Supplementary Materials

How Much Should We Trust Instrumental Variable Estimates in Political Science? Practical Advice Based on 67 Replicated Studies

A. Appendix A

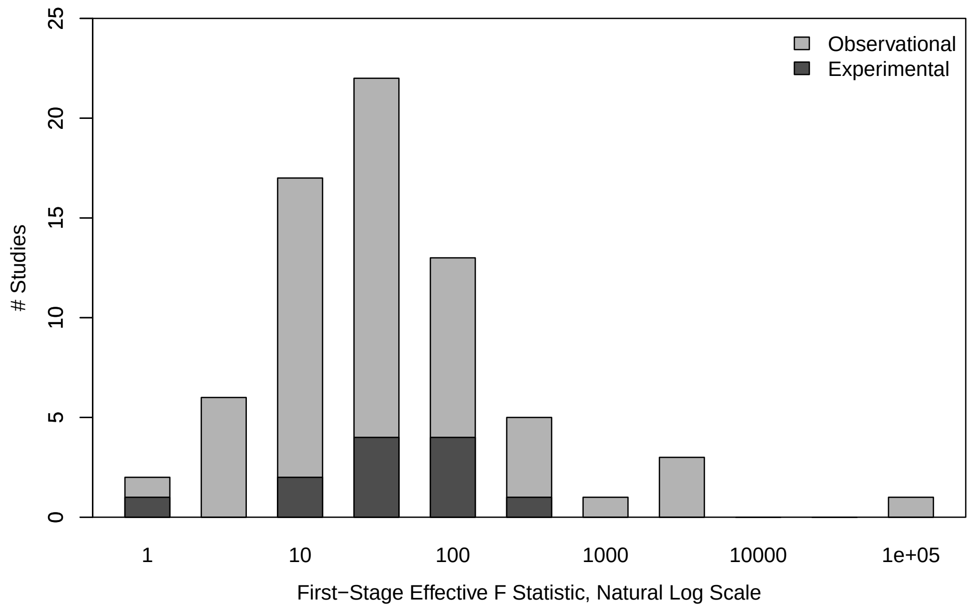
Table of Contents

A.1. Additional Information on the Replication Sample

A.1.1. Replication Sample

Figure A1 plots the histograms of effective F statistics using experiment-generated IVs (dark gray) and non-experimental IVs (light gray). The median effective F for experimental and observational designs are 67.7 and 53.5, respectively.

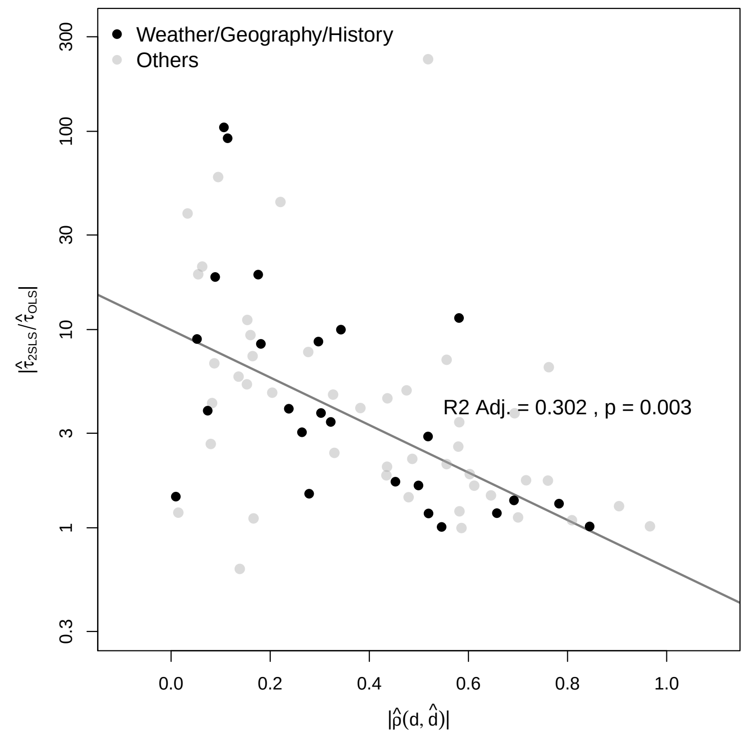
FIGURE A1. HISTOGRAM OF EFFECTIVE F STATISTIC



A.1.2. Instruments based on Climate/Weather/Geography/History

Based on a reviewer's suggestion, we highlighted studies in Figure 4 that use "geography/climate/weather", "history", and "treatment diffusion" as IVs. We show that the inverse relationship between the first-stage correlation coefficient and the 2SLS-OLS ratio is consistent with other observational studies in our dataset.

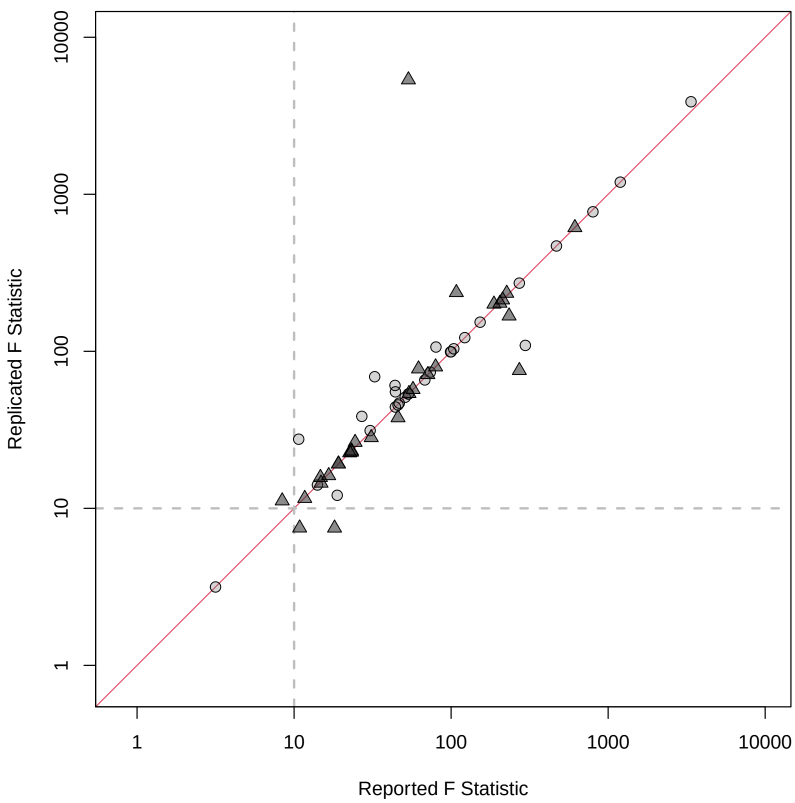
FIGURE A2. INSTRUMENTS BASED ON CLIMATE/WEATHER/GEOGRAPHY/HISTORY



A.1.3. Comparison of Multiple F Statistics

Figure A3 compares the reported and replicated first-stage partial F statistics (for studies that have reported the F statistics). The replicated F statistics are based on the authors' chosen model specifications and variance estimators in 2SLS estimation. The discrepancy arises from the fact that some authors report the first-stage F statistic based on a different variance estimator than the one used in the 2SLS estimation. In the paper, we use the replicated ones to maintain consistency.

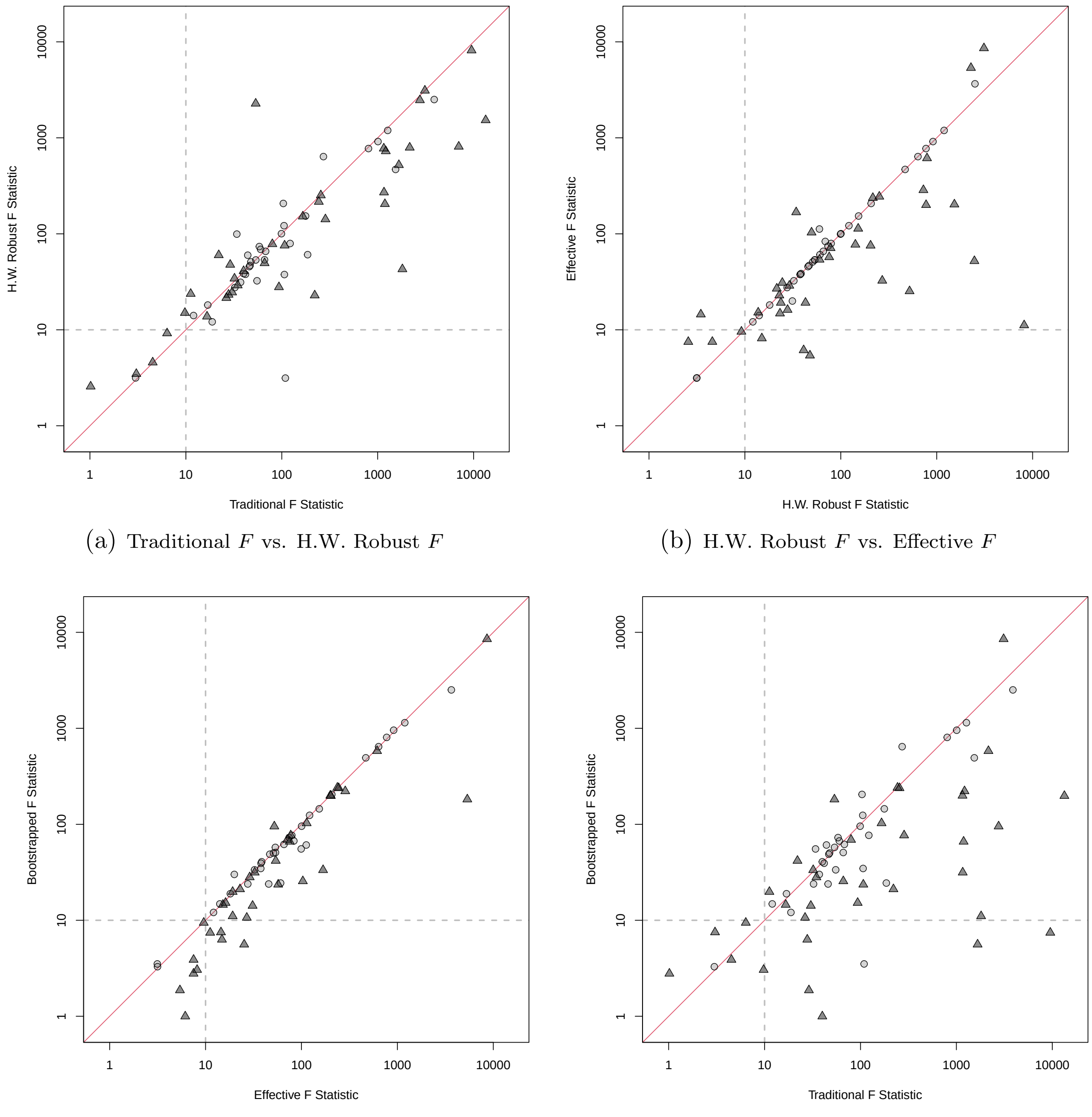
Figure A3. Reported vs. Replicated F Statistics



Note: Circles represent applications without a clustering structure and triangles represent applications with a clustering structure. Studies that do not report F statistics are not shown.

In Figure A4, we compare the traditional F statistics (based on classic analytic SEs), the Huber White robust F statistics, the effective F statistics (robust or cluster-bootstrap SEs) and (cluster-)bootstrapped F statistics. It shows that (cluster-)bootstrapped F statistics are usually the most conservative (smallest).

FIGURE A4. COMPARISON OF DIFFERENT F STATISTICS



(a) Traditional F vs. H.W. Robust F

(b) H.W. Robust F vs. Effective F

(c) Effective F vs. Bootstrapped F

(d) Traditional F vs. Bootstrapped F

Note: Circles represent applications without a clustering structure and triangles represent applications with a clustering structure.

