

The Limits of Decentralized Data Collection: Experimental Evidence from Colombia

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State information gathering

- “Statistics” famously derives from the word “state.”
- Modern states collect vast amounts of data for use in policymaking and public administration.
 - The classics: censuses, vital statistics, land cadasters
 - Increasingly, methods of passive surveillance/monitoring
 - Data produced, submitted by **bureaucrats** → **this talk!**

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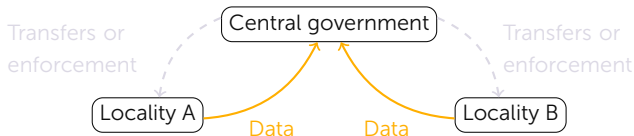
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 - Goal: Data inputs should be used to affect **policy**.

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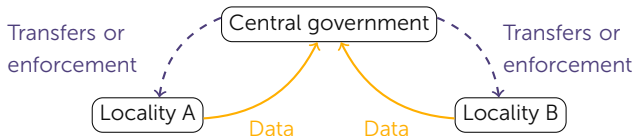
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 - Origin of many administrative datasets
 - Data requests from **central** to **decentralized** bureaucracies.



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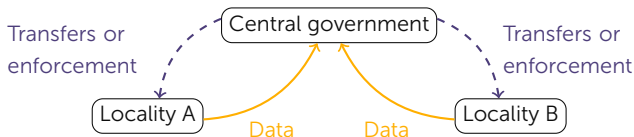
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- Is this really a thing?
 - Local bureaucrats complain about these requests.
 - **Time-use surveys** of local bureaucrats suggest that these requests are time consuming Kalaj, Rogger, and Somani (2022)
 - National bureaucrats **seek advice** on eliciting complete, honest reports.

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Overview

Framework: Simple decision theoretic model maps the behavior of decentralized bureaucrats onto statistical measurement framework.

- Bureaucrats choose how much **effort** to exert and whether to purposefully **distort** their reports to the central government.

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Design: A field experiment in collaboration with the Colombian Procuraduría General de la Nación on the annual national transparency index (ITA).

- Manipulates the visibility of PGN in using the data → measure the responses of bureaucrats in decentralized entities to **increased oversight**.
- An **independent audit** of a subset of items allows us to describe data quality.

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Framework: Decision theoretic model that maps the behavior of decentralized bureaucrats onto statistical measurement framework.

Design: A field experiment in collaboration with the Colombian Attorney Inspector General's office on the annual national transparency index (ITA).

Findings:

- Reporting behavior responds to the visibility of oversight in both **selection into reporting** and the **information reported**.
- The audit suggests that three pathologies of measurement: **selection**, **intentional distortions**, and the **random error** in reports covary with true quality.

Related Literature

- State information about **individual citizens** like censuses and vital statistics

(Scott, 1998; Lee and Zhang, 2017; Bowles, 2020; Sánchez-Talanquer, 2020)

- **Administrative data quality** usually in two settings:

- Autocratic regimes, esp. with respect to economic data (Guriev and Treisman, 2019; Martinez, 2021; Trinh, 2021; Lorentzen, 2014; Wallace, 2016; Edmond, 2013)
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Theoretical Framework



The output: administrative data

- Central government asks decentralized entities to report some **quantity, θ** , to the central government.
 - E.g., public service outputs, budget execution, or transparency practices.
- A bureaucrat (or office) in the entity chooses **whether to report, r** .
 - If they do not make a report, $r = \emptyset$.
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 - Intentional distortion, d .
 - Unintentional errors/random error, $\varepsilon \sim f(\cdot)$, where $f(\cdot)$ is a mean-zero density.

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Data outputs

- Maps onto standard formulations of **measurement error** in statistics (e.g., Cochran, 1968; Rubin, 1976)
- The central government wants to know θ but observes r , which can suffer from:
 - **Missingness** when the bureaucrat does not report $r = \emptyset$.
 - **Measurement error** due to:
 - Intentional distortions (d)
 - Unintentional distortions (ε)

$$\underline{r}_{\text{Report}} = \begin{cases} \underbrace{\theta}_{\text{Truth}} + \underbrace{d}_{\text{Intentional misreporting}} + \underbrace{\varepsilon}_{\text{Random error}} & \text{if bureaucrat reports} \\ \emptyset & \text{otherwise} \end{cases}$$

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- Central government may use data to:
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 - Target oversight or enforcement: sticks → our empirical setting.
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What are bureaucrats doing?

