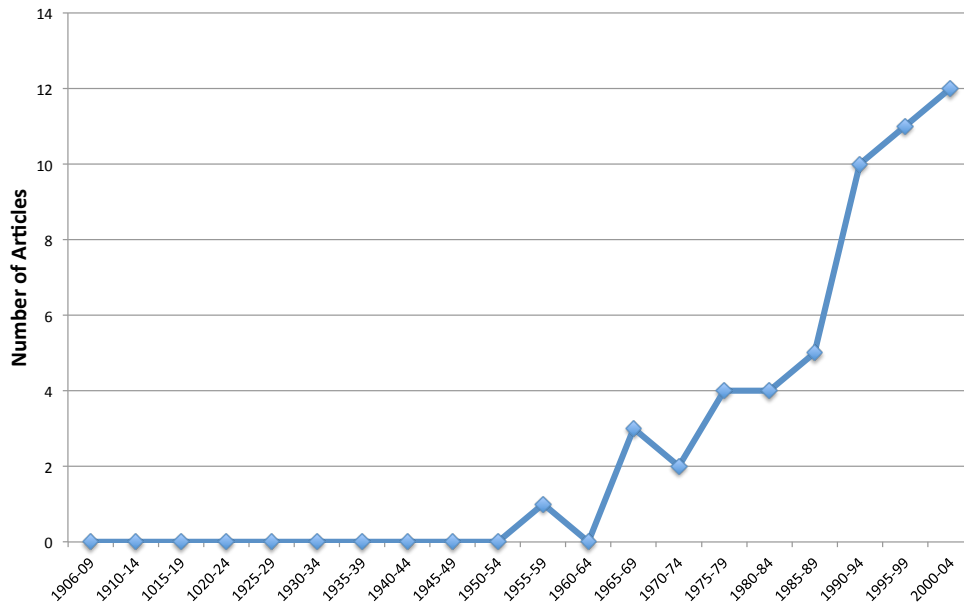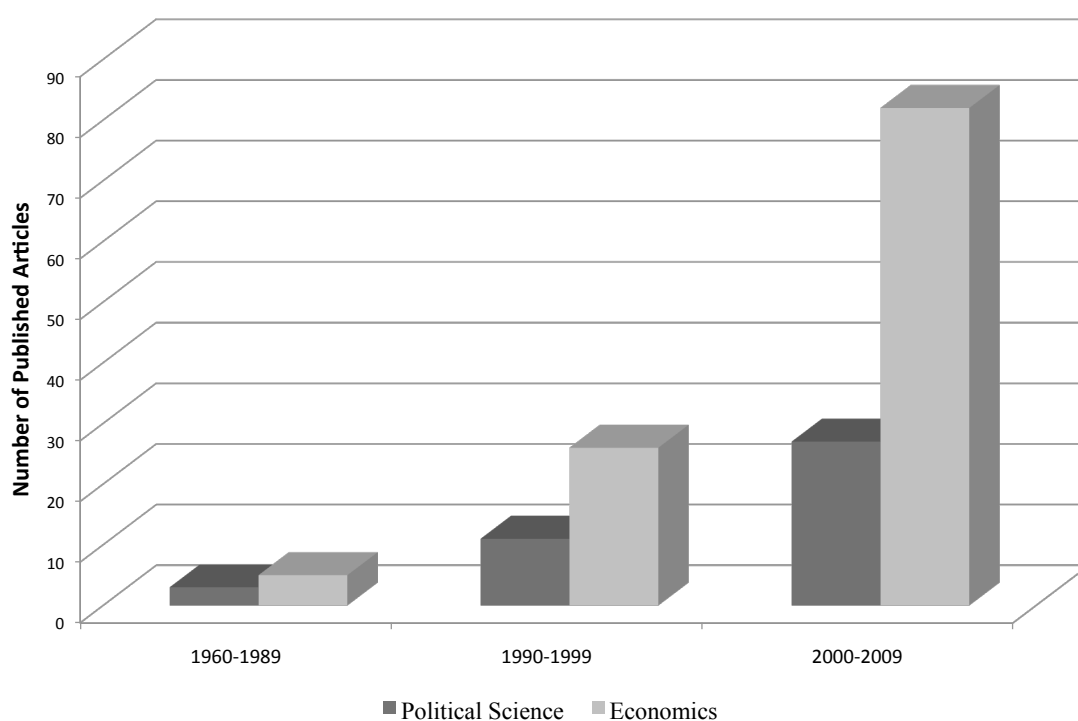# What Can We Learn from the Experimental Turn?

Thad Dunning
Department of Political Science
University of California, Berkeley

Randomized Controlled Experiments Published in the *American Political Science Review* (1906-2004)

Source: Jamie Druckman, Donald P. Green, James H. Kuklinski, and Arthur Lupia. 2006. "The Growth and Development of Experimental Research Political Science." *American Political Science Review* 100: 627-635.

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Natural Experiments in Political Science and Economics

Articles published in major political science and economics journals with "natural experiment" in the title or abstract (as tracked in the online archive JSTOR).