A.2. Monte Carlo Evidence

A.2.1. Comparing F Tests for Detecting Weak Instruments

We conduct a simulation study with a clustered DGP in order to evaluate the relative performance of analytic and bootstrap F tests to detect weak instruments. We simulate data from the following DGP

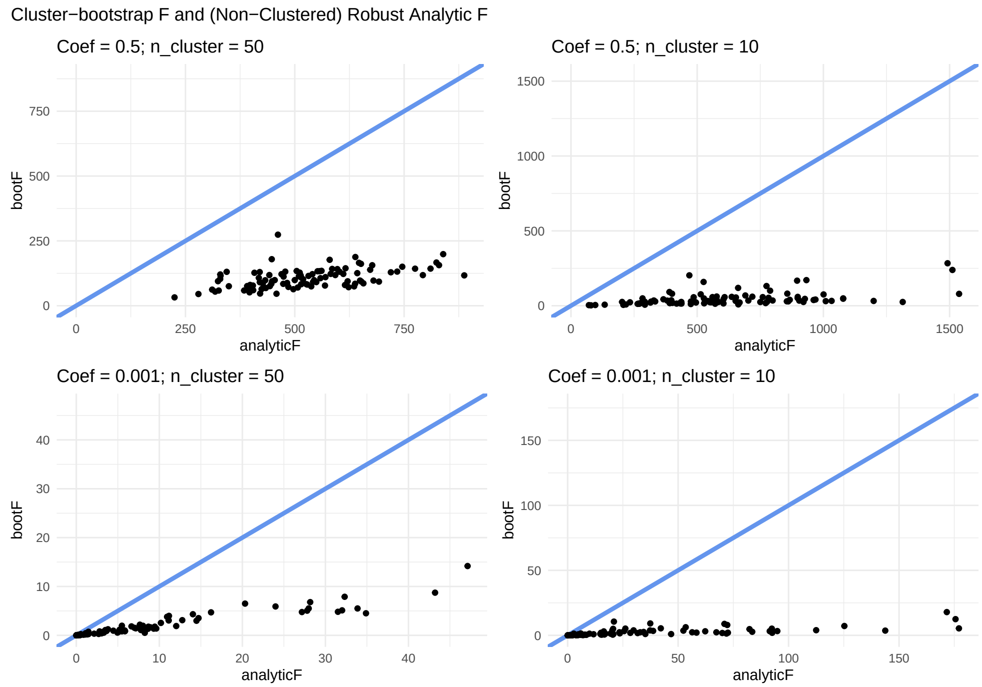
$$\begin{aligned} \text{clustered instrument and error components} \quad & \nu_j, \eta_j \sim \mathcal{N}(0, 0.5) \\ \text{instrument} \quad & z_i \sim \mathcal{N}(0,1) + \nu_j \\ \text{error} \quad & \varepsilon_i \sim \mathcal{N}(0,1) + \eta_j \\ \text{endogenous variable} \quad & x_i = \pi z_i + \varepsilon_i \end{aligned}$$

with errors and instrument components drawn from J clusters. This DGP ensures that the data has a dependent structure within each cluster j. We then evaluate the strength of the instrument analytically by computing the t-statistic for $H_0 : \pi = 0$, or by using the corresponding bootstrap statistic $\frac{\pi^2}{\widehat{\sigma}^2}$ where $\widehat{\sigma}^2$ is the bootstrap estimate of the variance of π. We evaluate the analytic and bootstrap F statistics for various values of π and J for 100 replications of the above DGP in Figure (A5).

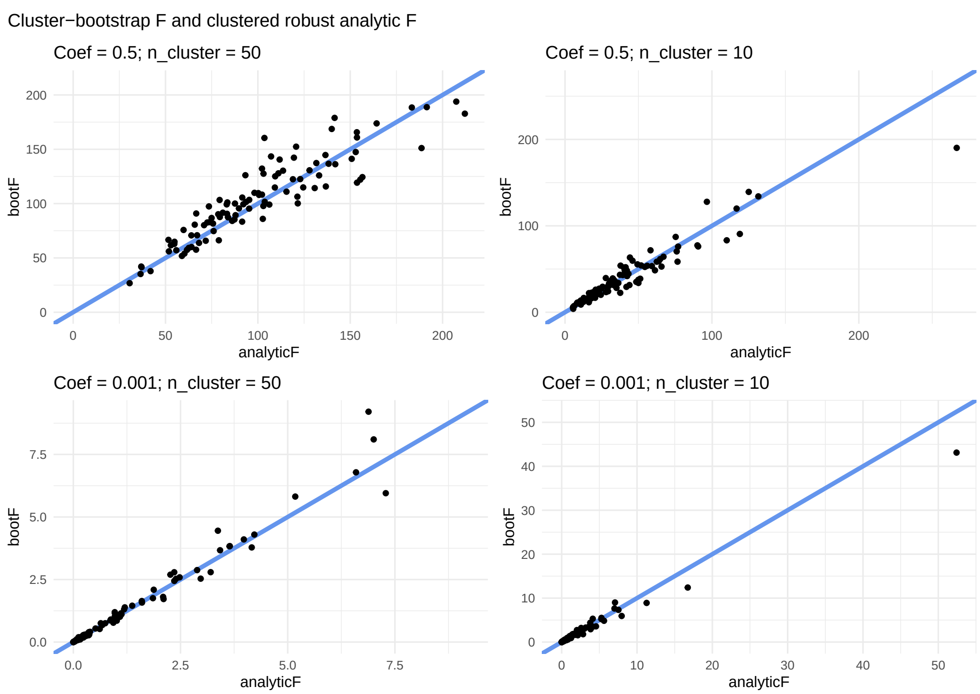
As seen in panel A, when robust analytic standard errors ignore the clustered structure, they vastly over-estimate the strength of the instrument relative to the cluster-bootstrap, with both "few" (10) and "many" (50) clusters and with "strong" ($\pi = 0.5$) and "weak" ($\pi = 0.001$) instruments. With appropriate clustered analytic SEs, however, the F statistic is typically comparable to the bootstrap based equivalent (panel B), although the bootstrap F is marginally more conservative with a small number of clusters and weak instrument.

In summary, we find that cluster-bootstrap F statistic and the cluster-robust F statistic, which is equivalent to the "effective" F (Olea and Pflueger, 2013) in just-identified settings such as this one, are comparable in detecting weak instruments and recommend reporting these statistics in applied settings. We also recommend reporting Anderson-Rubin confidence intervals for the IV coefficient, as it is robust to arbitrarily weak instruments (Andrews, Stock and Sun, 2019; Kang et al., 2021).

Figure A5. Comparisons of F Statistics



(a) Cluster-bootstrap F statistic vs. Huber-White (non-clustered) F statistic



(b) Cluster-bootstrap F statistic vs. cluster-robust analytic F statistic ($F_{\texttt{Eff}}$)

A.2.2. Explaining the 2SLS-OLS Discrepancy

In this section, we conduct Monte Carlo exercises to explore potential causes of the discrepancy between 2SLS and OLS estimates observed in the replication data. We consider three causes: (1) violations of the exclusion restriction (A2), (2) publication bias, and (3) heterogeneous treatment effects (HTE). Below is our data-generating process (DGP):

$$
\begin{aligned}
& y_i = 5 + \beta_i x_i + \mu z_i + u_i + b_i \\
& x_i^* = \delta_i z_i + (1-\delta_i) a_i + 0.2 v_i \quad \text{and} \quad \delta_i = \max(\min(\kappa_i \pi_i, 1), 0) \\
& x_i = x_i^*,\ z_i \overset{i.i.d.}{\sim} N(0,2) \qquad \text{(continuous-continuous case)} \\
\text{or} \quad & x_i = 1\{x_i^* > 0\},\ z_i \overset{i.i.d.}{\sim} \text{Bern}(0.5) \qquad \text{(binary-binary case)}
\end{aligned}
$$

in which z is the instrument, x is the treatment, and y is the outcome. We consider two scenarios: (1) both x and z are continuous, and (2) both are binary. Correlated errors $\begin{bmatrix} u_i \\ v_i \end{bmatrix} \overset{i.i.d.}{\sim} N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}\right)$; $a_i \overset{i.i.d.}{\sim} N(0,1)$, $b_i \overset{i.i.d.}{\sim} N(0,1)$ are i.i.d. errors. We use κ to control the strength of the instrument. HTE can be generated by $\begin{bmatrix} \beta_i \\ \pi_i \end{bmatrix} \overset{i.i.d.}{\sim} N\left(\begin{bmatrix} 2 \\ 1 \end{bmatrix}, \sigma_h^2 \begin{bmatrix} 1 & \lambda \\ \lambda & 0.5 \end{bmatrix}\right)$, in which σ_h controls the amount of heterogeneity in β_i and π_i while λ controls the correlation between the first stage and reduced form coefficients. δ_i is limited to be in $[0,1]$. When $\lambda > 0$, it means that a unit's treatment effect is positively correlated with its responsiveness to the IV.[A1] The sample size is fixed at 200.

Under constant treatment effect ($\sigma_h = 0$) and with a valid instrument ($\mu = 0$), the expected value of $\hat{\beta}_{2SLS}/\hat{\beta}_{OLS}$ is 0.74 for the continuous-continuous case and 0.57 for the binary-binary case. We consider four scenarios sequentially:

1. Violations of Assumption 2 are captured by $\mu \neq 0$ (failure of the exclusion restriction).

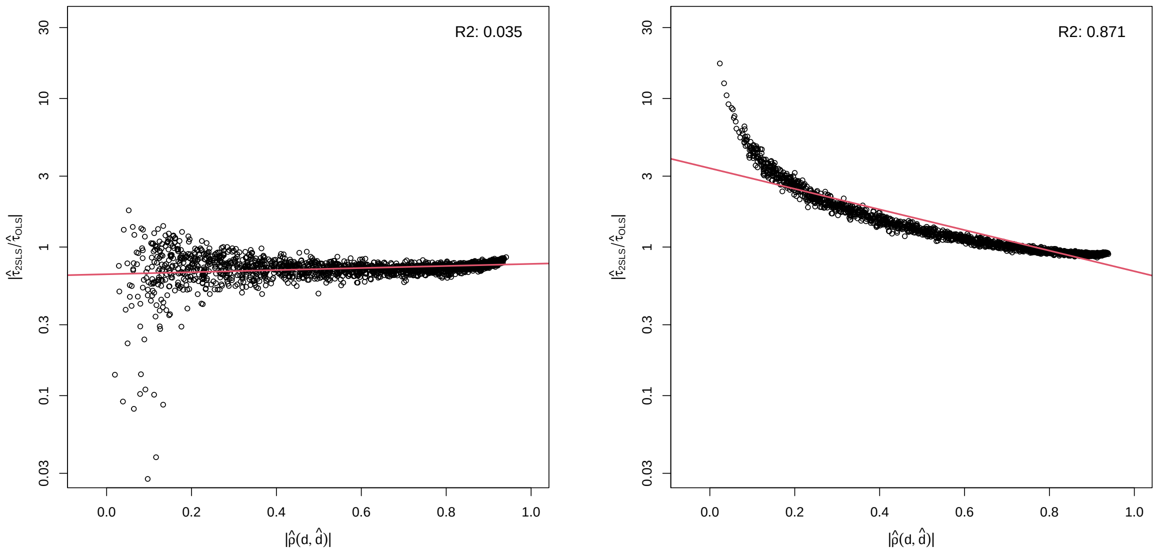
2. Publication bias can be simulated by dropping the cases in which the 2SLS estimates are statistically insignificant at the 5% using a conventional t test.