- When reporting, bureaucrats exert **effort** and choose **intentional distortions**
 - Effort, $e \geq 0 \rightarrow$
 - Missingness: when $e = 0$.
 - Unintentional distortions: $\uparrow e \rightarrow \downarrow \text{Var}(\epsilon)$.
 - Intentional distortions, d
- Bureaucrat's utility:

$$U_B = \underbrace{\underbrace{-\rho(r)}_{\text{Pr(Audit)}} \underbrace{P(\theta, r)}_{\text{Penalty}}}_{\text{Oversight}} - \underbrace{c(e)}_{\text{Cost of effort}}$$

- Note: bureaucrats may not know precisely how oversight is exercised.

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Learning about the observed administrative data

- An exogenous increase in (perceived) **oversight**:
 - Should **↑ rates of reporting**.
 - Changes the aggregate distribution of reports, conditional on reporting, by:
 1. ↑ Entities reporting;
 2. Changing incentives for intentional misreporting;
 3. ↓ Unintentional errors.
- Observation of the joint distribution of quality, θ , and reported quality, r , allow for learning about:
 - Bureaucrats' reporting behavior, including both effort and intentional distortions.
 - Bureaucrats' expectations about oversight by the central government.

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Case Context



Our partner: The PGN

- The Procuraduría General de la Nación (PGN), is the principal watchdog agency in Colombia.
- PGN is implementing of the National Transparency Law of 2014.
 - This law mandated the creation of the National Transparency Index (ITA), the measure that we study.

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 - This mandate seeks to prevent corruption or other public misconduct by monitoring of public officials and entities.

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The National Transparency Index (ITA)

- The Índice de Transparencia y Acceso a la Información, ITA, was first implemented in 2018.
 - We study the production of the 2020 index.
- $\approx 50k$ entities to report their compliance with ≈ 200 transparency practices.
 - All items are binary (yes/no).
 - Weighted to generate the 100-point ITA.
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- Unit of measurement, the **entity**, classified as:
 1. **Traditional** public sector entities including public entities, oversight bodies, and state-owned companies → our focus.
 2. **Non-traditional** entities are persons or legal entities that contract with the state to provide public services or manage public funds.
 3. **Political parties or social movements.**

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Research Design



Overview

1. A **field experiment** conducted in collaboration with the PGN in the collection of the 2020 ITA index. Allows us to answer:
 - How does the reporting behavior of bureaucrats respond to changes in the salience of **oversight**?
2. An **independent audit** of a subset of responses provided by a random sample of public sector (traditional) entities. Allows us to answer:
 - How does the reported data we observe relate to the truth?

Experimental design: treatment level 1

Status quo communication from sector heads in central government about ITA obligations

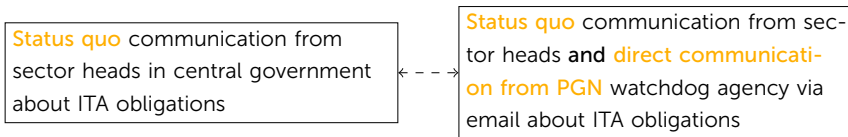


Status quo communication from sector heads and direct communication from PGN watchdog agency via email about ITA obligations

○ Interpretation of contrast and ATE:

- Make PGN's role and use of the data more visible.
- From ex-post semi-structured interviews with bureaucrats who filled out ITA:
 - PGN is known as a watchdog agency, seen as having some teeth.
 - Entities regularly asked to send data to different central government entities.
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Experimental design: treatment level 2

- **Nudges**—variation in message content—randomly assigned in $2 \times 2 \times 2 \times 2$ factorial design

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Status quo communication from sector heads and **direct communication from PGN** watchdog agency via email about ITA obligations

1. **Past oversight**: 2019 status

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2. **Future oversight** Possible audit

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3. **Reminder** email $\approx \uparrow$ dosage

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4. **Training** Links to training videos

- Benefits of the “nudge” manipulations:

- For PGN: sending direct messages has **costs**, can benefits be maximized at no additional cost?
- For us: (helps to) unbundle direct communication treatment.