Growth of Regression-Discontinuity Designs
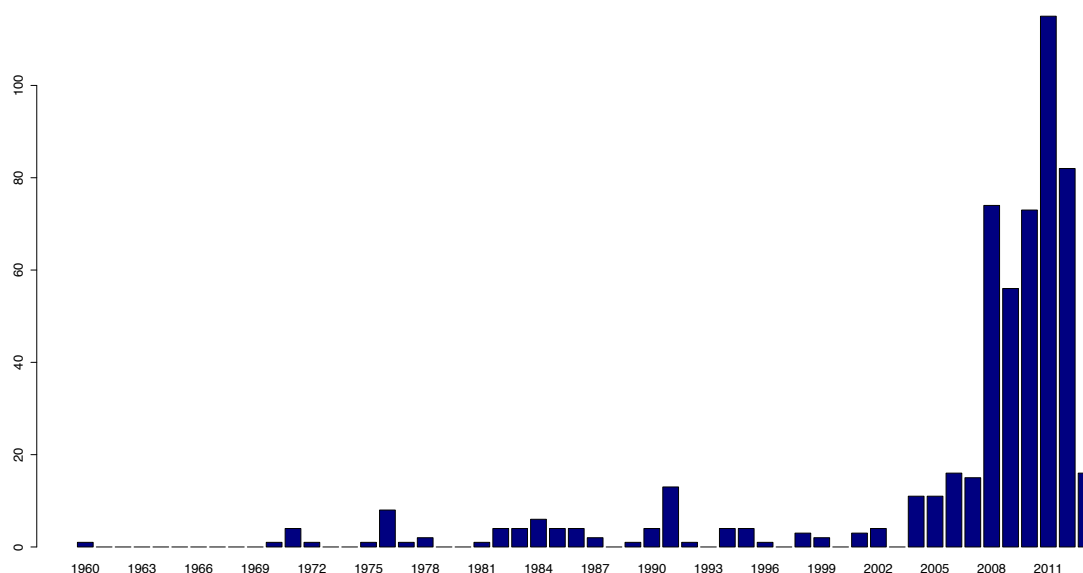
Figure : The figure shows the number of peer-reviewed journal publications in economics and political science that refer to an RD design in the title or abstract.

Promise and Pitfalls of the Experimental Turn

- Three (Qualified) Cheers for Design-Based Inference

Promise and Pitfalls of the Experimental Turn

- Three (Qualified) Cheers for Design-Based Inference
- The Challenge of Cumulative Learning

Promise and Pitfalls of the Experimental Turn

- Three (Qualified) Cheers for Design-Based Inference
- The Challenge of Cumulative Learning
- Whither the Experimental Turn?

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Cheer #1: From complicated models to credible multi-method research

- In principle, experiments and natural experiments are design-based rather than model-based methods

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Cheer #1: From complicated models to credible multi-method research

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- Inferential leverage comes more from the research design and not from modeling (e.g., multivariate regression, matching)
- A simple comparison of means may suffice to establish a causal effect
  - ▸ As Freedman (2009: 9) puts it, "It is the design of the study and the size of the effect that compel conviction."

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John Snow's famous study of cholera

Death rate from cholera in London, by source of water supply

	Rate per 10,000 houses
Southwark & Vauxhall	315
Lambeth	37
Rest of London	59

(adapted from Snow 1855, Table IX)

Digital Democratization (Danny Hidalgo 2011)

RESULTS: INVALID VOTES
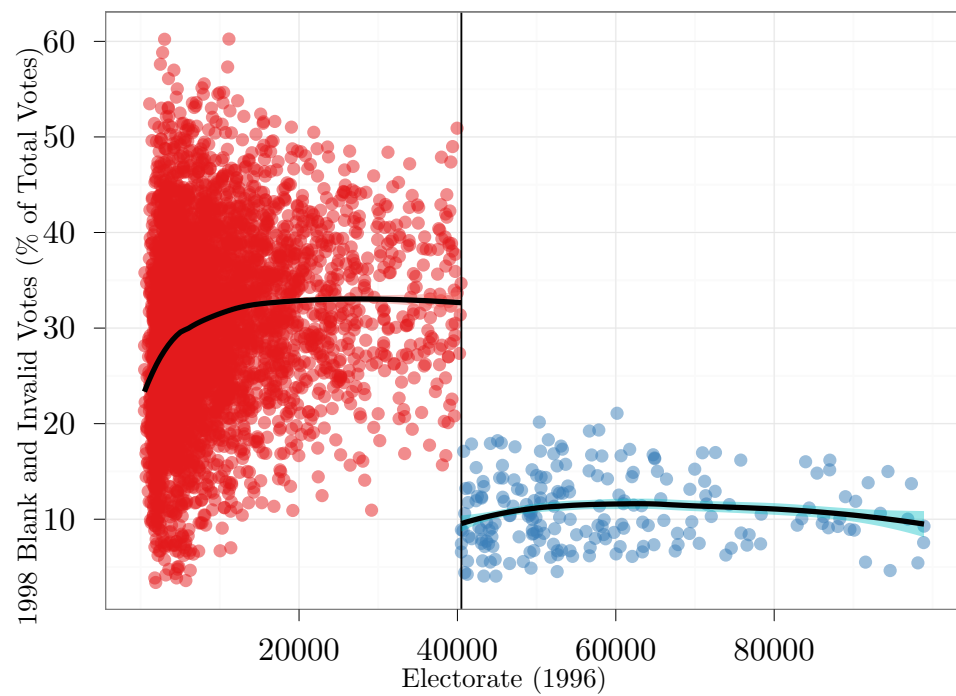
Simple analysis: graphical balance tests (Hidalgo 2011)