3. HTE is generated by setting $\sigma_h = 0.05$ and $\lambda = 0.7$, i.e., β_i and π_i are highly correlated.

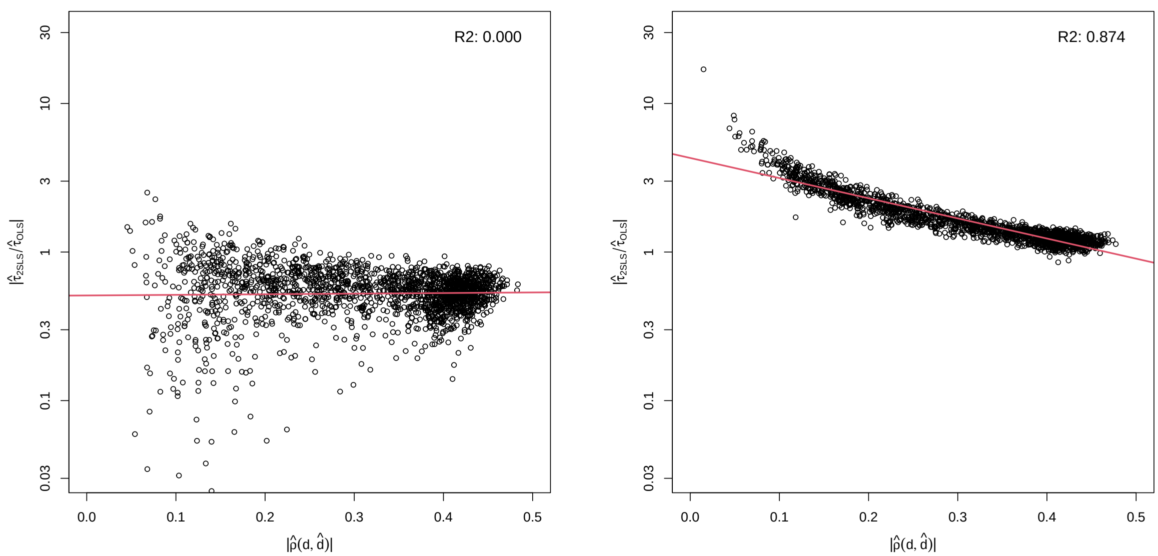
4. The combination of HTE and publication bias.

[A1] For example, under selection-on-gains type settings, which are typically considered in generalized Roy models underlying MTE approaches to IV.

Figure A6. Consequences of Exclusion Restriction Failure under Constant Effect



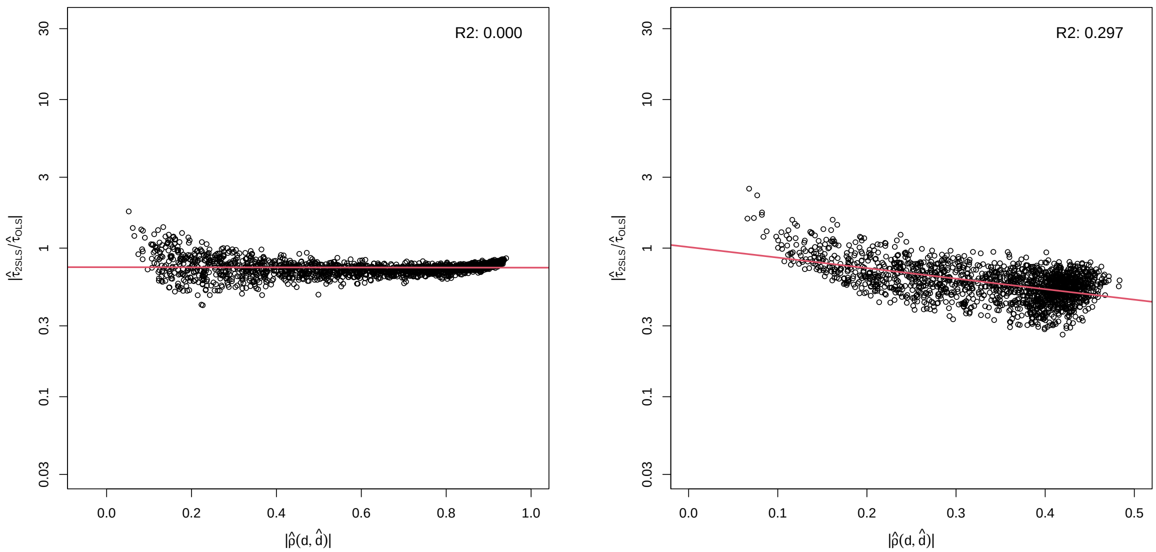
(a) Continuous-Continuous Case: w/o and w/ exclusion restriction failure



(b) Binary-Binary Case: w/o and w/ exclusion restriction failure

Violating Assumption 2. The results for Scenario 1 are shown in Figure A6. Each dot represents one simulated sample. Figure A6 shows that, in both continuous-continuous and binary-binary setups, when the treatment effect is constant ($\beta_i = \beta, \pi_i = \pi$), in expectation, there is no mechanical negative relationship between the correlation coefficient between d and $\hat{d}$ and the 2SLS-OLS discrepancy (left panels in both subfigures). However, when the exclusion restriction fails, e.g., $\mu = 1$ (right panels in both subfigures), a strong negative correlation appears. These results support our argument in the paper that a weak first stage amplifies the bias from the failure of Assumption 2.

Figure A7. Consequences of Publication Bias under Constant Treatment Effect



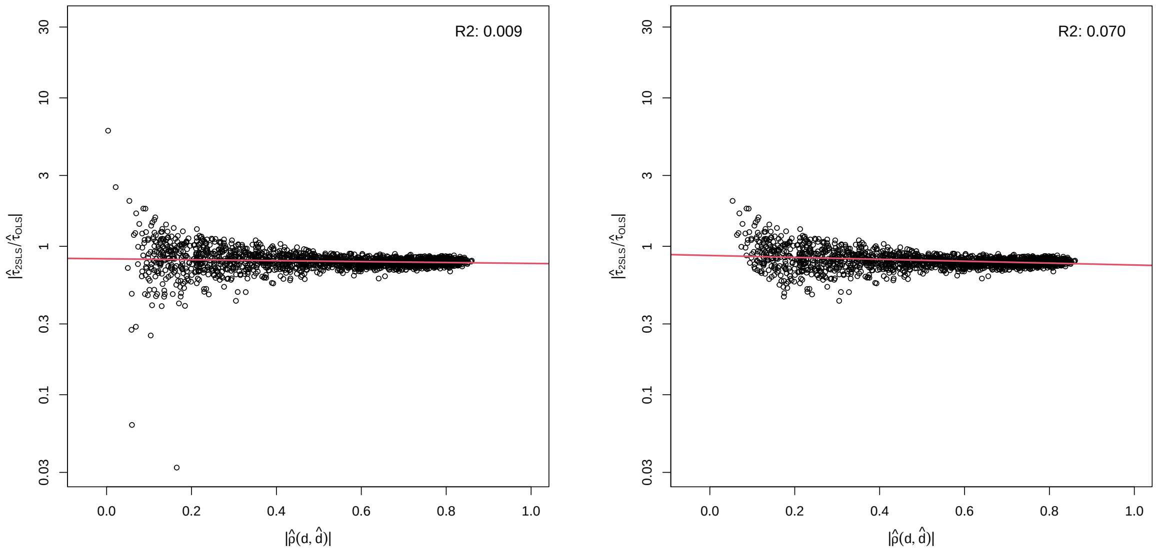
(a) Continuous-Continuous Case

(b) Binary-Binary Case

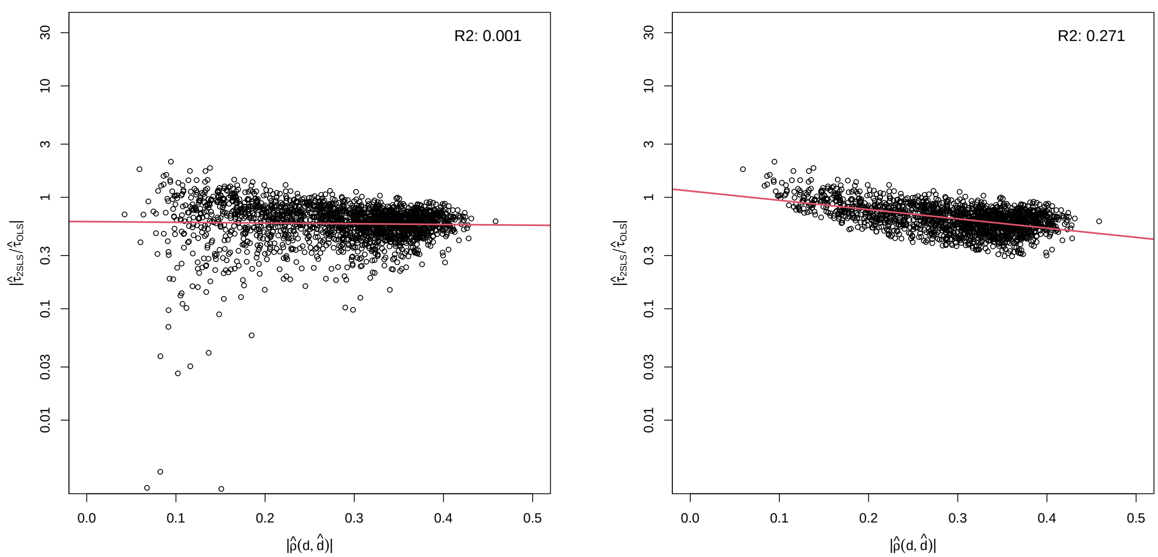
Publication bias. Figure A7 illustrates the consequences of publication bias (Scenario 2), where statistically insignificant results are omitted. In the binary-binary case, we observe a moderate negative correlation; however, this correlation is much weaker than those caused by exclusion restriction failures.

HTE and publication bias. Finally, we investigate the consequences of HTE (Scenario 3) and its interaction with publication bias (Scenario 4). Figures A8 shows results under HTE, i.e., $\sigma_h > 0$ and $\lambda = 0.7$ (β_i and π_i are highly positively correlated). On the logarithmic scale, the correlation is almost nonexistent (left panels in Figure A8). When we revert to the original scale, we do observe a small to moderate negative correlation in both continuous-continuous and binary-binary cases (figures not shown). When we further introduce publication bias, we begin to see weak negative correlations between the first stage ρ and the 2SLS-OLS discrepancy on the logarithmic scale, especially in the binary-binary case. However, their magnitudes are much smaller than what we observed in Figure A6 under the exclusion restriction failure. This suggests that the observed strong negative relationship in

FIGURE A8. CONSEQUENCES OF PUBLICATION BIAS UNDER HTE



(a) Continuous-Continuous Case: w/o and w/ publication bias



(b) Binary-Binary Case: w/o and w/ publication bias

the paper is unlikely to be solely explained by HTE and different levels of responsiveness to the IV.

In summary, the Monte Carlo exercises demonstrated that the strong negative correlations between the first stage ρ and the 2SLS-OLS discrepancy are most likely caused by violations of Assumption 2. Other factors, such as publication bias and HTE, may also play a role.

A.3. Evaluating the Exogeneity Assumption

Assumption 2 is a strong and generally untestable assumption that underlies the validity of the instrument; indeed, researchers typically spend considerable effort arguing for both unconfoundedness and the exclusion restrictions in their particular setting. However, some placebo tests have recently become popular as a way to argue for the validity of identification assumptions in causal designs (Eggers, Tuñón and Dafoe, 2021), especially in observational settings where the choice of IV is guided by detailed domain knowledge. Bound and Jaeger (2000) suggest first using an auxiliary regression on a subsample where the IV is not expected to influence treatment assignment, known as "zero-first-stage" (ZFS) tests. The primary intuition is that in a subsample that one has a strong prior that the first stage is zero—hence, they are "never takers," to use the language of the LATE framework—the reduced form effect should also be zero if Assumption 2 is satisfied. In other words, motivated by a substantive prior that the first-stage effect of the IV is likely zero for a subsample of the population (henceforth, the "ZFS subsample"), the researcher then proceeds to show that the reduced-form coefficient for the IV (by regression Y on Z) is approximately zero *in the ZFS subsample*, which is suggestive evidence in favor of IV validity. Most observational instruments ought to yield some ZFS subsample based on substantive knowledge of the assignment mechanism.

