Corruption information and vote share: A meta-analysis and lessons for survey experiments

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Introduction

Research Question

Do voters hold politicians accountable for corruption?

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- ARPS review: "Empirical evidence to date is mixed, and it often suggests that the electoral punishment of corruption is rather mild." (De Vries & Solaz 2017)
- Recent explosion of experimental research on this subject.
- What have we learned from this research? Is evidence actually mixed?

Methods

Meta-Analysis

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- Includes both published articles and working papers.

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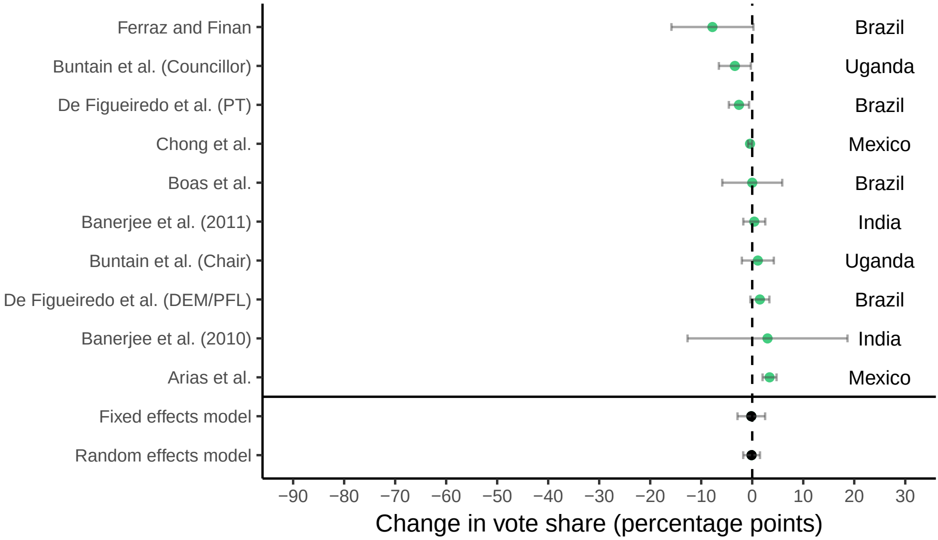
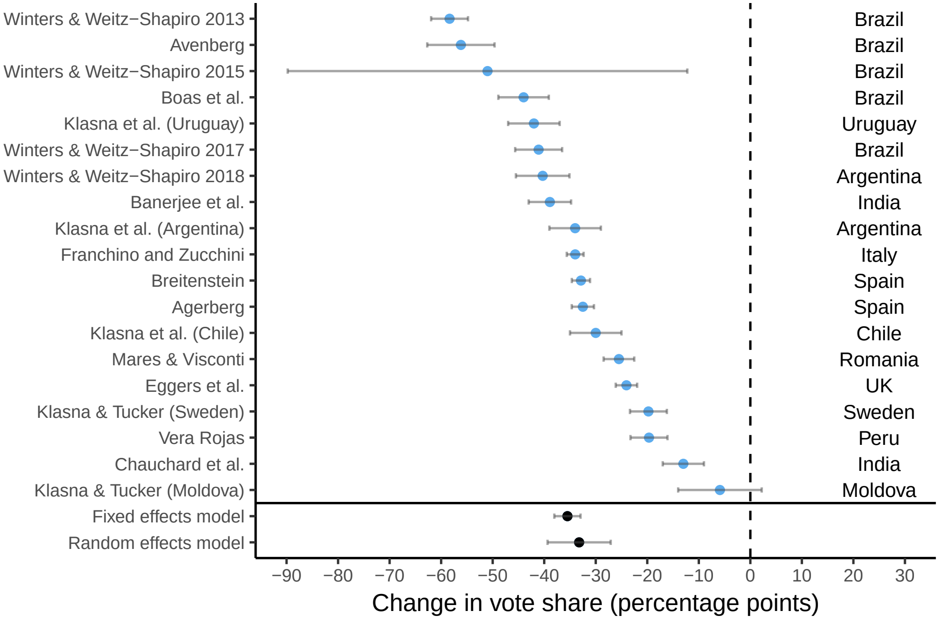
- Random effects likely more appropriate in this case.
    - Fixed effects assumes one true effect size across all studies, with differences in effects due to sampling error. Details
    - Random effects assumes effect sizes vary due to population heterogeneity, differences in treatment, etc.
    - In random effects, effect sizes are therefore assumed to represent a random sample of a distribution of effect sizes.
- In this case, differences in estimated effect size between the two methods are minor.