BALANCE

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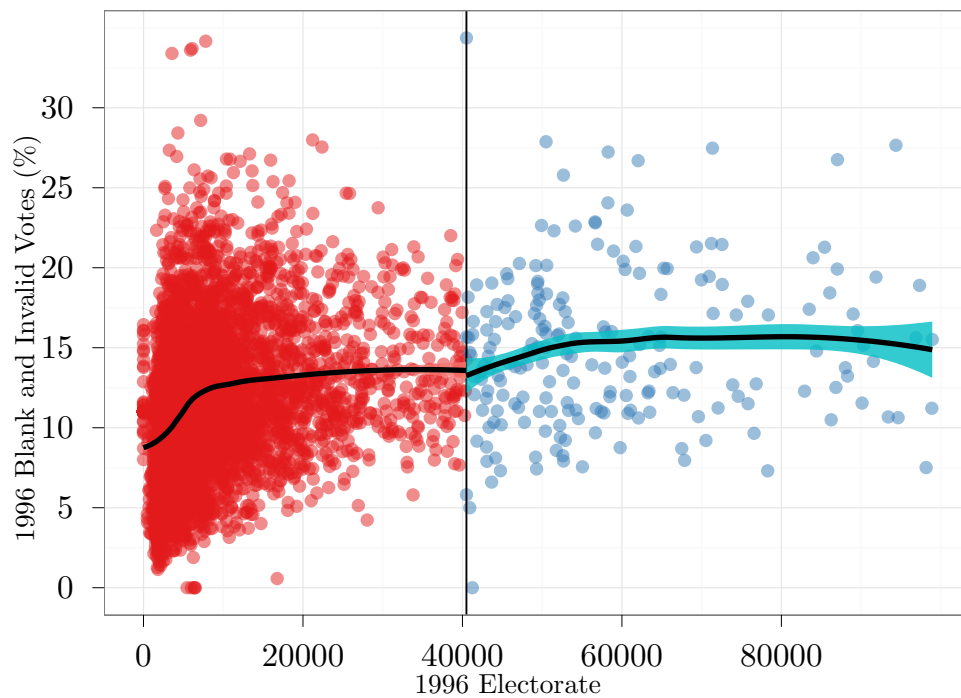
But how credible is the model?
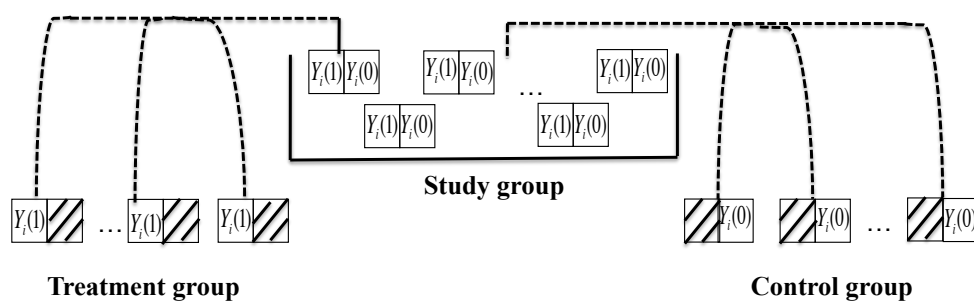
If the model applies, analysis is simple ...

Study group

Treatment group   Control group
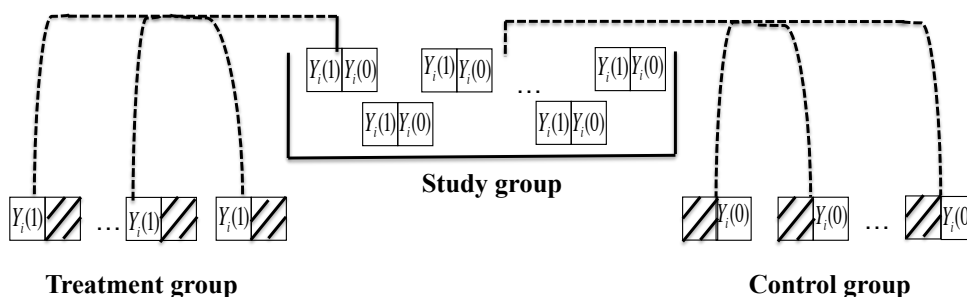
The estimand: $\dfrac{1}{N}\sum_{i=1}^{N}[Y_i(1) - Y_i(0)]$

An unbiased estimator: $\dfrac{1}{m}\sum_{i=1}^{m}[Y_i \mid T_i = 1] - \dfrac{1}{N-m}\sum_{i=m+1}^{N}[Y_i \mid T_i = 0]$

where T_i is an indicator for treatment assignment. Under this model, a random subset of size *m<N* units is assigned to treatment. The units assigned to the treatment group are indexed from 1 to *m*.

...but simplicity and credibility are not guaranteed.

| | | Case Management | |
		No	Yes
	No	(A) 10.5%	(B) 9.0%
Cash			
Incentives	Yes	(C) 14.8%	(D) 19.7%

The table displays high-school graduation rates of teenage mothers randomly assigned to receive: (B) case management; (C) cash incentives; (A) neither; or (D) both. Results are shown for mothers who were not in school at program entry. Adapted from Mauldon et al (2000, 35), N=531.

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A model-based alternative

- Logistic regression is a common choice for analyzing experimental data with dichotomous outcomes. According to a latent-variables formulation,

$$Y_i = 1 \text{ iff } \alpha + \beta_1 C_i + \beta_2 F_i + \beta_3 (C_i * F_i) + u_i > 0, \quad (1)$$

where u_i is a random variable drawn from the standard logistic distribution; the u_i are assumed to be independent and identically distributed (i.i.d.) across subjects. Here, $C_i = 1$ if mother i is assigned to case management and $F_i = 1$ if assigned to financial incentives; if she graduates from high school, $Y_i = 1$.

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Where the modeling goes awry

- Why is there a latent variable u_i, and why are its realizations i.i.d.? Why are the probabilities independent across i? Why the logistic distribution function?

Where the modeling goes awry

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  - ▸ The assumptions are quite different from the box model, where observations are neither independent nor identically distributed—and there is no latent variable u_i in the picture.