This style of placebo is particularly popular in studies of historical political economy, where particular historical or geographic features are argued to be valid instruments for treatment assignment, and thus they are unlikely to be driving treatment assignments outside a specific context. For example, Nunn (2008) studies the effects of the slave trade on modern-day development in Africa using sailing distance from each country to the nearest locations of demand for slave labor as an IV for the normalized number of slaves taken. The author then argues that distance to demand locations in the New World are likely to be a valid IV by using a placebo test that the first-stage effect (the IV regressed on the outcome, modern-day GDP) is approximately zero for countries outside Africa, where the posited mechanism (that places close to demand locations exported more slaves only in the transatlantic slave trade) has no traction, thereby providing a candidate ZFS sample. In a related paper, Nunn and Wantchekon (2011) use the same strategy to show that the distance to slave-trade ports do not predict modern-day trust attitudes in the Asiabarometer, while they do in the Afrobarometer (which is the primary study population). Acharya, Blackwell and Sen (2016) perform a similar exercise where they believe that their instrument (cotton suitability) predicts the treatment (slaves per capita) in the Southern States but not the Northern states, and therefore find that the reduced form effect of cotton suitability on modern-day racial attitudes is approximately zero in the Northern states.

A.3.1. The ZFS Test and Modified Inference

While this is a useful heuristic check that we advise most observational IV papers adopt, it is an informal test and provides no debiasing procedure to correct potentially biased IV estimates. Van Kippersluis and Rietveld (2018) suggest that the ZFS test can be fruitfully combined with the "plausibly exogenous" method suggested by Conley, Hansen and Rossi (2012) (henceforth, CHR 2012). To illustrate the method, we first rewrite the IV simultaneous equations in CHR (2012)'s notation:

$$Y = X\beta + Z\gamma + \varepsilon; \quad X = Z\Pi + \nu, \tag{A1}$$

where Z also enters the structural equation, and the exclusion restriction amounts to a dogmatic prior that $\gamma = 0$. CHR (2012) suggest that this assumption can be relaxed, and replaced with a user-specified assumption on a plausible value, range, or distribution for γ depending on the researcher's beliefs regarding the degree of exclusion restriction violation. They propose three different approaches for inference that involve specifying the range of values for γ, a prior distributional assumption for γ, and a fully Bayesian analysis that requires priors over all model parameters and corresponding parametric distributions. We focus on the second method, which CHR (2012) call the "local to zero" (LTZ) approximation because of its simplicity and transparency. The LTZ approximation considers "local" violations of the exclusion restriction[A2] and requires a prior over γ alone. CHR (2012) show that replacing the standard assumption that $\gamma = 0$ with the weaker assumption that $\gamma \sim \mathbb{F}$, a prior distribution, implies distribution for $\widehat{\beta}$ in Equation (A2).

$$\widehat{\boldsymbol{\beta}} \sim^a \mathcal{N}\left(\boldsymbol{\beta}, \mathbb{V}_{2SLS}\right) + \mathbf{A}\gamma \ \text{ where } \mathbf{A} \equiv (\mathbf{X}'\mathbf{Z}(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}'\mathbf{X})^{-1}\mathbf{X}'\mathbf{Z} \tag{A2}$$

$$\widehat{\boldsymbol{\beta}} \sim^a \mathcal{N}\left(\boldsymbol{\beta} + \mathbf{A}\mu_\gamma, \mathbb{V}_{2SLS} + \mathbf{A}\boldsymbol{\Omega}\mathbf{A}'\right) \tag{A3}$$

where the original 2SLS asymptotic distribution is inflated by the additional term. While a simulation-based approach can be used to implement Equation (A2) for an arbitrary distribution for γ, the distribution takes its most convenient form when one uses a Gaussian prior over $\gamma \sim \mathcal{N}\left(\mu_\gamma, \Omega_\gamma\right)$, which simplifies Equation (A2) to Equation (A3), with a posterior being a Gaussian centered at $\boldsymbol{\beta} + \mathbf{A}\mu_\gamma$.

[A2] LTZ asymptotics consider a sequence of constants $\gamma = C/\sqrt{N}$ for some constant C and sample size N

CHR (2012) suggest that researchers use domain knowledge to choose $\mu_\gamma, \Omega_\gamma$, since they often hold strong priors about instruments anyway (which presumably motivates the choice of the instrument). Van Kippersluis and Rietveld (2018) suggest that a principled method to choose μ_γ is to estimate Equation (A1) on the ZFS population (wherein Π is assumed to be zero), and use this estimate $\widehat{\gamma}_{ZFS}$ as μ_γ. This approach combines the informal ZFS test with the plausibly exogenous method in a straightforward manner, and software to implement it is available in both `R` (accompanying this paper) and `STATA` (Clarke, 2014). We begin with a simulation-based illustration and illustrate the application of this method to a published empirical paper next.

A.3.2. Simulation Evidence

In this subsection, we demonstrate the LTZ method when the exclusion restriction is not satisfied. Consider the following DGP,

$$\begin{aligned} Y_i =& \beta_i D_i + \gamma Z_i + \varepsilon_i \\ D_i =& \mathbf{1}\{D_i^* > 0\} \\ D_i^* =& \alpha_i + \pi_i Z_i + \varepsilon_i \end{aligned}$$

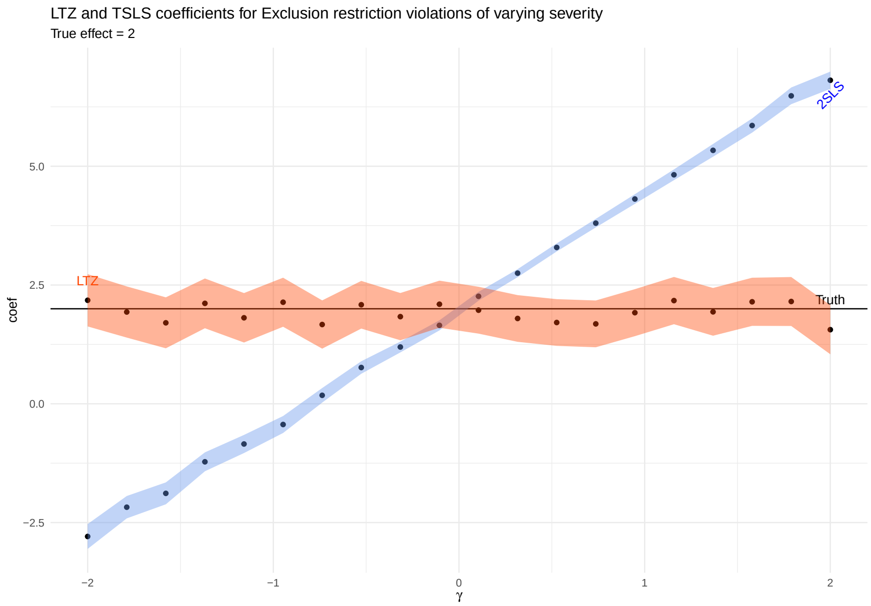
in which $Z_i \sim$ Bernoulli(0.5) is a binary instrument, $\pi_i \sim \mathsf{U}[1.5, 2.5]$, $\alpha_i \sim \mathcal{N}(-1, 1)$, $\varepsilon_i \sim \mathcal{N}(0, 1)$, $\beta_i \sim \mathcal{N}(1, 0.25)$. We generate Y_i with Z_i directly entering the structural equation, which allows us to vary the magnitude of the exclusion restriction violation. We then estimate $\widehat{\beta}_{2SLS}$ using conventional 2SLS on this data. As we vary γ, $\hat{\beta}_{2SLS}$ is inconsistent for all values except when $\gamma = 0$. We set $\pi = 0$ for the last 20% observations of the simulated data (the ZFS subsample). We then estimate the reduced-form regression on this (known) subsample and use the coefficient as a prior for μ_γ, and compute the LTZ IV estimate.

Figure A9 shows, unlike the 2SLS estimator (blue), the LTZ estimator (orange) uncovers the true value of $\beta = 2$ even for large degrees of exclusion restriction violations (large $|\gamma|$).

A.3.3. A Case Study

We illustrate the diagnostics described above by applying it to the IV analysis in Guiso, Sapienza and Zingales (2016) (henceforth GSZ 2016), who revisit Putnam, Leonardi and Nanetti (1993)'s conjecture that Italian cities that achieved self-government in the Middle Ages have higher modern-day levels of social capital. More specifically, they study the effects

Figure A9. IV and LTZ Estimates for Varying γ



of free city-state status on social capital as measured by the number of non-profits and organ donations per capita, and a measure of whether students cheat in mathematics.

Table A1. Replication of GSZ (2016) Table 6
Reduced Form Regressions

Outcome Variables	North		South (ZFS)	
	Nonprofit (1)	Organ Donation (2)	Nonprofit (3)	Organ Donation (4)
Bishop (IV)	1.612 (0.219)	0.472 (0.047)	0.178 (0.137)	0.189 (0.065)
Observations	5,357	5,535	2,175	2,178

Note: Bootstrapped SEs are in the parentheses. See Figure A4 in the SM for the original table.

GSZ (2016) use a dummy for whether the city was the seat of a bishop in the Middle Ages, based on historical accounts of coordination preceding commune formation in the Middle Ages as an IV for the "free-city experience" (Section 5). They argue that conditional on a host of geographic covariates, this IV, a bishop seat, influences contemporary social capital solely through its increasing the likelihood of commune formation. As suggestive evidence for the validity of their instrument, they estimate the reduced-form effect of medieval bishop presence of contemporary social capital measures separately in the north (where the IV is conjectured to have an effect) and the south (where it is conjectured to be irrelevant). They

FIGURE A10. TABLE 6 IN GUISO, SAPIENZA AND ZINGALES (2016)

TABLE 6. Validating the instrument.

A. Regressions of civic capital in the Center–North and in the South

	Center–North sample			South sample		
	(I) Nonprofit org.	(II) Organ donation org.	(III) Cheating in mathematics	(IV) Nonprofit org.	(V) Organ donation org.	(VI) Cheating in mathematics
Ease of coordination	1.61**	0.47***	−0.66***	0.18	0.19***	−0.04
	(0.219)	(0.047)	(0.118)	(0.137)	(0.065)	(0.309)
Elevation	1.93***	−0.25***	0.94**	1.43***	−0.04	0.72
	(0.475)	(0.062)	(0.441)	(0.257)	(0.083)	(0.541)
Max difference in elevation	1.35***	0.01	0.26*	−0.08	−0.05*	0.06
	(0.219)	(0.026)	(0.143)	(0.084)	(0.029)	(0.145)
City is on the coast	−0.27	−0.08*	0.03	0.23**	−0.02	0.13
	(0.264)	(0.046)	(0.119)	(0.115)	(0.044)	(0.108)
City more than 5 km from the coast	1.10*	0.07	−0.21	0.02	−0.03	1.46
	(0.634)	(0.072)	(0.227)	(0.143)	(0.048)	(1.098)
Current population	−3.38***	1.48***	−1.85***	−9.11***	1.10*	−3.50
	(1.886)	(0.290)	(0.523)	(2.242)	(0.582)	(2.849)
Current population squared	1.03	−1.12***	1.87***	6.23***	−0.86*	4.47
	(1.423)	(0.218)	(0.480)	(1.924)	(0.469)	(2.816)
Gini income inequality index	0.08	0.04	0.04	3.49**	2.05***	−21.66***
	(0.449)	(0.076)	(0.438)	(1.505)	(0.547)	(5.646)
Gini inequality index of land ownership	9.83***	2.17***	−8.61***	1.61***	0.35***	1.75
	(1.883)	(0.377)	(2.382)	(0.351)	(0.098)	(1.330)
Observations	5,357	5,535	1,911	2,175	2,178	1,210
R^2	0.083	0.587	0.023	0.329	0.574	0.027