Results

Results: Field Experiments



Results: Survey Experiments



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- Corrupt candidates punished by approximately zero percentage points in field experiments.
- Punished by between 33 percentage points (random effects) and 35 percentage points (fixed effects) in survey experiments.

Assessing within study heterogeneity

How much heterogeneity across studies is accounted for by type of experiment?

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- Subtract residual heterogeneity from total heterogeneity and divide by total heterogeneity.
- 68% of the total heterogeneity across studies accounted for by including a dummy variable for type of experiment.

Discussion

What might account for the discrepancy between field and survey experiments?

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- Publication bias and/or p-hacking
- Social desirability bias
- Survey context does not mirror real-world settings:
    - Non-compliance
    - Differences in outcome choices
    - Costliness/decision complexity

Publication bias and p-hacking

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- Tests for funnel plot asymmetry. Figures
- P-value not a significant predictor of publication status. Table

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- Five of eight papers published. Three unpublished papers all have null findings. Figure
- Not enough data for formal tests.

Social desirability bias

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- No costs to selecting the socially desirable option in hypothetical vignette.
- Voting against corruption in the abstract may therefore reflect the respondents' actual preferences.
- In actual election voters may discount information, or have strong material/ideological incentives to stick with candidate.

Differences in experimental context: non compliance

Treatments are weak and easily missed in field experiments.

- In survey experiments ITT = ATE = CACE (LATE)
- Field experiments measure ITT as they do not know the non compliance rate. Non compliance necessarily reduces the ITT.
    - $ITT = CACE \times \pi_C$

Differences in experimental context: outcome choice

Choice set offered to voters is not necessarily identical across experiments. Example:

- Field experiment: Candidate A is randomly revealed to be corrupt, and voters can cast vote for corrupt candidate A, or candidate B, who may be clean or corrupt.

- Survey experiment: Candidate A is randomly revealed to be corrupt, and voters can cast vote for corrupt candidate A, or counterfactual Candidate A who *is not* corrupt.

Differences in experimental context: complexity, costliness and conjoint experiments

Conjoint experiments: Randomizing more candidate characteristics may capture variety of moderating factors and reduce social desirability bias.

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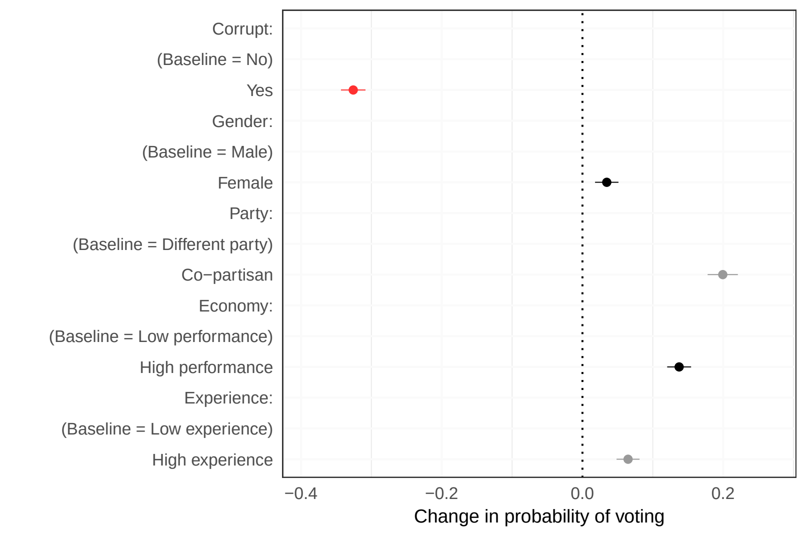
- But, traditional method of analysis (comparing magnitudes of individual average marginal component effects) may be misleading.

