverty level with SECC 2012 (back)
- Village level nightlights with SHRUG
- Collect village level day-light satellites [MOSAIKS, Rolf et al., 2021]

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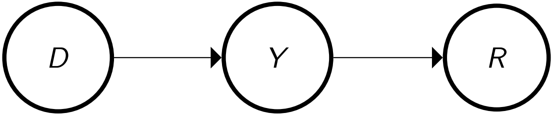
	Outside Study	Control	Buffer Control	Treatment
Number of Shrids	2,260	853	2,931	2,276
Number mandals	105	44	136	111
Average pop	2,143	2,296	2,285	2,604
Urban area	0.002	0.001	0.003	0.004
Average male pop	0.512	0.508	0.506	0.508
Average female pop	0.489	0.492	0.495	0.493

Calibrated simulations. Draw



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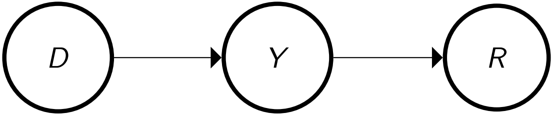

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- $Y(1) \sim \mathrm{Bern}(\mathbb{E}_n[Y(1)] + \tau)$ ($Y(0) \sim \mathrm{Bern}(\mathbb{E}_n[Y(0)] + \tau)$)

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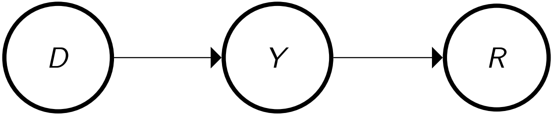

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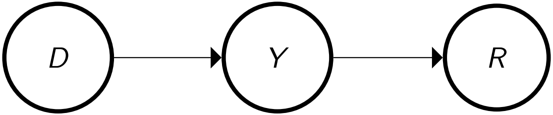

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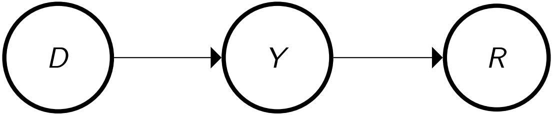

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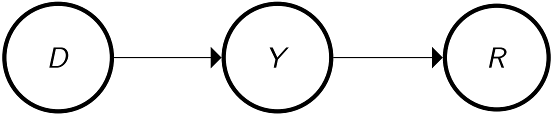

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- Remove outcomes info for treated (back) individuals

Calibrated simulations: Surrogate vs RSV Method (RMSE)

(a) RMSE ($n = 2000$) (b) RMSE ($n = 3000$)