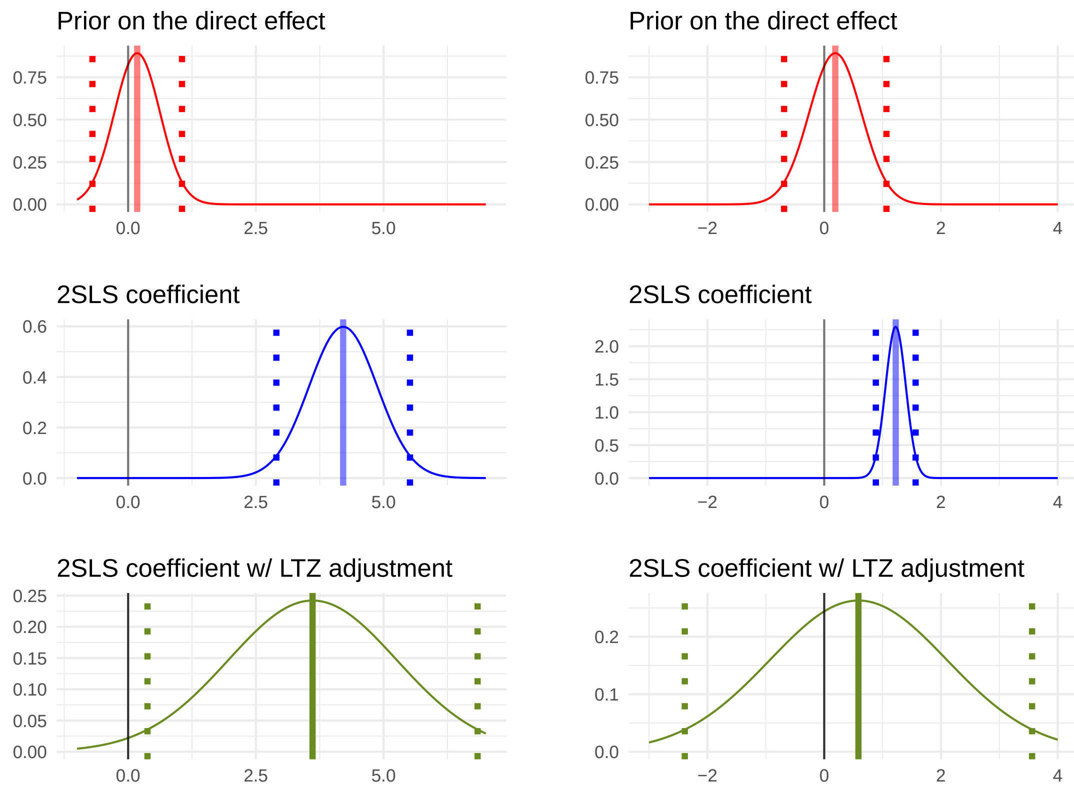
Note: "Ease of coordination" is the IV "Bishop in city." We replicated columns (I), (II), (IV), and (V).

fail to reject the null of no effects in the south, conclude that the IV appears to have face validity, and proceed to use bishop's presence as an IV for their IV estimates.

We begin by calculating the first-stage partial F statistic based on bootstrapped SEs for the north sample, which is 67.3. Because there were no "free cities" in the south, the F statistic for the south is zero by definition. We then replicate their reduced-form estimates in Table A1. The separate north and south reduced-form estimates in GSZ (2016) can be readily used for the LTZ test described above. The authors substantively believe that the south is a ZFS sample where bishop presence is irrelevant for treatment assignment,[A3] we can use the reduced-form estimates of 0.178 and 0.189 in the south for non-profits per capita and organ donation (columns 3-4 in Table A1) as the prior μ_γ for the direct effect of the IV on the

[A3]The authors claim this indirectly by reporting the reduced form effects separately for the north and south subsamples in Table 6, and state that since the reduced form is attenuated in the south, this justifies the use of bishop presence as an IV (p. 1427).

Figure A11. IV Coefficients for Non-profits and Organ Donation



(a) Non-Profit (b) Organ Donation

outcome. Finally, we report the analytic, bootstrap, and LTZ IV results in Figure A11. We find that conventional robust SEs understate the uncertainty of the estimates relative to the bootstrap and that accounting for direct effect using LTZ attenuates GSZ (2016)'s estimates somewhat and substantially increases the SE of the estimate for the non-profit outcome. For organ donation, however, where we suspect a violation of Assumption 2 because the reduced form effect is statistically distinguishable from zero, the use of the LTZ method to account for this exclusion restriction violation yields a smaller and substantially more uncertain estimate whose CI contains 0. This example shows how researchers may take advantage of the ZFS test and the LTZ technique to gauge the robustness of their findings based on an IV strategy.

A.4. Summary of Replicated Papers

Table A2. Summary of Replicated Papers

Paper	Instrument	Treatment	Outcome	IV Type	Justification for IV Validity
APSR					
Gerber, Huber and Washington (2010)	Being sent mail	Aligning party identification with latent partisanship	Voting and party alignment scale	Experiment	NA
Meredith (2013)	Governor's home county	Democratic governor	Down-ballot Democratic candidates' vote share	Theory (Other)	"The validity of the instruments hinges on the assumption that, conditional on the control variables, coattail effects are the only channel through which the place of birth or residence of a party's gubernatorial candidate affects the vote shares received by its down-ballot candidates."(p.745)
Blattman, Hartman and Blair (2014)	Assignment to treatment blocks	Mass education campaign for dispute resolution	Serious land dispute	Experiment	NA
Laitin and Ramachandran (2016)	Geographic distance from the origins of writing	Language choice	Human development index	Theory (Geography)	"[T]he distance from these sites of invention should have no independent impact on socioeconomic development today, except through the channel of affecting the probability of possessing a writing tradition." (p. 470)
Ritter and Conrad (2016)	Rainfall	Mobilized dissent	Repression	Theory (Weather)	"[R]ainfall is an exogenous predictor of dissent onset, meeting the key criteria for the instrumental analysis to allow for causal inference."(p.89)
Croke et al. (2016)	Access to the secondary education	Education attainment	Political participation	Rules & policy changes (Change in exposure)	"There are, however, good reasons to believe that the secondary education reform only affects participation through its effect on educational attainment."(p.592)
Dower et al. (2018)	Level of serfdom	Frequency of unrest	Peasant representation and unrest	Theory (History)	"After conditioning on these covariates, we are left with that portion of serfdom largely determined by idiosyncratic variation in land grants to the nobility decades or centuries before the zemstvo reform of 1864." (p. 133)

Dower et al. (2018)	Religious polarization	Frequency of unrest	Peasant representation and unrest	Theory (History)	"After conditioning on these covariates, we are left with that portion of serfdom largely determined by idiosyncratic variation in land grants to the nobility decades or centuries before the zemstvo reform of 1864." (p. 133)
Nellis and Siddiqui (2018)	Narrow victory by secular parties in a district	The proportion of MNA seats in a district won by secularist candidates	Religious violence	Theory (Election)	"Our identifying assumption is that the outcomes of such close elections are as good as randomly decided." (p. 50)
Kapoor and Magesan (2018)	Changes in entry costs.	Number of independent candidates	Voter turnout	Rules & policy changes (Change in exposure)	"It is worth reiterating that the deposit increases had nothing to do with historical differences in voter and candidate participation across reserved and open constituencies." (p. 681)
Colantone and Stanig (2018*a*)	Imports from China to the United States × local industrial structure	Regional-level import shock from China	Leave support in Brexit	Econometrics (Interaction)	"[The]instrument is meant to capture the variation in Chinese imports, which is due to the exogenous changes in supply conditions in China, rather than to domestic factors in the United Kingdom that could be correlated with electoral outcomes." (p. 206)
Hager, Krakowski and Schaub (2019)	Distance to the nearest location where armored military vehicles were stolen	Ethnic riots (destruction)	Prosocial behavior	Theory (Other)	"[W]e present a falsification test which corroborates that the instrument is unrelated to prosocial behavior in a sample of 136 nearby villages, thus underlining the exclusion restriction." (p. 1037)
Baccini and Weymouth (2021)	Bartik instrument	Manufacturing Layoffs	Change of Democratic Vote Share	Econometrics (Interaction)	"Since layoffs are not randomly assigned, we develop an instrumental variables strategy using shift-share methodology (Bartik 1991) derived from national layoff shocks, weighted by initial county-level employment."(p.550)
Hager and Krakowski (2022)	Number of corrupted Catholic priests	Number of secret police officers	Resistance	Theory (History)	"In the early days of the regime, the secret police's ability to servile citizens depended critically on the cooperation of the Catholic Church...Importantly, the corruptibility of priests was plausibly exogenous: priests were sent to municipalities by the Catholic Church, often when another priest had retired." (p.565)

Kuipers and Sahn (2022)	Statewide assignment mandate	Civil service reform	Descriptive representation on an unrestricted sample	Rules & policy changes (Assignment)	"First, we assume that state-level mandates are a strong instrument for city adoption; we verify the strength of the instrument in the main presentation of the results. The exclusion restriction, which is untestable, seems a reasonable assumption in our case."(p.9)
			AJPS		
Kocher, Pepinsky and Kalyvas (2011)	Past insurgent control	Aerial bombing	Changes in local control	Theory (Other)	"Because instrumental variables require only conditional independence between instruments and the error term, we need only assume that there are no unobserved hamlet-specific variables that affected insurgent control in July, August, and December 1969, but not in September of that year as well." (p. 212)
Vernby (2013)	Immigration Inflow 1940–1950; immigration Inflow 1960–1967	Share of noncitizens in the electorate	Municipal education and social spending	Theory (History)	"Furthermore, it is unlikely that the initial locations of these refugees were affected by the level of local public services, suggesting that the instrument is also valid." (p. 25)
Tajima (2013)	Distance to health station	Distance to police posts (as a proxy for exposure to military intervention)	Incidence of communal violence	Theory (Geography)	"According to a Health Department official, primary health stations must be located in every subdistrict at their population centers, regardless of the propensity for violence of those locations" (p. 112)
De La O (2013)	Random assignment to early coverage	Early coverage of Conditional Cash Transfer	Incumbent party's vote share	Experiment	NA
McClendon (2014)	Assignment to treatment	Reading social esteem promising email	Participation in LGBTQ events	Experiment	NA
Barth, Finseraas and Moene (2015)	Adjusted bargaining coverage and effective number of union confederations	Wage inequality	Welfare support	Theory (Other)	"Yet conditional on union density and country fixed effects, we argue that certain properties of the bargaining system are likely to affect wages, but not union involvement in politics." (p. 574)

Stokes (2016)	Wind speed	Turbine location	Vote turnout	Theory (Climate)	“Wind speed is theoretically orthogonal to precinct boundaries but predicts the placement of wind turbine locations.” (p. 965)
Coppock and Green (2016)	Mailing showing 2005 Vote	Voting in November 2007 municipal elections	Voting in the 2008 presidential primary	Experiment	NA
Trounstine (2016)	The number of waterways in a city combined with logged population	Racial segregation	Direct general expenditures	Theory (Geography)	“I focus on waterways (including large streams and rivers), which vary in number across cities and are arguably exogenous to segregation and spending.” (p. 717)
Carnegie and Marinov (2017)	Being a former colony of one of the Council members	Foreign aid	CIRI Human Empower-ment index	Theory (History)	“In 1965, the EU stipulated that countries would hold the presidency for 6 months at a time [...] and would rotate alphabetically according to each member state’s name as spelled in its own language. ” (p. 676)
Zhu (2017)	Weighted geographic distance from economic centers	MNC activity	Corruption	Theory (Geography)	“This instrumental variable (IV) is rooted in the gravity models of international trade and FDI flows.” (p. 90)
Rueda (2017)	The size of the polling station	Actual polling place size	Citizens’ reports of electoral manipulation	Rules & policy changes (Fuzzy RD)	“The institutional rule predicts sharp reductions in the size of the average polling station of a municipality every time the number of registered voters reaches a multiple of the maximum number of voters allowed to vote in a polling station.” (p. 173)
Lelkes, Sood and Iyengar (2017)	State-level ROW index	Number of providers	Affective polarization (partisan hostility)	Theory (Other)	“[A]n index of state regulation of right-of-way laws strongly predicts the number of providers in a county, which, as we discuss later, is a good proxy for broadband uptake.” (p. 4).
Goldstein and You (2017)	Direct flight from city to Washington DC	Lobbying spending	Total earmarks or grants awarded	Theory (Other)	“The existence of a direct flight captures the convenience of travel to Washington, DC, from each city.” (p. 865)