Differences in experimental context: complexity, costliness and conjoint experiments



Differences in experimental context: complexity, costliness and conjoint experiments

Proposal: When researchers have strong theories about the conditions that shape voter decision-making, a more appropriate method may be to calculate average marginal effects in order to present predicted probabilities of voting for a candidate under these conditions.

- E.g. Compare the probability of voting for a realistic candidate with outlier characteristics such as corruption to the probability of voting for a realistic candidate without this characteristic. Example 1 Example 2 Example 3

Differences in experimental context: complexity, costliness and conjoint experiments

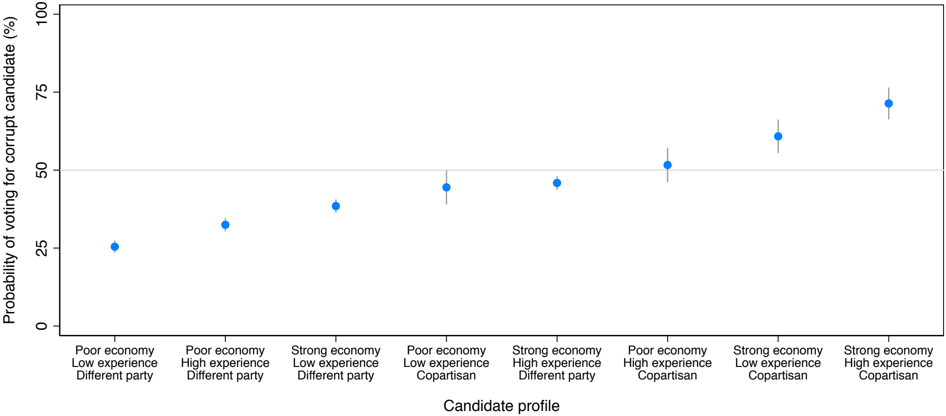


Figure 2: Breitenstein (2019) conjoint: can the right candidate overcome corruption?

Differences in experimental context: complexity, costliness and conjoint experiments

Proposal: When we do not have strong theories about the conditions that shape voter decision-making, we can use regression trees to illuminate them.

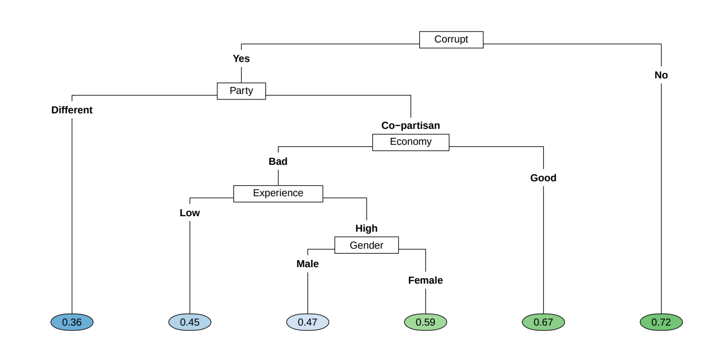


Figure 3: Breitenstein (2019) conjoint decision tree: predicted probabilities of voting for candidate

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  - Zero in field experiments.
  - -33 to -35 percentage points in survey experiments.
- Discrepancy does not seem to be driven by publication bias/p-hacking.
- May arise from:
  - Social desirability bias
  - Survey context failing to mirror real-world settings:
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- Researchers should exercise caution when interpreting actions taken in hypothetical vignettes as indicative of real world behavior such as voting.

Feedback

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- Other possible reasons behind the discrepancy?
- Are empirical tests of the reasons I have already identified necessary?
- If so, what tests would you find convincing?