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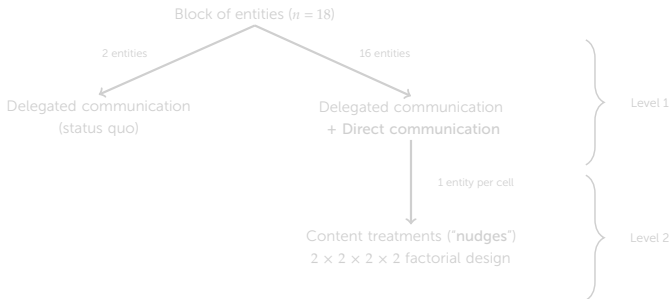
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Experimental design: sample and treatment assignment

- Sample consists of 6,556 public sector entities in Colombia.
- Blocked assignment: random assignment within blocks of 18 entities:
 - Exact blocking on 2019 ITA completion
 - Minimize Mahalanobis distance on (1) PGN's classification of organizational or entity type; (2) department.

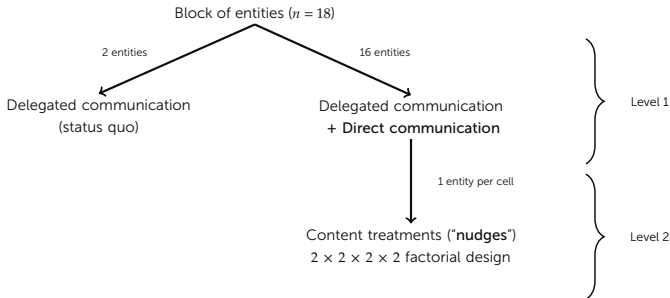
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Estimation of treatment effects

- We estimate the ATE of direct communication and AMCEs of the nudge treatments effects by OLS:

$$Y_{ib} = \beta_1 \text{Direct Communication}_i + \beta_2 \text{Reminder}_i + \beta_3 \text{Training}_i + \beta_4 \text{Retrospective Oversight}_i + \beta_5 \text{Prospective Oversight}_i + \psi_b + \epsilon_{ib}$$

- The estimators of the treatment effects are:
 - β_1 : The ATE of direct communication
 - $\beta_2, \beta_3, \beta_4, \beta_5$: The AMCEs of the factorial message treatments.

Independent audit design

- Stratified random sample of 2,400 of 6,556 public sector entities
 - Crucially, we sampled entities regardless of whether they **completed the 2020 ITA**.
 - So we observe reporters and non-reporters symmetrically in the audit.
- Provides **validation** of self-reported transparency practices through an independent audit of a subset of index items:
 - Conducted outside partnership with PGN.
 - Audited items worth 27.75/100 points on the index.
 - We **measure θ** (quality) for this subset of the index.

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Measurement of parameters of interest

○ Reported data (r):

- Submission of the ITA matrix (yes/no)
- ITA score (0-100) conditional on submission.

○ Quality (θ for subset of index):

- Use index weighting scheme from full index to construct a "true" score between 0 and 27.75 points.
- We can also reconstruct the reported score on this subset from micro-data.

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 - By assumption $E[\epsilon] = 0$, so we will examine $E[r - \theta]$.
 - Link between variance of r and effort (e).

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Results I: Experimental Findings



Experimental results

- ATE and AMCE estimates on submission of ITA matrix.

	Completed ITA	
	(1)	(2)
Direct communication	0.029 (0.022)	0.030 (0.020)
Oversight of past completion	0.000 (0.012)	-0.001 (0.011)
Possible future audit	-0.005 (0.012)	-0.005 (0.011)
Direct reminder	0.013 (0.012)	0.012 (0.011)
Training	-0.008 (0.012)	-0.007 (0.011)
Observations	6556	6556
Sample	All	All
Block FE		✓
Control mean	0.68	0.68
Control std. dev.	0.47	0.47
DV range	{0,1}	{0,1}

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

Experimental results

- “Post-treatment” estimand on reported scores.

	Completed ITA		ITA Score	
	(1)	(2)	(3)	(4)
Direct communication	0.029 (0.022)	0.030 (0.020)	-6.066*** (1.477)	-5.886*** (1.473)
Oversight of past completion	0.000 (0.012)	-0.001 (0.011)	0.587 (0.950)	0.540 (0.936)
Possible future audit	-0.005 (0.012)	-0.005 (0.011)	-0.453 (0.950)	-0.666 (0.936)
Direct reminder	0.013 (0.012)	0.012 (0.011)	-2.836*** (0.949)	-2.763*** (0.932)
Training	-0.008 (0.012)	-0.007 (0.011)	-1.094 (0.950)	-1.191 (0.939)
Observations	6556	6556	4446	4446
Sample	All	All	Completed	Completed
Block FE		✓		✓
Control mean	0.68	0.68	73.37	73.37
Control std. dev.	0.47	0.47	29.4	29.4
DV range	{0,1}	{0,1}	[0,100]	[0,100]