Spenkuch and Tillmann (2018)	Individual princes' decisions concerning whether to adopt Protestantism	Religion of voters living in the same areas more than three and a half centuries later	Nazi vote share	Theory (History)	"The historical record, however, suggests that princes' decisions may plausibly satisfy this exogeneity assumption, especially after controlling for economic conditions at the end of the Weimar Republic as well as all factors known to have influenced rulers." (p. 27)
Colantone and Stanig (2018*b*)	Chinese imports to the United States ×regional industrial structure	Regional import shock from China	Economic nationalism	Econometrics (Interaction)	"This instrument is meant to capture the variation in Chinese imports due to exogenous changes in supply conditions in China, rather than to domestic factors that could be correlated with electoral outcomes." (p. 6)
Hager and Hilbig (2019)	Mean elevation	Equitable inheritance customs	Female representation	Theory (Geography; History)	"Rivers are exogenous, but no longer should have a strong effect on inequality other than through the treatment." (p. 767)
Hager and Hilbig (2019)	Distance to rivers	Equitable inheritance customs	Female representation	Theory (Geography; History)	"Rivers are exogenous, but no longer should have a strong effect on inequality other than through the treatment." (p. 767)
Chong et al. (2019)	Treatment assignment in get-out-to-vote campaigns	Actual proportion of households treated in the locality	Voted in 2013 presidential election	Experiment	NA
Kim (2019)	Population threshold	Democratic institutions	Women political engagement	Rules & policy changes (Fuzzy RD)	"[L]ocalities with a population greater than 1,500 must create a municipal council [...] whereas those with a population below that threshold were free to choose between the status quo direct democracy and representative democracy." (p. 6).
Sexton, Wellhausen and Findley (2019)	Soldier fatalities	Health budget	Welfare outcome	Theory (Other)	"We substantiate [the exclusion restriction] below by ruling out the key alternative channel that local insecurity could affect citizens' use of health services." (p. 359)
López-Moctezuma et al. (2022)	Assignment to treatment	Town-hall meetings	Voting behavior	Experiment	NA

Blair, Di Salvatore and Smidt (2022)	Average fragmentation of all ongoing PKO mandates	Fragmentation of any given PKO mandate	Process performance	Theory (Other)	"We view the first of these assumptions as mostly uncontroversial. As discussed above, most PKO mandates are only loosely tailored to conditions in their host countries. It is highly unlikely that the mandates of all other PKOs in Africa are tailored to the host country conditions of any given PKO. This should mitigate independence concerns." (p.11)
Hong, Park and Yang (2022)	Geographic terrain elevation and slope	NVM subsidies	Park's vote share in 2012	Theory (Geography)	"The logic behind this choice is as follows: each village's performance in the NVM is evaluated based on their baseline conditions. Therefore, an unfavorable terrain before the movement likely indicates an initial lack of infrastructure in a poorer environment, and thus gives a village an advantageous benchmark from which to generate a notable and visible improvement within a short period compared to other villages." (p.11)
Wood and Grose (2022)	Random audit	Incumbent found to have campaign finance violations	Legislator retired	Experiment	NA
			JOP		
Gehlbach and Keefer (2012)	Whether the first ruler in a nondemocratic episode is a military leader	Age of ruling party less leader years in office	Private investment/GDP	Theory	"[D]ictators who come to power with the backing of the military require less popular support to remain in power and are therefore less likely to promote private investment by allowing supporters to organize." (p. 628)
Healy and Malhotra (2013)	Whether the younger sibling is a sister	The share of a respondent's siblings who are female	1973 gender-role attitude	Theory (Others – Biology)	"However, under Assumption 1, all siblings have an impact only through the overall gender makeup of the household." (p. 1027)
Dube and Naidu (2015)	US military aid to countries outside of Latin America	US military aid to Colombia	The number of paramilitary attacks	Theory (Diffusion)	"The instrument is valid since US funding to the rest of the world is determined by the broad geopolitical outlook of the American government, reflecting factors such as the party of the president or other major world events, and can thus be considered exogenous to the conflict in Colombia."(p.256)

Flores-Macias and Kreps (2013)	Lagged values of country's energy production	Trade volume	Foreign policy convergence	Theory (Other)	"The logic is that trade and trade salience in Africa and Latin America are significantly related to countries' energy production, but there is no reason to believe that either of them is correlated with the error term in the equation predicting foreign policy convergence" (p. 365)
Charron and Lapuente (2013)	Consolidation of clientelistic networks in regions where rulers have historically less constraints to their decisions	Clientelism	Quality of government	Theory (History)	"[W]e also find that constraints are directly correlated with current regional institutional quality (yet in his analysis regional GDP and GDP growth are used), thus rendering it an imperfect instrument for clientelism"(p.576)
Kriner and Schickler (2014)	Number of days Congress is in session	Committee investigations	Presidential approval	Theory (Other)	"[T]here is no theoretical reason drawn from existing literatures to expect the calendar to be independently correlated with presidential approval." (p. 525)
Lorentzen, Landry and Yasuda (2014)	Large firm dominance in 1999	Large firm dominance in 2007	Pollution information transparency index	Econometrics (Lagged treatment)	"[The instrument was measured] well before transparency reforms were a major focus of discussion." (p. 187)
Dietrich and Wright (2015)	Constructed "internal" excluded instrument	Economic aid	Transitions to multipar-tyism	Econometrics (Lewbel instrument)	"[We]show that the excluded instruments are generally uncorrelated with alternative channels through which they might influence the outcome variables." (p. 223)
Feigenbaum and Hall (2015)	Chinese exports to other economies $\times$local exposure	Localized trade shocks in congressional districts	Trade score	Econometrics (Interaction)	"[We] use an instrument that depends [...] on Chinese import growth to other rich, Western economies" and "the lagged version is unaffected by Chinese trade shock." (p.1019)
Alt, Marshall and Lassen (2016)	Assignment to receiving an aggregate unemployment forecast	Unemploy-ment expectations	Vote intention	Experiment	NA
Johns and Pelc (2016)	Trade stake of the rest of the world	The number of other countries that became third parties	Becoming a third party	Theory (Other)	"[E]ach state's participation decision is not directly affected by the trade stake of other countries. The trade stake of other countries matters only to the extent that it shapes a player's belief about how other countries will behave." (p. 99)

Acharya, Blackwell and Sen (2016)	Measures of the environmental suitability for growing cotton	Slave proportion in 1860	proportion Democrat	Theory (History)	“We present results from this analysis showing that, outside the South, the relationship between cotton suitability and political attitudes is either very small or in the opposite direction as in the South.” (p. 628)
Schleiter and Tavits (2016)	Prime Minister dissolution power	Opportunis-tic election calling	Vote share of Prime Minister’s party	Theory (Other)	“The instrument correlates directly with the treatment of interest—opportunistic election calling—without being linked to anticipated incumbent electoral performance.” (p. 840)
Henderson and Brooks (2016)	Rain around Election day	Democratic vote margins	Incumbent roll call positioning	Theory (Weather)	“Rain several days before an election may dampen the willingness to make plans, arrange transportation, and schedule time off work to go to the polls.”(p.657)
Henderson and Brooks (2016)	Rain around Election weekend	Democratic vote margins	Incumbent roll call positioning	Theory (Weather)	“Rain several days before an election may dampen the willingness to make plans, arrange transportation, and schedule time off work to go to the polls.”(p.657)
Charron et al. (2017)	Proportion of Protestant residents in a region; aggregate literacy in 1880	More developed bureaucracy	Percent of single bidders	Theory (History)	“[C]ross-country data show that, while the least corrupted countries in the world all have had near universal literacy for decades, other countries considered highly corrupt, [...] have, for the entire postwar era, also been some of the most highly literate places in the world.” (p.97)
West (2017)	IEM (prediction market) price	Obama win	Policy efficacy	Theory (Other)	“The identifying assumption is that there is no unobservable factor that simultaneously affects black (female) political efficacy and perceptions of the likelihood of an Obama (Clinton) victory.” (p.352)
Stewart and Liou (2017)	Log total border length and the total number of that state’s neighbors	Foreign territorial control	Civilian casualties	Theory (Geography)	“[T]he longer a state’s borders or the greater its number of neighbors, the more accessible border regions in neighboring states will be to rebels, independent of the dynamics of their conflict with the government. Further, total border length or the number of bordering states is not likely to affect rebel targeting of civilians other than through their effects on the likelihood of rebel group’s controlling foreign territory.” (p. 291)
Lerman, Sadin and Trachtman (2017)	Born 1946 or 1947	Public (p 1) versus only private (p 0) health insurance	Support ACA	Rules & policy changes (Change in exposure)	“We can confirm across a host of observable covariates that these two age groups are similar on almost every dimension, with the exception of insurance.” (p. 631)

Grossman, Pierskalla and Boswell Dean (2017)	The number of distinct landmasses; length of medium and small streams; over-time variation in the number of regional governments	Government fragmentation	Public goods provision	Theory (Geography / diffusion)	"Territorial structure of neighboring countries will affect the local discourse on institutional reforms and increase the likelihood that a country will adopt similar reforms" and "The other two instruments build on the fact that administrative and political boundaries are drawn around geographic landmarks." (p. 831)
Cirone and Van Coppenolle (2018)	Random assignment of budget incumbents to bureaux	Budget committee service	Legislator sponsorship on a budget bill	Theory (Other)	"Conceptually, the competitiveness of the randomly assigned group acts similarly to a form of encouragement design." (p. 953)
Bhavnani and Lee (2018)	Early-career job assignment to districts	Bureaucrats' embeddedness	Proportion of villages with high schools	Theory (Other)	"[T]he IAS posting orders that we obtained suggest that heuristics such alphabetical order and serial number—which are arbitrary and orthogonal to district and officer characteristics—are used to match officers to districts." (p. 78)
Pianzola et al. (2019)	Random assignment of the e-mail treatment	Smartvote use	Vote intention	Experiment	NA
Arias and Stasavage (2019)	Trade shock × UK bond yield	Government expenditures	Regular leader turnover	Econometrics (Interaction)	"The logic here is that when costs of external borrowing are high, a government experiencing a trade shock is more likely to cut expenditures because the option of borrowing to maintain or increase expenditures is too costly. This interaction term is the excluded instrument while the Trade Shock variable is included in both the first- and the second-stage estimates" (p. 1519)
Ziaja (2020)	Constructed instrument	Number of democracy donors	Democracy scores	Econometrics (Interaction)	"[T]here is no reason to believe that the gender composition of a donor country's parliament should affect democracy in a recipient country directly."(p.439)
Schubiger (2021)	counterinsurgent mobilization	exposure to state violence	Location of a community inside or outside the emergency zone	Theory(Geography)	"Destination choices were typically driven by economic and social factors (e.g., Degregori 1998, 151; Del Pino 1996, 164). Moreover, it is unlikely that local residents were able to anticipate the boundaries of the emergency zones and whether, when, and where they would change over time." (p.1389)

DiGiuseppe and Shea (2022)	Echelon corridor	US support	Fiscal capacity	Theory(Geography)	“Like Aklin and Kern (2019), we find that the echelon is plausibly exogenous to a state’s capacity, property rights, or risk of conflict. Instead, whether a state is located in the echelon corridor is a function of happenstance geography.” (p.777)
Lei and Zhou (2022)	Whether the city has more than 3 million residents	Subway approval	Mayor promotion	Rules & policy changes (Fuzzy RD)	“the city’s population exceeds 3 million people, and (4) more than 30,000 people per hour are expected to use a subway line” (p.463)
Urpelainen and Zhang (2022)	Time trend multiplied by the wind resource of the electoral district	Wind turbine capacity	Democratic vote	Econometrics(Interaction)	“Validity of the average wind resource instrument hinges on two criteria: relevance and exclusion restriction...” (pp.1313-1314)
Webster, Connors and Sinclair (2022)	Treatment assignment	Percentage of angry words that a respondent wrote in emotional recall prompts	Social polarization	Experiment	NA

Note: Justifications are omitted in the case of randomized controlled trials.

References

Acharya, Avidit, Matthew Blackwell and Maya Sen. 2016. "The Political Legacy of American Slavery." *The Journal of Politics* 78(3):621–641.