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- Note that the difference between average potential outcomes in the cash*case condition and the control is *not*

$$\Lambda(\alpha + \beta_1 + \beta_2 + \beta_3) - \Lambda(\alpha). \tag{2}$$

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$$\Lambda(\alpha + \beta_1 + \beta_2 + \beta_3) - \Lambda(\alpha). \tag{2}$$

- For this difference, you need to ignore the β_1 and β_2 terms, leaving $\Lambda(\alpha + \beta_3) - \Lambda(\alpha)$.
  - ▸ But the counterfactual reasoning is bizarre: according to the model, when $C_i = 1$ and $F_i = 1$, β_1 and β_2 should not drop out.

The importance of assumptions

- The Neyman model is flexible and general; for experiments and natural experiments, it often provides the right starting point.

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- Key point: in some studies, the assumptions are plausible; in others, they are more suspect.

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- Key point: in some studies, the assumptions are plausible; in others, they are more suspect.
- With design-based research assumptions have more precise implications—and thus are amenable to partial verification, through simple analysis.

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Cheer #2: Close engagement with research contexts

- Design-based inference often requires close engagement with the field

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- This is "extracting ideas at close range" (Collier 1999)

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- This is "extracting ideas at close range" (Collier 1999)
- Thus, natural complementaries between design-based approaches and traditional strengths of area studies

How do property rights affect the poor? (Galiani and Schargrodsky 2006, 2007)

- In 1981, squatters organized by the Catholic church occupied an urban wasteland in the province of Buenos Aires, dividing the land into similar parcels

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- The authors administered surveys to both groups

Effects of property rights

The Effects of Land Titles on Children's Health

	Property Right Offer=1	Property Right Offer=0	Difference of Means
Weight-for-Height Z-score	0.279 [239]	0.065 [132]	0.214 [371]
Height-for-Age Z-score	0.398 [277]	0.314 [147]	0.084 [424]
Teenage Pregnancy Rate	0.079 [63]	0.208 [24]	0.128 [87]

Source: Galiani and Schargrodsky (2004). Notice that this is intention-to-treat analysis. In the first two rows, data for children ages 0-11 are shown; in the third row, data for teenage girls aged 14-17 are shown. The number of observations is in brackets.

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Was the ceding of titles as-if random?

- For the Argentina land-titling study, one can do quantitative tests of design (e.g. tests for balance on pre-treatment covariates).

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  - ▸ They did not anticipate the expropriation of land by the state
  - ▸ They had no basis for predicting which particular plots of land would have been expropriated, and thus for assigning plots to particular squatters
- This information does not come from data analysis (or Data Set Observations; see Collier and Brady 2010) but rather from knowledge of context and process (a.k.a., causal process observations)

Process tracing

- Qualitative methods and contextual knowledge are often *required* for designing and validating natural experiments.

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Process tracing

- Qualitative methods and contextual knowledge are often *required* for designing and validating natural experiments.
  - ▸ **Treatment-Assignment CPOs**: pieces or nuggets of information about the process by which units were assigned to treatment and control conditions. Do key actors have the information, incentives, and capacity to undermine random assignment?

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  ▸ **Model-Validation CPOs**: Information that contributes to validating or undermining assumptions of causal models (e.g., non-interference, exclusion restrictions).

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Process tracing

- Qualitative methods and contextual knowledge are often *required* for designing and validating natural experiments.

  ▸ **Treatment-Assignment CPOs**: pieces or nuggets of information about the process by which units were assigned to treatment and control conditions. Do key actors have the information, incentives, and capacity to undermine random assignment?

  ▸ **Model-Validation CPOs**: Information that contributes to validating or undermining assumptions of causal models (e.g., non-interference, exclusion restrictions).

- The information contained within a CPO typically reflects in-depth knowledge of one or more units, and/or the broader context in which data-set observations were generated.

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What can go wrong?

- Freedman (2010) discusses the use of qualitative tools in epidemiological research.

What can go wrong?

- Freedman (2010) discusses the use of qualitative tools in epidemiological research.
  - ▸ A possible concern: illustrations of successful use of CPOs may select on the dependent variable.

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What can go wrong?

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- Often, the deep contextual knowledge required to validate a natural experiment is esoteric.

What can go wrong?

- Freedman (2010) discusses the use of qualitative tools in epidemiological research.
  - ▸ A possible concern: illustrations of successful use of CPOs may select on the dependent variable.
- Often, the deep contextual knowledge required to validate a natural experiment is esoteric.
- How can we validate the quality of the CPOs in any given application?

Mixed-Method Experimental Research

- Dunning and Harrison (2010) study the social institution of cousinage ties (joking kinship) in Mali—which cross-cut ethnic ties.

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Mixed-Method Experimental Research

- Dunning and Harrison (2010) study the social institution of cousinage ties (joking kinship) in Mali—which cross-cut ethnic ties.

- Can cousinage help explain low levels of ethnic voting in Mali?

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Experimental Design

TABLE 1. Experimental Design: Subjects Assigned to Treatment and Control Conditions

	Subject and politician are joking cousins	Subject and politician are not joking cousins
Subject and politician are from the same ethnic group	$N = 136$	$N = 122$
Subject and politician are from different ethnic groups	$N = 124$	$N = 152$
	Control conditions	
Politician's last name not given	$N = 132$	
Subject and politician have the same last name	$N = 158$	

Assignment Matrix

TABLE 2. Typical Row of Our Random Assignment Matrix						
Subject's Surname (Ethnicity)	(1) Coethnic/ Cousin	(2) Coethnic/ Not Cousin	(3) Not Coethnic/ Cousin	(4) Not Coethnic/ Not Cousin	(5) No Name	(6) Same Name
Keita (Maninka)	1. Sissoko 2. Konaté	1. Diané	1. Doucouré 2. Sacko 3. Sylla 4. Coulibaly 5. Touré	1. Diallo 2. Cissé 3. Dambelé 4. Théra 5. Touré 6. Togola 7. Watarra	Pas de nom	Keita