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Decomposing the “effect” on scores

- Post-treatment estimates suggests that direct communication \rightarrow ↓ scores, but there are two possible explanations.
 1. **Treatment effect:** Those that would always report submit lower scores when subjected to oversight.
 2. **Selection/compositional change:** Those that report because of treatment report lower average reported scores than those that always report.
- Assuming monotonicity, we can **decompose** post-treatment estimand into:
 - CATE on always-reporters \rightarrow Lee (2009) trimming bounds!
 - **Average outcomes** (scores) of if-treated reporters \rightarrow boundable if we have post-treatment estimate, treatment effect on reporting, and CATEs.

Decomposition

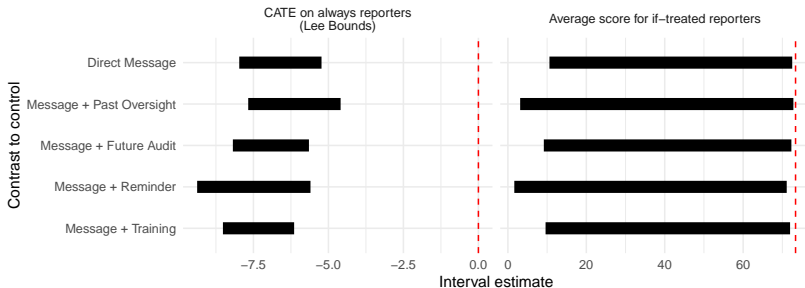
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Decomposition

Treatment effects or selection?

- Evidence of **both** treatment effects and selection:
 - ↓ scores among always reporters.
 - Lower-than-average scores among if-treated reporters.



What do/don't we learn from the experiment?

- Manipulation of the role of the PGN/visibility of oversight:
 - Induce public sector entities to report **less desirable** scores.
 - Change the **composition** of entities that report to the national government.
- What we cannot observe from the experiment:
 - Who **selects** into reporting?
 - **Accuracy**: how do reported scores relate to actual quality?

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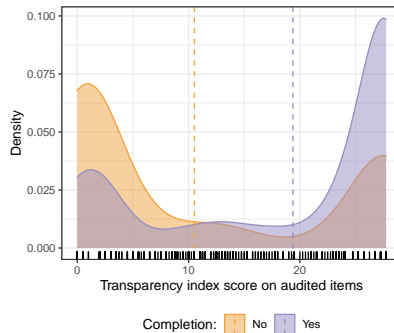
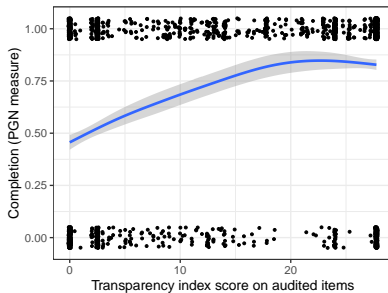
- Manipulation of the role of the PGN/visibility of oversight:
 - Induce public sector entities to report **less desirable** scores.
 - Change the **composition** of entities that report to the national government.
- What we cannot observe from the experiment:
 - Who **selects** into reporting?
 - **Accuracy**: how do reported scores relate to actual quality?

Results II: Audit Findings



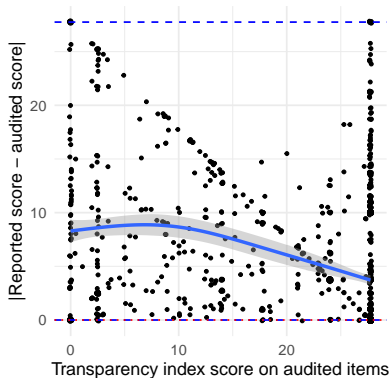
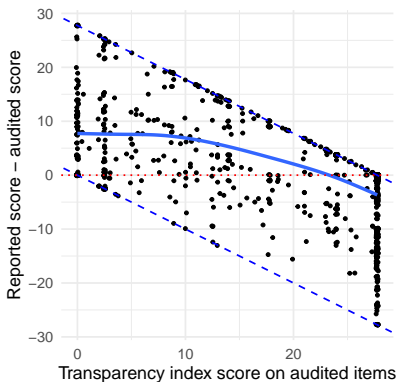
Which entities select into reporting?

- **Positive selection** into reporting as a function of “true” transparency practices, θ .