Supplemental material

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- Point estimates, standard errors and/or confidence intervals are not always explicitly reported (4 cases). In these cases standard errors are estimated by digitally measuring coefficient plots.
- Two field experiments include general anti-corruption treatments not specific to candidates. Robustness check excludes these studies.

Fixed versus random effects estimation Back

Fixed effects:

$\hat{\theta} = \frac{\sum w_i \theta_i}{\sum w_i}$ where $w_i = \frac{1}{var_i}$

Random effects:

$\hat{\theta} = u + u_i$ where $u_i \sim N(0, \tau^2)$ and:

u is equal to the average "true effect", and τ^2 is the heterogeneity amongst true effects.

Lab experiments Back

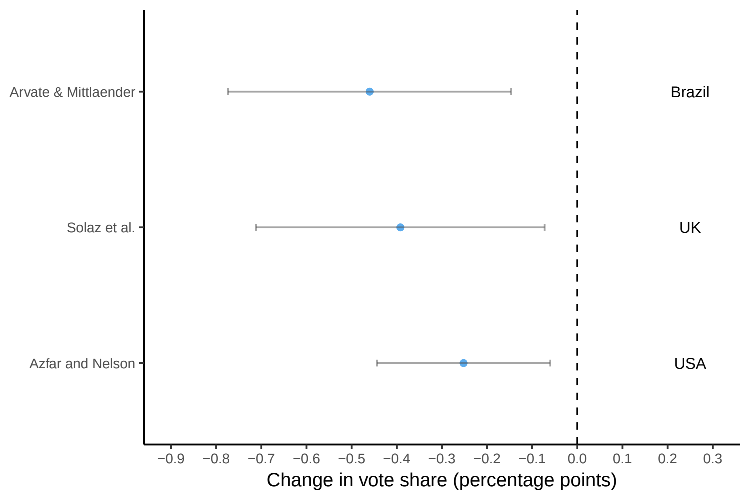


Figure 4: Lab experiments: Average treatment effect of corruption information on vote share

Robustness checks

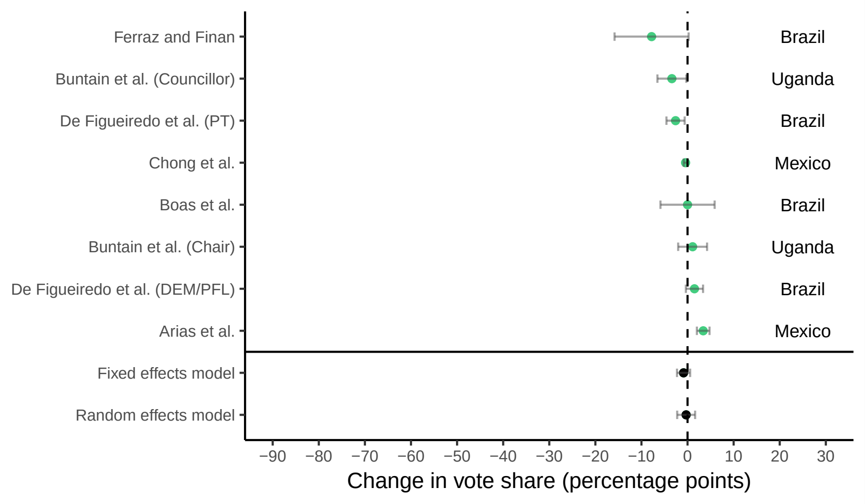


Figure 5: Field experiments: Average treatment effect of corruption information on incumbent vote share (excluding Banerjee et al. (2010) and Banerjee et al. (2011))

Mixed effects meta-analysis with survey experiment moderator

Back

Table 1: Mixed effects meta-analysis with survey experiment moderator

Value	Estimate
Constant	-0.005
	(0.035)
Survey experiment moderator	-0.326
	(0.043)

Note: Standard errors in parenthesis.