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Experimental Effects

FIGURE 1.   Average Candidate Evaluations, by Treatment Assignment
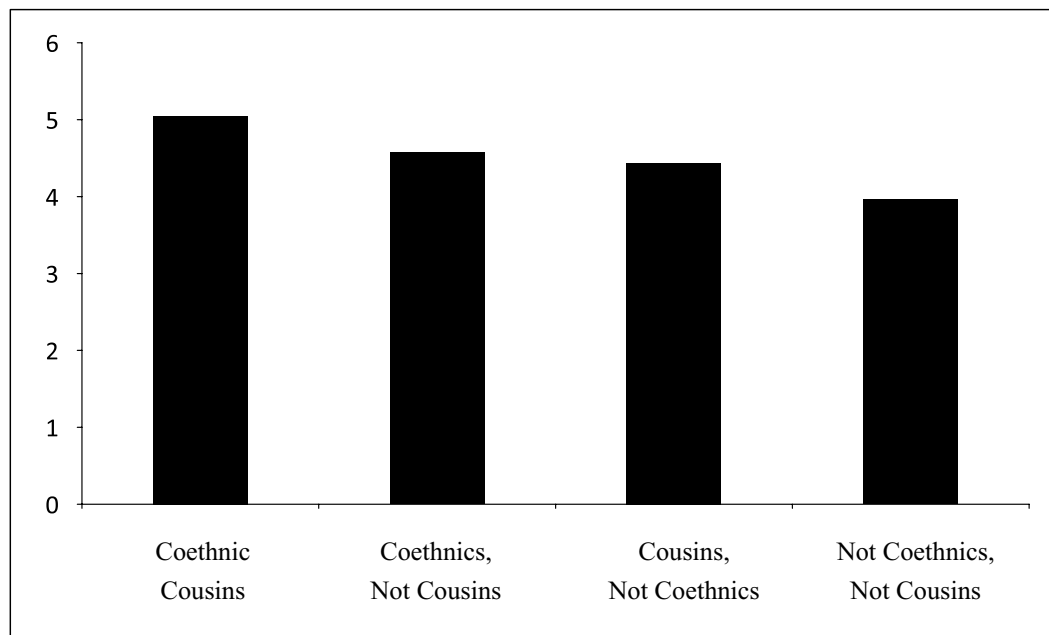
The figure reports average answers by treatment assignment category to the question, "On a scale of 1 to 7, how much does this speech make you want to vote for (*name of politician/this candidate*)?"

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Engagement with the field

- Dunning and Harrison (2010) drew on local informants to learn about which surname pairs create cousinage ties, which is required for constructing the assignment matrix.

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- Dunning and Harrison (2010) drew on local informants to learn about which surname pairs create cousinage ties, which is required for constructing the assignment matrix.
- There can be a real complementarity between experiments in the field and various qualitative methods—often, the latter are *required* for the former:

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  - ▸ Design of treatments.

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  - ▸ Measurement of outcomes.

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  - ▸ Interpretation of results.

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- There can be a real complementarity between experiments in the field and various qualitative methods—often, the latter are *required* for the former:
  - ▶ Design of treatments.
  - ▶ Measurement of outcomes.
  - ▶ Interpretation of results.
  - ▶ Identification of mechanisms through "experimental ethnography" (Paluck 2010).

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Engagement with the field

- Dunning and Harrison (2010) drew on local informants to learn about which surname pairs create cousinage ties, which is required for constructing the assignment matrix.
- There can be a real complementarity between experiments in the field and various qualitative methods—often, the latter are *required* for the former:
  - ▸ Design of treatments.
  - ▸ Measurement of outcomes.
  - ▸ Interpretation of results.
  - ▸ Identification of mechanisms through "experimental ethnography" (Paluck 2010).
- Experiments are sometimes viewed as a "quantitative" method, but many of the features and attributes of qualitative field research are crucial.

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Cheer #3: Planned and registered analysis

- A growing movement towards pre-planning and registration of data analysis protocols.

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Cheer #3: Planned and registered analysis

- A growing movement towards pre-planning and registration of data analysis protocols.
  - ▸ Helps distinguish between ex-ante and ex-post hypotheses. Ex-post analysis is fine and useful—but it is helpful to know the difference.

Cheer #3: Planned and registered analysis

- A growing movement towards pre-planning and registration of data analysis protocols.
  - ▶ Helps distinguish between ex-ante and ex-post hypotheses. Ex-post analysis is fine and useful—but it is helpful to know the difference.
  - ▶ Substantially limits inferential problems from data mining and allows for meaningful/credible adjustment for multiple statistical comparisons.

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Cheer #3: Planned and registered analysis

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- For design-based inference, it helps a lot to think things through first!

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- But will registration solve the problems it seems designed to solve?