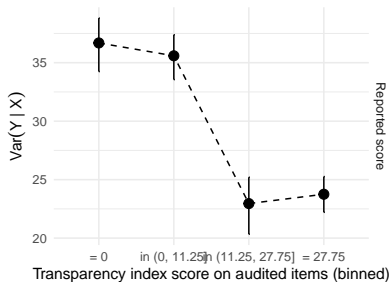
Are reported scores accurate?

- At lower levels of θ , reported scores are **less accurate**.
 - In general, scores are **over-reported**.



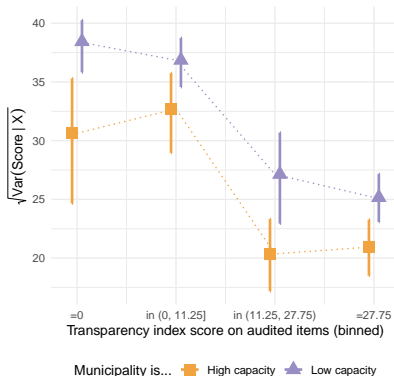
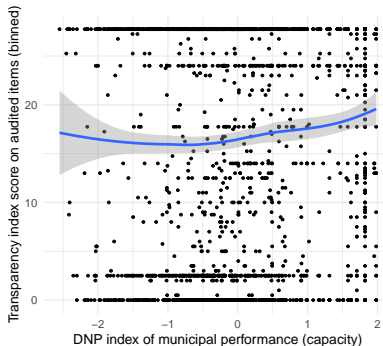
When are reported scores less noisy?

- Variance of reported scores is **decreasing** in θ .
 - Observed pattern not driven (exclusively) by **state capacity** or **intentional distortion**.
 - Within framework, suggests that lower θ entities exert less effort.



Is this all just variation in state capacity?

- State capacity arguably increases **costs of effort**, $c(e)$.
 - Should \downarrow effort $\rightarrow \uparrow$ variance of ε
- Using Departamento Nacional de Planeación's medición de desempeño municipal we stratify on **municipal capacity**
 - We still observe decrease in conditional variance in θ .



Discussion



The central government's problem

- By experimenting, we have abstracted away from the **central government's problem**: When can data collected from decentralized entities be used to inform policies concerning those entities?
 - A preoccupation of central government entities.
- In our problem, recall that there are two **policy instruments** that central governments set:
 - Probability of oversight: $p(r) \in (0,1)$.
 - Penalties imposed when oversight reveals poor outcomes: $P(\theta, r) > 0$.

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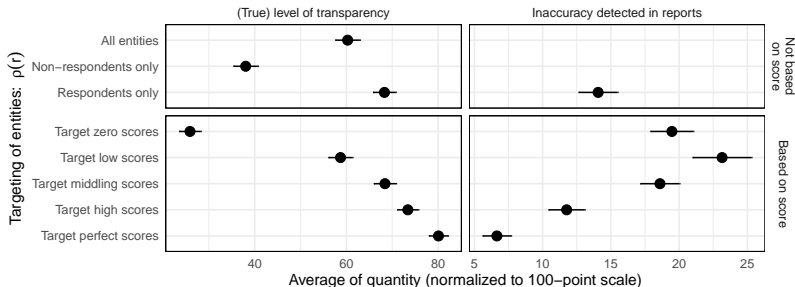
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 - But, we can think about what the government would "see" under different instruments fixing the "mechanism" from the experiment.

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Reporting behavior conditions what PGN find

- We **simulate** what the PGN should observe depending on how they target preventative efforts, $\rho(r)$.
 - PGN sees **reports** (r).
 - We observe **reports** (r) and the **truth** (\boxtimes).



Take-aways

- Administrative data as a bureaucratic output and **political outcome** matters:
 - to **you** as a producer/consumer of empirical social science.
 - to **governments** that collect data in order to use it.
- Data production as an understudied aspect of **intergovernmental relations**.

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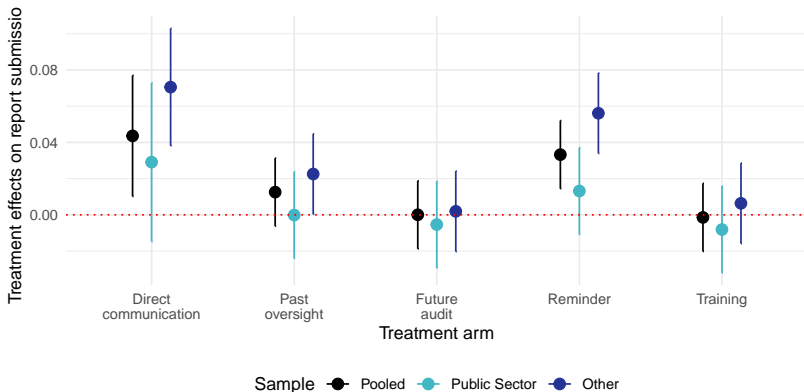
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Thank you!