Funnel plot asymmetry

Back

Table 2: Regression tests for funnel plot asymmetry

Studies included	p value
All	0.0004
All with moderator	0.765
Field	0.840
Survey	0.630

Funnel plot asymmetry

Back

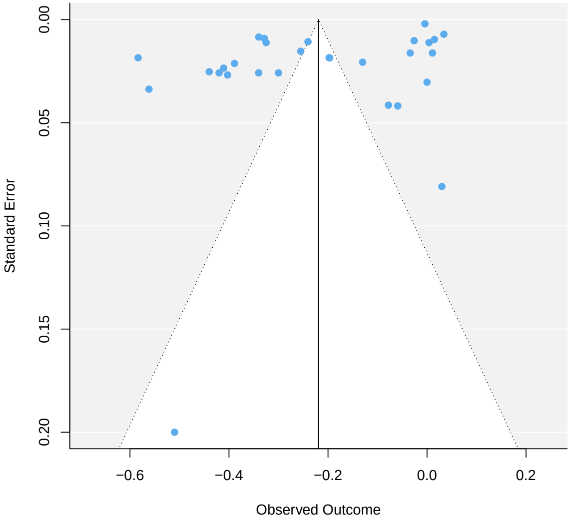


Figure 6: Funnel plot: All experiments

Funnel plot asymmetry

Back

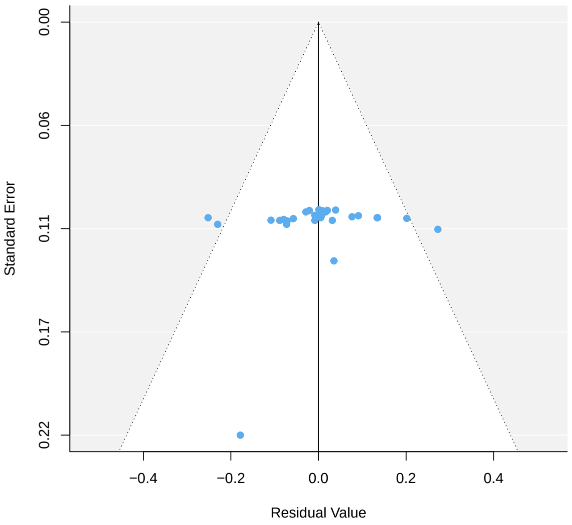


Figure 7: Funnel plot: All experiments with field experiment moderator

Funnel plot asymmetry Back

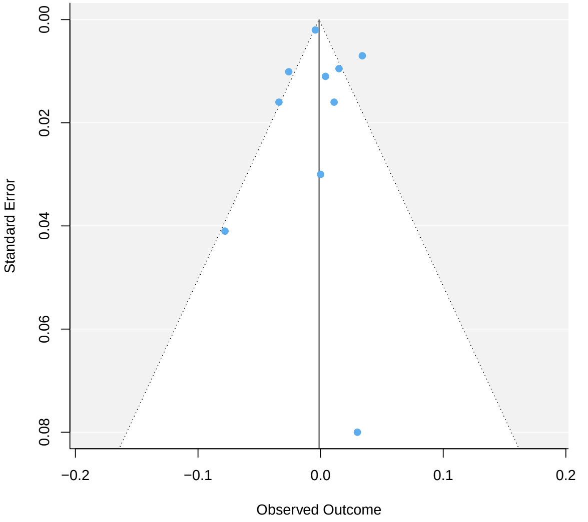


Figure 8: Funnel plot: Field experiments

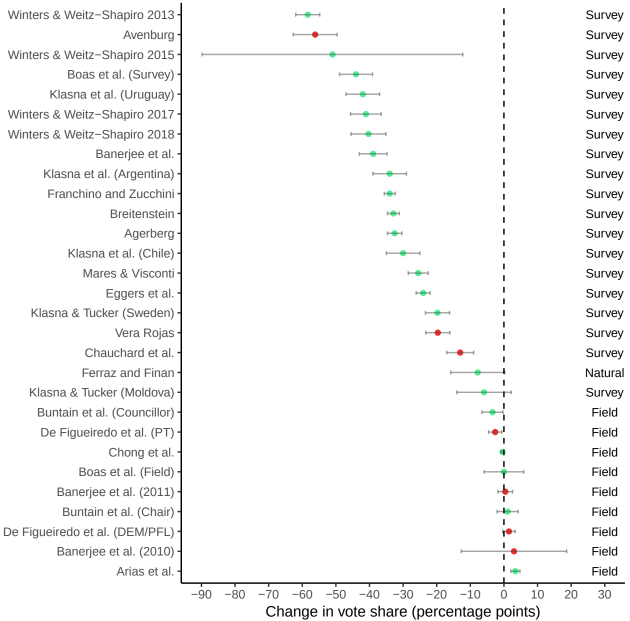
Does p-value predict publication status? Back