Evidence of publication bias #1
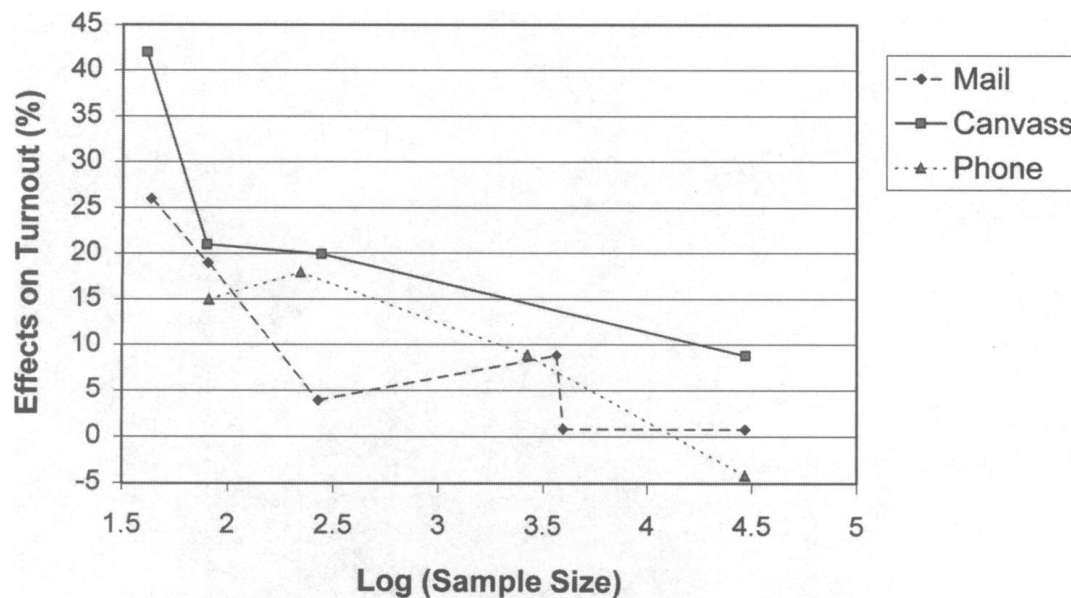
Fig. 1   Relationship between sample size and effect size.

Gerber, Green and Nickerson (2001)

Source:

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Evidence of publication bias #2
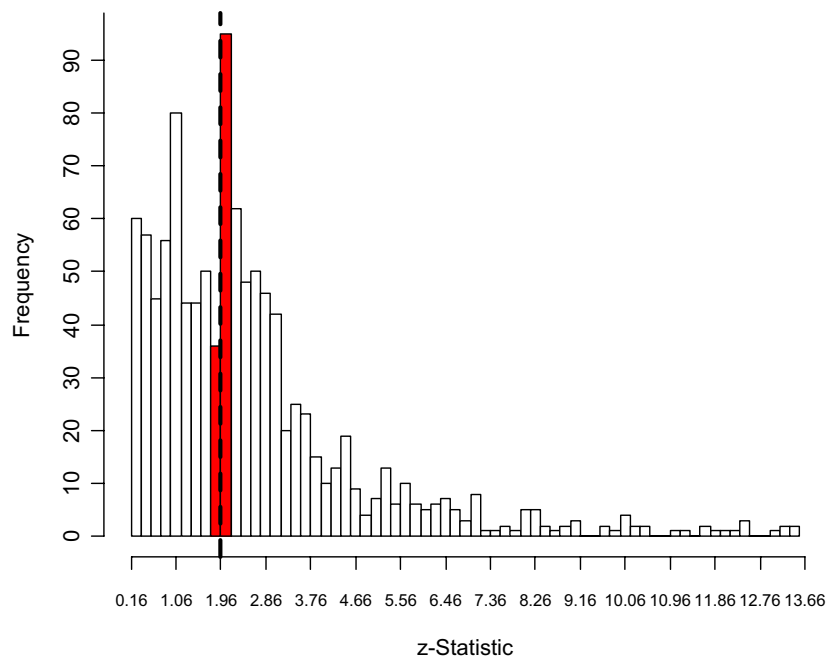
Figure 1(a). Histogram of z-statistics, *APSR & AJPS* (Two-Tailed). Width of bars (0.20) approximately represents 10% caliper. Dotted line represents critical z-statistic (1.96) associated with $p = 0.05$ significance level for one-tailed tests.

Source:

Gerber and Malhotra (2008)

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What practices could fix publication bias?

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What practices could fix publication bias?

- **Study registration**
  - ▶ Allows description of universe of studies

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What practices could fix publication bias?

- **Study registration**
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  - ▸ But also leaves substantial researcher degrees of freedom

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  - ▸ But does not necessarily limit publication bias
- **Results-blind review**

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  - ▸ Allows evaluation based on the quality of the research question and strength of the design not the statistical significance of estimated effects