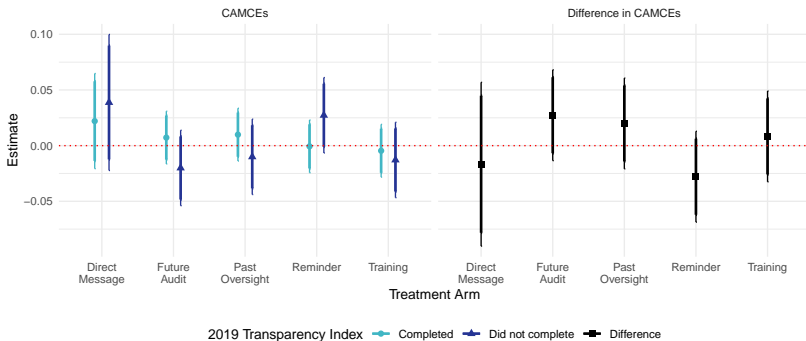
Benchmark: Private Sector Entity Completion

- We estimate the **ATE** of direct communication and the **AMCEs** of the messages in the factorial design. Estimator
- Outcome: Indicator for ITA data submission.



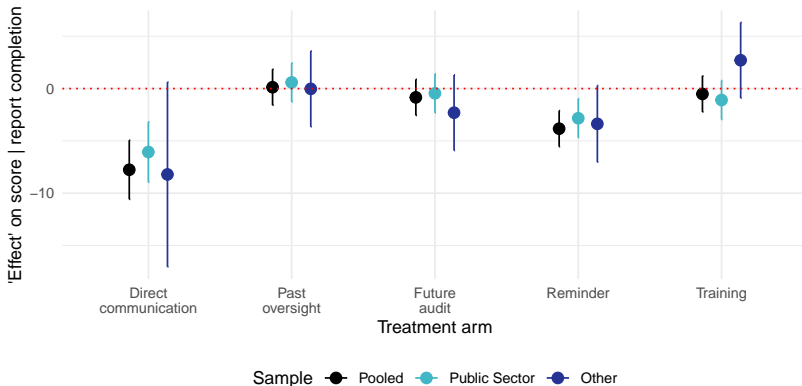
Was treatment solely informational?

- We estimate the **CATE** of direct communication and the **CAMCEs** of the messages conditioning on 2019 ITA completion. Estimator
- Outcome: Indicator for ITA data submission.



Benchmark: Private Sector Entity Scores

- We estimate the same specification with scores as the outcome, but condition on reporting.
- Estimates of a **post-treatment** estimand that contains both a causal effect and a “selection” effect.



Decomposition of post-treatment estimand

- Under monotonicity, there are three strata: Always reporters, if-Treated reporters, Never reporters
 - Denote types by $j \in \{A, T, N\}$ with shares π_j , where $\sum_j \pi_j = 1$.
- The “post-treatment” estimand is \mathcal{P} . We can express this quantity as:

$$\begin{aligned}\mathcal{P} &= \frac{\pi_A}{\pi_A + \pi_T} \underbrace{\left(E[S(Z=1)|j=A] - E[S(Z=0)|j=A] \right)}_{\text{Change in scores reported}} + \\ &\quad \frac{\pi_T}{\pi_A + \pi_T} \underbrace{\left(E[S(Z=1)|j=T] - E[S(Z=0)|j=A] \right)}_{\text{Change in composition of reporters}} \\ &= \frac{\pi_A}{\pi_A + \pi_T} CATE + \frac{\pi_T}{\pi_A + \pi_T} \left(E[S(Z=1)|j=T] - E[S(Z=0)|j=A] \right)\end{aligned}\tag{1}$$

- We have point estimates for: \mathcal{P} , $\frac{\pi_A}{\pi_A + \pi_T}$, $\frac{\pi_T}{\pi_A + \pi_T}$, and $E[S(Z=0)|j=A]$ (under monotonicity).
- We can use Lee (2019) bounds to generate an interval estimate of $CATE$.
- We can then use algebra to generate an interval estimate of $E[S(Z=1)|j=T]$.