Table 3: Do p-values predict publication status?

	Dependent variable:	
	Published	
	OLS	Logit
Reference: P less than 0.01	0.84***	1.67***
	(0.10)	(0.63)
P less than 0.05	−0.18	−0.98
	(0.27)	(1.38)
P less than 0.1	0.16	14.89
	(0.44)	(2, 399.54)
P greater than 0.1	−0.34	−1.67
	(0.20)	(1.03)
Observations	29	29
Note:	*p<0.1; **p<0.05; ***p<0.01	

All experiments by publication status

Back



Additional conjoint replications: Franchino and Zucchini (2015)

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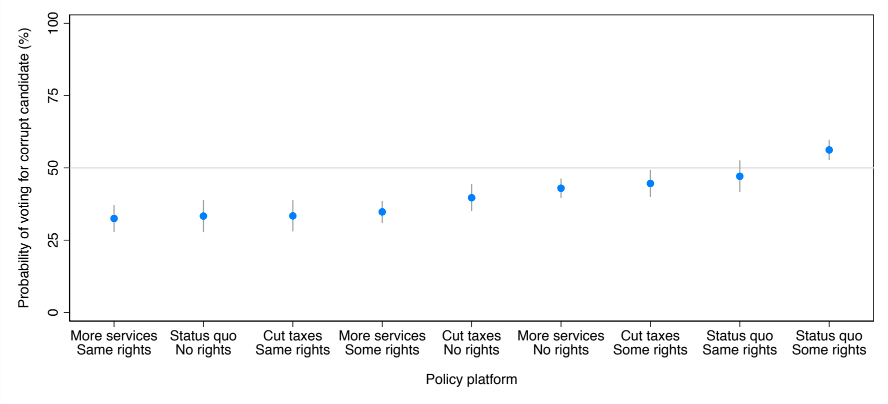

Figure 10: Franchino and Zucchini (2015) conjoint: can policy positions overcome corruption (conservative respondents)?

Additional conjoint replications: Franchino and Zucchini (2015)

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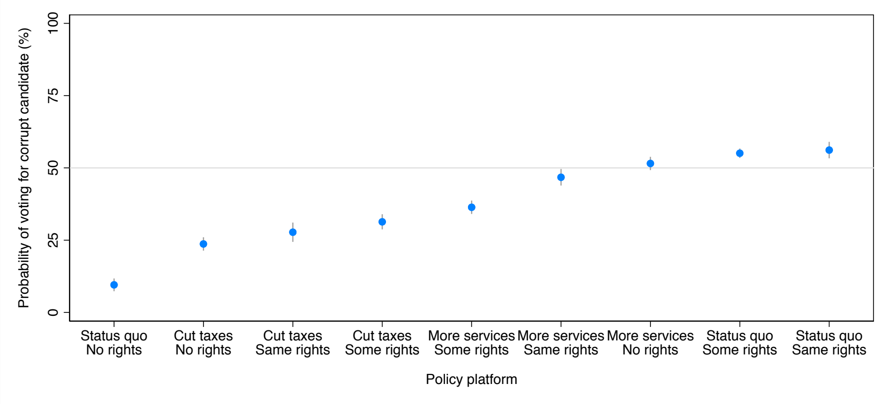

Figure 11: Franchino and Zucchini (2015) conjoint: can policy positions overcome corruption (liberal respondents)?

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