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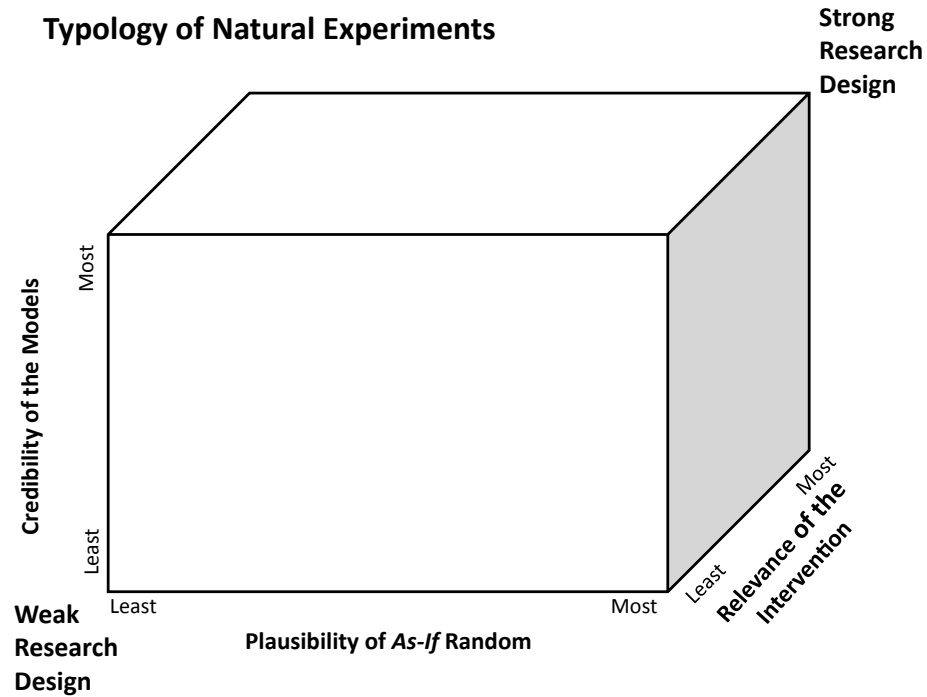
- **Pre-analysis plans**
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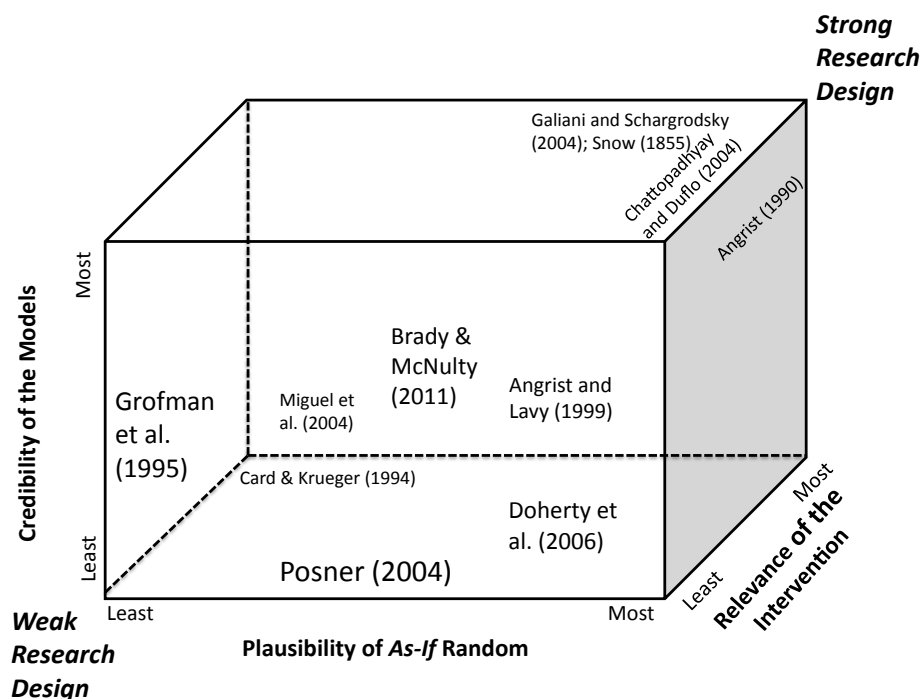
- **Results-blind review**
  - ▶ Allows evaluation based on the quality of the research question and strength of the design not the statistical significance of estimated effects
  - ▶ A potentially powerful tool for limiting publication bias (but not practiced yet); some potential drawbacks but not insurmountable

What is strong design? (from Dunning, *Natural Experiments in the Social Sciences*, 2012)

Typology of Natural Experiments

What is strong design? (from Dunning, *Natural Experiments in the Social Sciences*, 2012)

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The challenge of cumulative learning: an example on community monitoring

This paper presents a randomized field experiment on community-based monitoring of public primary health care providers in Uganda. Through two rounds of village meetings, localized nongovernmental organizations encouraged communities to be more involved with the state of health service provision and strengthened their capacity to hold their local health providers to account for performance. A year after the intervention, treatment communities are more involved in monitoring the provider, and the health workers appear to exert higher effort to serve the community. We document large increases in utilization and improved health outcomes—reduced child mortality and increased child weight—that compare favorably to some of the more successful community-based intervention trials reported in the medical literature.

Source: Bjorkmann and Svensson 2009

But perhaps only top-down monitoring matters...

This paper presents a randomized field experiment on reducing corruption in over 600 Indonesian village road projects. I find that increasing government audits from 4 percent of projects to 100 percent reduced missing expenditures, as measured by discrepancies between official project costs and an independent engineers' estimate of costs, by eight percentage points. By contrast, increasing grassroots participation in monitoring had little average impact, reducing missing expenditures only in situations with limited free-rider problems and limited elite capture. Overall, the results suggest that traditional top-down monitoring can play an important role in reducing corruption, even in a highly corrupt environment.

Source: Olken 2007

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Or perhaps community monitoring doesn't matter at al

We study a randomized educational intervention in 550 households in 26 matched villages in two Kenyan districts. The intervention provided parents with information about their children's performance on literacy and numeracy tests, and materials about how to become more involved in improving their children's learning. We find the provision of such information had no discernible impact on either private or collective action. In discussing these findings, we articulate a causal chain linking information provision to changes in citizens' behavior, and assess the present intervention at each step. Future research on information provision should pay greater attention to this causal chain.

Source: Tsai, Lieberman, and Posner 2013

Challenges to cumulation

- Similar questions arise in many settings—e.g. the effects of information on political accountability

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Challenges to cumulation

- Similar questions arise in many settings—e.g. the effects of information on political accountability
- Answers from distinct research projects could differ for many reasons:

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Challenges to cumulation

- Similar questions arise in many settings—e.g. the effects of information on political accountability
- Answers from distinct research projects could differ for many reasons:
  - ▶ The interventions are different

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- Similar questions arise in many settings—e.g. the effects of information on political accountability
- Answers from distinct research projects could differ for many reasons:
  - ▸ The interventions are different
  - ▸ The outcomes are different
  - ▸ "It depends"

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- Similar questions arise in many settings—e.g. the effects of information on political accountability
- Answers from distinct research projects could differ for many reasons:
  - ▸ The interventions are different
  - ▸ The outcomes are different
  - ▸ "It depends"
- Publication biases are also a real concern.