Alt, James E, John Marshall and David D Lassen. 2016. "Credible Sources and Sophisticated Voters: When does New Information Induce Economic Voting?" *The Journal of Politics* 78(2):327–342.

Andrews, Isaiah, James H. Stock and Liyang Sun. 2019. "Weak Instruments in Instrumental Variables Regression: Theory and Practice." *Annual Review of Economics* 11(1):727–753.

Arias, Eric and David Stasavage. 2019. "How Large are the Political Costs of Fiscal Austerity?" *The Journal of Politics* 81(4):1517–1522.

Baccini, Leonardo and Stephen Weymouth. 2021. "Gone for Good: Deindustrialization, White Voter Backlash, and US Presidential Voting." *American Political Science Review* 115(2):550–567.

Barth, Erling, Henning Finseraas and Karl O. Moene. 2015. "Political Reinforcement: How Rising Inequality Curbs Manifested Welfare Generosity." *American Journal of Political Science* 59(3):565–577.

Bhavnani, Rikhil R. and Alexander Lee. 2018. "Local Embeddedness and Bureaucratic Performance: Evidence from India." *The Journal of Politics* 80(1):71–87.

Blair, Robert A, Jessica Di Salvatore and Hannah M Smidt. 2022. "When do UN Peacekeeping Operations Implement their Mandates?" *American Journal of Political Science* 66(3):664–680.

Blattman, Christopher, Alexandra C. Hartman and Robert A. Blair. 2014. "How to Promote Order and Property Rights under Weak Rule of Law? An Experiment in Changing Dispute Resolution Behavior through Community Education." *American Political Science Review* 108(1):100–120.

Bound, John and David A Jaeger. 2000. "Do Compulsory School Attendance Laws Alone Explain the Association between Quarter of Birth and Earnings?" *Research in Labor Economics* 19(4):83–108.

Carnegie, Allison and Nikolay Marinov. 2017. "Foreign Aid, Human Rights, and Democracy Promotion: Evidence from a Natural Experiment." *American Journal of Political Science* 61(3):671–683.

Charron, Nicholas, Carl Dahlström, Mihaly Fazekas and Victor Lapuente. 2017. "Careers, Connections, and Corruption Risks: Investigating the Impact of Bureaucratic Meritocracy on Public Procurement Processes." *The Journal of Politics* 79(1):89–104.

Charron, Nicholas and Victor Lapuente. 2013. "Why do Some Regions in Europe Have a Higher Quality of Government?" *The Journal of Politics* 75(3):567–582.

Chong, Alberto, Gianmarco León-Ciliotta, Vivian Roza, Martín Valdivia and Gabriela Vega. 2019. "Urbanization Patterns, Information Diffusion, and Female Voting in Rural Paraguay." *American Journal of Political Science* 63(2):323–341.

Cirone, Alexandra and Brenda Van Coppenolle. 2018. "Cabinets, Committees, and Careers: The Causal Effect of Committee Service." *The Journal of Politics* 80(3):948–963.

Clarke, Damian. 2014. "PLAUSEXOG: Stata Module to Implement Conley et al's Plausibly Exogenous Bounds.". https://econpapers.repec.org/RePEc:boc:bocode:s457832 (accessed July, 2023).

Colantone, Italo and Piero Stanig. 2018*a*. "Global Competition and Brexit." *American Political Science Review* 112(2):201–218.

Colantone, Italo and Piero Stanig. 2018*b*. "The Trade Origins of Economic Nationalism: Import Competition and Voting Behavior in Western Europe." *American Journal of Political Science* 62(4):936–953.

Conley, Timothy G, Christian B Hansen and Peter E Rossi. 2012. "Plausibly Exogenous." *The Review of Economics and Statistics* 94(1):260–272.

Coppock, Alexander and Donald P. Green. 2016. "Is Voting Habit Forming? New Evidence from Experiments and Regression Discontinuities." *American Journal of Political Science* 60(4):1044–1062.

Croke, Kevin, Guy Grossman, Horacio A. Larreguy and John Marshall. 2016. "Deliberate Disengagement: How Education can Decrease Political Participation in Electoral Authoritarian Regimes." *American Political Science Review* 110(3):579–600.

De La O, Ana L. 2013. "Do Conditional Cash Transfers Affect Electoral Behavior? Evidence from a Randomized Experiment in Mexico." *American Journal of Political Science* 57(1):1–14.

Dietrich, Simone and Joseph Wright. 2015. "Foreign Aid Allocation Tactics and Democratic Change in Africa." *The Journal of Politics* 77(1):216–234.

DiGiuseppe, Matthew and Patrick E Shea. 2022. "Us Patronage, State Capacity, and Civil Conflict." *The Journal of Politics* 84(2):767–782.

Dower, Paul Castaneda, Evgeny Finkel, Scott Gehlbach and Steven Nafziger. 2018. "Collective Action and Representation in Autocracies: Evidence from Russia's Great Reforms." *American Political Science Review* 112(1):125–147.

Dube, Oeindrila and Suresh Naidu. 2015. "Bases, Bullets, and Ballots: The Effect of US Military Aid on Political Conflict in Colombia." *The Journal of Politics* 77(1):249–267.

Eggers, Andrew C, Guadalupe Tuñón and Allan Dafoe. 2021. "Placebo Tests for Causal Inference." *Unpublished manuscript. https://pelg. ucsd. edu/Eggers_2021. pdf* .

Feigenbaum, James J. and Andrew B. Hall. 2015. "How Legislators Respond to Localized Economic Shocks: Evidence from Chinese Import Competition." *The Journal of Politics* 77(4):1012–1030.

Flores-Macias, Gustavo A. and Sarah E. Kreps. 2013. "The foreign policy consequences of trade: China's commercial relations with Africa and Latin America, 1992–2006." *The Journal of Politics* 75(2):357–371.

Gehlbach, Scott and Philip Keefer. 2012. "Private Investment and the Institutionalization of Collective Action in Autocracies: Ruling Parties and Legislatures." *The Journal of Politics* 74(2):621–635.

Gerber, Alan S., Gregory A. Huber and Ebonya Washington. 2010. "Party Affiliation, Partisanship, and Political Beliefs: A Field Experiment." *American Political Science Review* 104(4):720–744.

Goldstein, Rebecca and Hye Young You. 2017. "Cities as Lobbyists." *American Journal of Political Science* 61(4):864–876.

Grossman, Guy, Jan H. Pierskalla and Emma Boswell Dean. 2017. "Government Fragmentation and Public Goods Provision." *The Journal of Politics* 79(3):823–840.

Guiso, Luigi, Paola Sapienza and Luigi Zingales. 2016. "Long-term Persistence." *Journal of the European Economic Association* 14(6):1401–1436.

Hager, Anselm and Hanno Hilbig. 2019. "Do Inheritance Customs Affect Political and Social Inequality?" *American Journal of Political Science* 63(4):758–773.

Hager, Anselm and Krzysztof Krakowski. 2022. "Does State Repression Spark Protests? Evidence from Secret Police Surveillance in Communist Poland." *American Political Science Review* 116(2):564–579.

Hager, Anselm, Krzysztof Krakowski and Max Schaub. 2019. "Ethnic Riots and Prosocial Behavior: Evidence from Kyrgyzstan." *American Political Science Review* 113(4):1029–1044.

Healy, Andrew and Neil Malhotra. 2013. "Childhood Socialization and Political Attitudes: Evidence from a Natural experiment." *The Journal of Politics* 75(4):1023–1037.

Henderson, John and John Brooks. 2016. "Mediating the Electoral Connection: The Information Effects of Voter Signals on Legislative Behavior." *The Journal of Politics* 78(3):653–669.

Hong, Ji Yeon, Sunkyoung Park and Hyunjoo Yang. 2022. "In Strongman We Trust: The Political Legacy of the New Village Movement in South Korea." *American Journal of Political Science* .

Johns, Leslie and Krzysztof J. Pelc. 2016. "Fear of Crowds in World Trade Organization Disputes: Why Don't More Countries Participate?" *The Journal of Politics* 78(1):88–104.

Kang, Hyunseung, Yang Jiang, Qingyuan Zhao and Dylan S Small. 2021. "Ivmodel: An R Package for Inference and Sensitivity Analysis of Instrumental Variables Models with One Endogenous Variable." *Observational Studies* 7(2):1–24.

Kapoor, Sacha and Arvind Magesan. 2018. "Independent Candidates and Political Representation in India." *American Political Science Review* 112(3):678–697.

Kim, Jeong Hyun. 2019. "Direct Democracy and Women's Political Engagement." *American Journal of Political Science* 63(3):594–610.

Kocher, Matthew Adam, Thomas B. Pepinsky and Stathis N. Kalyvas. 2011. "Aerial Bombing and Counterinsurgency in the Vietnam War." *American Journal of Political Science* 55(2):201–218.

Kriner, Douglas L. and Eric Schickler. 2014. "Investigating the President: Committee Probes and Presidential Approval, 1953–2006." *The Journal of Politics* 76(2):521–534.

Kuipers, Nicholas and Alexander Sahn. 2022. "The Representational Consequences of Municipal Civil Service Reform." *American Political Science Review* pp. 1–17.

Laitin, David D. and Rajesh Ramachandran. 2016. "Language Policy and Human Development." *American Political Science Review* 110(3):457–480.

Lei, Zhenhuan and Junlong Aaron Zhou. 2022. "Private Returns to Public Investment: Political Career Incentives and Infrastructure Investment in China." *The Journal of Politics* 84(1):455–469.

Lelkes, Yphtach, Gaurav Sood and Shanto Iyengar. 2017. "The Hostile Audience: The Effect of Access to Broadband Internet on Partisan Affect." *American Journal of Political Science* 61(1):5–20.

Lerman, Amy E., Meredith L. Sadin and Samuel Trachtman. 2017. "Policy Uptake as Political Behavior: Evidence from the Affordable Care Act." *American Political Science Review* 111(4):755.

López-Moctezuma, Gabriel, Leonard Wantchekon, Daniel Rubenson, Thomas Fujiwara and Cecilia Pe Lero. 2022. "Policy Deliberation and Voter Persuasion: Experimental Evidence from an Election in the Philippines." *American Journal of Political Science* 66(1):59–74.

Lorentzen, Peter, Pierre Landry and John Yasuda. 2014. "Undermining Authoritarian Innovation: The Power of China's Industrial Giants." *The Journal of Politics* 76(1):182–194.

McClendon, Gwyneth H. 2014. "Social Esteem and Participation in Contentious Politics: A Field Experiment at an LGBT Pride Rally." *American Journal of Political Science* 58(2):279–290.

Meredith, Marc. 2013. "Exploiting Friends-and-neighbors to Estimate Coattail Effects." *American Political Science Review* 107(4):742–765.

Nellis, Gareth and Niloufer Siddiqui. 2018. "Secular Party Rule and Religious Violence in Pakistan." *American Political Science Review* 112(1):49.

Nunn, Nathan. 2008. "The Long-term Effects of Africa's Slave Trades." *The Quarterly Journal of Economics* 123(1):139–176.

Nunn, Nathan and Leonard Wantchekon. 2011. "The Slave Trade and the Origins of Mistrust in Africa." *American Economic Review* 101(7):3221–3252.

Olea, José Luis Montiel and Carolin Pflueger. 2013. "A Robust Test for Weak Instruments." *Journal of Business & Economic Statistics* 31(3):358–369.

Pianzola, Joëlle, Alexander H. Trechsel, Kristjan Vassil, Guido Schwerdt and R. Michael Alvarez. 2019. "The Impact of Personalized Information on Vote Intention: Evidence from a Randomized Field Experiment." *The Journal of Politics* 81(3):833–847.

Putnam, Robert D, Robert Leonardi and Rafaella Y Nanetti. 1993. *Making Democracy Work: Civic Traditions in Modern Italy*. Princeton, NJ: Princeton University Press.

Ritter, Emily Hencken and Courtenay R. Conrad. 2016. "Preventing and Responding to Dissent: The Observational Challenges of Explaining Strategic Repression." *American Political Science Review* 110(1):85–99.