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EGAP *Metaketa*

- The Experiments in Governance and Politics (EGAP) group, in conjunction with the Center on the Politics of Development at Berkeley, is currently leading an effort emphasizing:

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  - ▸ integrated research programs

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EGAP *Metaketa*

- The Experiments in Governance and Politics (EGAP) group, in conjunction with the Center on the Politics of Development at Berkeley, is currently leading an effort emphasizing:
  - ▸ integrated research programs
  - ▸ teams of researchers

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Cumulative Learning?
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  - ▸ integrated research programs
  - ▸ teams of researchers
  - ▸ projects in parallel around the world
  - ▸ generalizable answers to major questions of scholarly and policy importance(hopefully!)

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The motivation

- Individual researchers working do not necessarily generate the optimal set of studies for knowledge cumulation
- Publication bias

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The motivation

- Individual researchers working do not necessarily generate the optimal set of studies for knowledge cumulation
- Publication bias
- Little replication of existing studies
- Value of being first
- Little coordination across countries, even with similar interventions

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Background on Metaketa Round 1

- Challenge to come up with a question that:

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Background on Metaketa Round 1

- Challenge to come up with a question that:
  - ▶ Fit with the general predefined substantive area

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Background on Metaketa Round 1

- Challenge to come up with a question that:
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  - ▸ Is important to policymakers and academics
  - ▸ Includes interventions and outcomes that can be unified across multiple studies

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Background on Metaketa Round 1

- Challenge to come up with a question that:
  - ▸ Fit with the general predefined substantive area
  - ▸ Is important to policymakers and academics
  - ▸ Includes interventions and outcomes that can be unified across multiple studies
  - ▸ Leaves sufficient leeway to researchers to innovate (publish)

Research question: Why do voters select underperforming politicians?

- Two-arm proposal structure:

Research question: Why do voters select underperforming politicians?

- Two-arm proposal structure:
  - ▸ A common informational arm, focused on performance of politicians

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Research question: Why do voters select underperforming politicians?

- Two-arm proposal structure:
  - ▸ A common informational arm, focused on performance of politicians
  - ▸ At least one alternate arm that may vary across projects.

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Research question: Why do voters select underperforming politicians?

- Two-arm proposal structure:
  - ▸ A common informational arm, focused on performance of politicians
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- This structure promotes replication and comparability—through the first treatment arm—while preserving room for innovation through the second arm.

Research question: Why do voters select underperforming politicians?

- Two-arm proposal structure:
  - ▶ A common informational arm, focused on performance of politicians
  - ▶ At least one alternate arm that may vary across projects.
- This structure promotes replication and comparability—through the first treatment arm—while preserving room for innovation through the second arm.
  - ▶ Challenges: Capacity to generate integrated projects is untested; failure rate of individual studies may be high; heterogeneous treatment effects.

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Projects in Metaketa Round #1

Project	Title	PIs	Information on...	Method
Benin	Can Common Knowledge Improve Common Goods?	Adida, Gottlieb, McClendon, &Kramon	legislative performance of **deputies in the National Assembly**	Legislator performance info provided publicly or privately and a civics message
Mexico	Common Knowledge, Relative Performance, & Political Accountability	Larreguy, Arias, Querubin, & Marshall	corruption and the misuse of public funds by **local government officials**	Leaflets distr. door-to-door vs. leaflets w/cars using loudspeakers
India	Using Local Networks to Increase Accountability	Chauchard &Sircar	financial crimes against **Members of the state assembly**	Door-to-door campaigns vs. public rallies
Brazil	Accountability & Incumbent Performance in Brazilian Northeast	Hidalgo, Boas, & Melos	performance gathered from audit reports of the **local government**	Report cards & an oral message
Burkina Faso	Citizens at the Council	Lierl & Holmlund	service delivery by the **municipal government**	Scorecard vs. attending local council meeting
Uganda I	Information & Accountability in Primary & General Elections	Raffler &Platas Izama	service delivery by the **local government**	Recorded candidate statements viewed publicly &privately
Uganda II	Repairing Information Underload	Nielson, Buntaine, Bush, Pickering & Jablonski	service delivery by the **local government/** variation in info effect if $ from foreign donors?	Information sent by SMS to randomly sampled households.

What do these projects have in common?

- Each provides performance information relevant to voter welfare
- Each provides relative performance information
- Each provides information that is attributable to a candidate
- Each provides the information privately to individuals
- Each uses publicly available performance information.
- There is no deception involved in any of the interventions.
- Each is implemented in collaboration with a local partner.

How can we characterize their differences?

RELEVANCE FOR INDIVIDUAL WELFARE

Low   **High**

Programmatic stances	Legislative performance	Performance audits	Malfeasance, corruption, criminality	Public service delivery	Targeted policies
Raffler/Izama	(attendance records): Adida et al., Nielson et al.	(accounting, procurement): Hidalgo/Boas, Nielson et al.	Arias et al., Chauchard, Sircar	Nielson et al., Lierl/ Holmlund, Raffler/Izama	Hidalgo/Boas crop guarantee

What do these projects have in common?

- All projects in the Metaketa will abide by a common set of principles above and beyond minimal requirements:
  - ‣ Principles on research transparency (http://egap.org/resources/egap-statement-of-principles/)
  - ‣ Protect staff: Do not put research staff in harms way.
  - ‣ Informed consent: Participantsknow that information they get is provided as part of a research project. Core project data will be publicly available in primary languages at http://egap.org/research/metaketa/
  - ‣ Partnership with local civil society actors
  - ‣ Non-partisan interventions
  - ‣ Approval from the relevant electoral commission when appropriate

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Some challenges

- Seven studies participating in Metaketa I
- EGAP Metaketa I committee staff facilitating coordination across teams of researchers
- Drafting committee and PIs wrote plan of plans
- New challenges emerged
  - ▶ Meta-analysis; links to theory; what to do about covariate adjustment . . .