Rueda, Miguel R. 2017. "Small Aggregates, Big Manipulation: Vote Buying Enforcement and Collective Monitoring." *American Journal of Political Science* 61(1):163–177.

Schleiter, Petra and Margit Tavits. 2016. "The Electoral Benefits of Opportunistic Election Timing." *The Journal of Politics* 78(3):836–850.

Schubiger, Livia Isabella. 2021. "State Violence and Wartime Civilian Agency: Evidence from Peru." *The Journal of Politics* 83(4):1383–1398.

Sexton, Renard, Rachel L. Wellhausen and Michael G. Findley. 2019. "How Government Reactions to Violence Worsen Social Welfare: Evidence from Peru." *American Journal of Political Science* 63(2):353–367.

Spenkuch, Jörg L. and Philipp Tillmann. 2018. "Elite Influence? Religion and the Electoral Success of the Nazis." *American Journal of Political Science* 62(1):19–36.

Stewart, Megan A. and Yu-Ming Liou. 2017. "Do Good Borders Make Good Rebels? Territorial Control and Civilian Casualties." *The Journal of Politics* 79(1):284–301.

Stokes, Leah C. 2016. "Electoral Backlash against Climate Policy: A Natural Experiment on Retrospective Voting and Local Resistance to Public Policy." *American Journal of Political Science* 60(4):958–974.

Tajima, Yuhki. 2013. "The Institutional Basis of Intercommunal Order: Evidence from Indonesia's Democratic Transition." *American Journal of Political Science* 57(1):104–119.

Trounstine, Jessica. 2016. "Segregation and Inequality in Public Goods." *American Journal of Political Science* 60(3):709–725.

Urpelainen, Johannes and Alice Tianbo Zhang. 2022. "Electoral Backlash or Positive Reinforcement? Wind Power and Congressional Elections in the United States." *The Journal of Politics* 84(3):1306–1321.

Van Kippersluis, Hans and Cornelius A Rietveld. 2018. "Beyond Plausibly Exogenous." *The Econometrics Journal* 21(3):316–331.

Vernby, Kare. 2013. "Inclusion and Public Policy: Evidence from Sweden's Introduction of Noncitizen Suffrage." *American Journal of Political Science* 57(1):15–29.

Webster, Steven W, Elizabeth C Connors and Betsy Sinclair. 2022. "The Social Consequences of Political Anger." *The Journal of Politics* 84(3):1292–1305.

West, Emily A. 2017. "Descriptive Representation and Political Efficacy: Evidence from Obama and Clinton." *The Journal of Politics* 79(1):351–355.

Wood, Abby K and Christian R Grose. 2022. "Campaign Finance Transparency Affects Legislators' Election Outcomes and Behavior." *American Journal of Political Science* 66(2):516–534.

Zhu, Boliang. 2017. "MNCs, Rents, and Corruption: Evidence from China." *American Journal of Political Science* 61(1):84–99.

Ziaja, Sebastian. 2020. "More Donors, more Democracy." *The Journal of Politics* 82(2):433–447.

Supplemental Materials
Appendix B

How Much Should We Trust Instrumental Variable Estimates in Political Science? Practical Advice based on 67 Replicated Studies

16 September 2023

Contents

Readme

- est_ols stores treatment effect estimates from the naive OLS estimation. 'Analytic' corresponds to analytic asymptotic standard errors (SEs) and confidence intervals (CIs). 'Boot.c' and 'Boot.t' represent inferential methods based on bootstrapped coefficients and bootstrapped t-statistics, respectively.
- est_2sls stores treatment effect estimates from the 2SLS estimation.
- AR stores results from the Anderson-Rubin test. The confidence region (CR) is produced by the inversion method. 'AR.bounded = TRUE' means that the CR is bounded and not empty.
- F.stat stores F statistics based on classic SEs (F.standard), H.W. robust SEs (F.robust), cluster-robust SEs (F.cluster), bootstrapped or cluster-bootstrapped SEs (F.bootstrap) and the effective F (F.effective). In the one-treatment-one-instrument case, F.effective is the same as F.robust (if there is no clustering structure) or F.cluster (if there is one).
- rho stores the partial correlation coefficient between the treatment and the predicted treatment from the first stage regression.
- tf.cF stores the results from the tF-cF procedure. Specifically, cF corresponds to the adjusted critical value based on the first stage (effective) F statistic for the subsequent t-test.
- est_rf stores the results from the reduced form regression. The control variables are partialled out.
- est_fs stores the results from the first stage regression. The control variables are partialled out.
- p_iv stores the number of instruments. N and N_cl stores the the number of observations and the number of clusters (if there is a clustering structure), respectively. df stores the degree of freedom from the 2SLS regression.
- nvalues stores the numbers of unique values in the outcome, treatment, and instrument.

APSR

Baccini and Weymouth (2021)

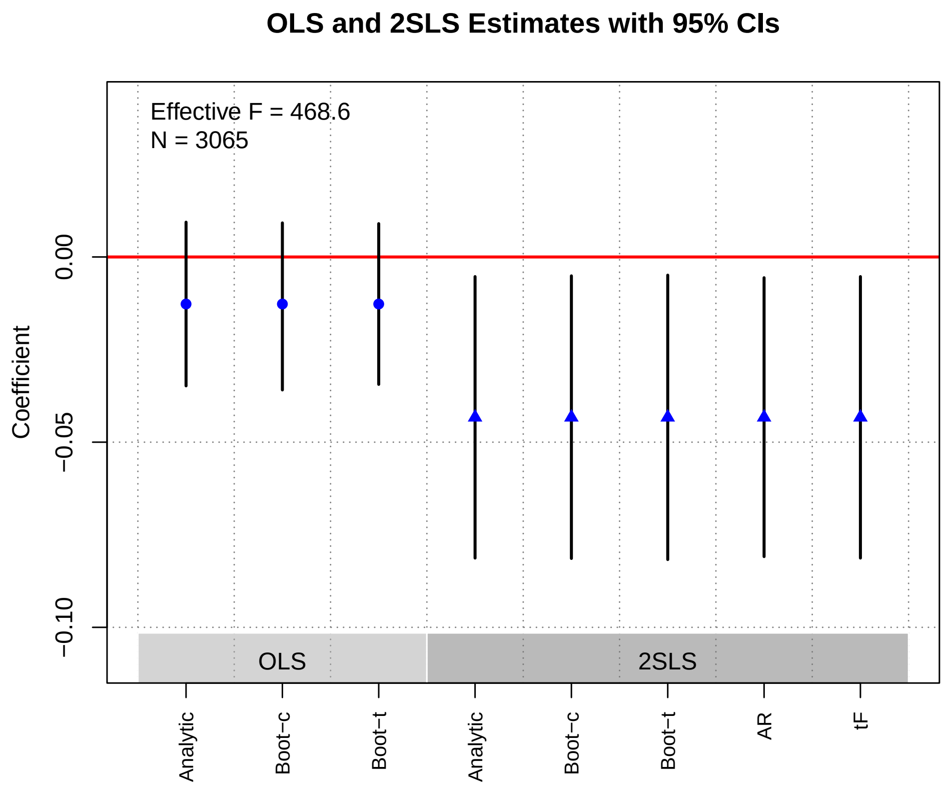
Replication Summary	
Unit of analysis	county
Treatment	Manufacturing Layoffs
Instrument	Bartik instrument
Outcome	Change of Democratic Vote Share
Model	Table2(3)

```
df <- readRDS("./data/apsr_baccini_etal_2021.rds")
D <-"msl_pc4y2"
Y <- "ddem_votes_pct1"
Z <-  "bartik_leo5"
controls <- c("LAU_unemp_rate_4y", "pers_m_total_share_4y", "pers_coll_share_4y",
              "white_counties_4y", "msl_service_pc4y")
cl <- NULL
FE <- "id_state"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.0127 0.0113 -1.1240 -0.0348   0.0094   0.261
## Boot.c   -0.0127 0.0112 -1.1332 -0.0359   0.0092   0.248
## Boot.t   -0.0127 0.0113 -1.1240 -0.0344   0.0090   0.251
##
## $est_2sls
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.0433 0.0194 -2.2308 -0.0813  -0.0053  0.0257
## Boot.c   -0.0433 0.0193 -2.2444 -0.0814  -0.0051  0.0240
## Boot.t   -0.0433 0.0194 -2.2308 -0.0817  -0.0049  0.0240
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    5.0579    1.0000 3063.0000    0.0246
##
## $AR$ci.print
## [1] "[-0.0809, -0.0056]"
##
## $AR$ci
## [1] -0.0809 -0.0056
```

```
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##   1537.5647    468.6180          NA    444.3045    468.6180
##
## $rho
## [1] 0.5815
##
## $tF
##        F       cF     Coef       SE        t   CI2.5%  CI97.5%  p-value
## 468.6180   1.9600  -0.0433   0.0194  -2.2308  -0.0813  -0.0053   0.0257
##
## $est_rf
##                Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## bartik_leo5 -4.5381 2.0355  0.0258 2.0178  -8.3919   -0.5561     0.024
##
## $est_fs
##                 Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## bartik_leo5 104.8786 4.8448       0 4.9756  96.2948  115.6565         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 3065
##
## $N_cl
## NULL
##
## $df
## [1] 3010
##
## $nvalues
##      ddem_votes_pct1 msl_pc4y2 bartik_leo5
## [1,]            3062      2913        2771
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Blattman et al. (2014)

Replication Summary	
Unit of analysis	resident
Treatment	mass education campaign for dispute resolution
Instrument	assignment to treatment blocks
Outcome	serious land dispute
Model	Table9(8)

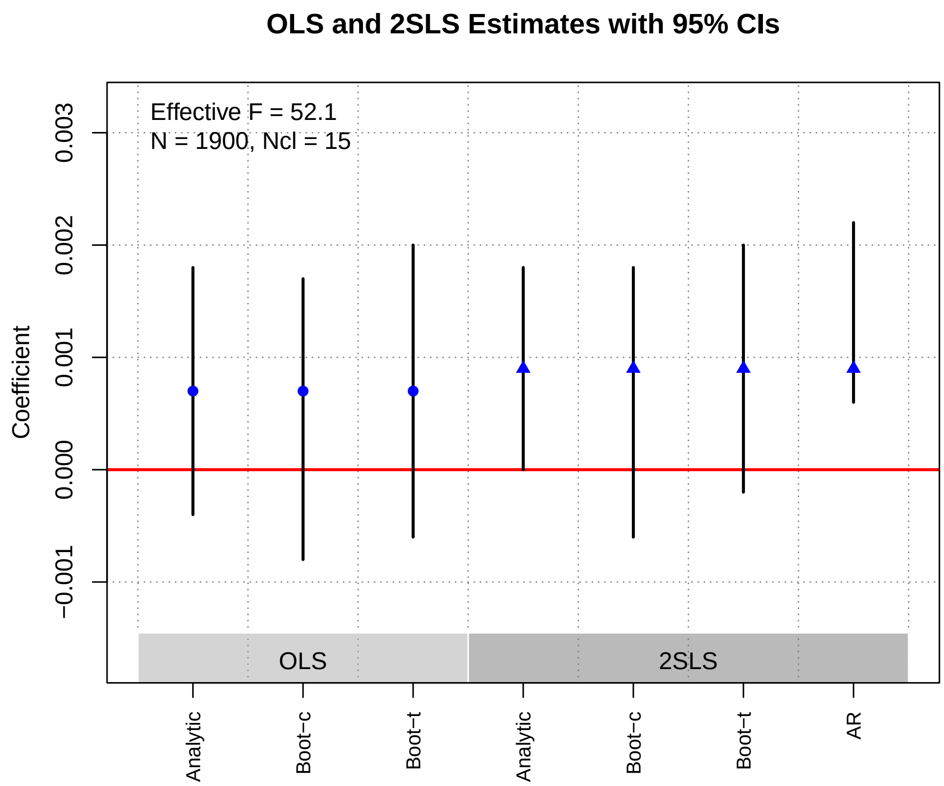
```
df <- readRDS("./data/apsr_Blattman_etal_2014.rds")
df$district <- 0
for (i in 1:15) {df$district[which(df[,paste0("district",i)]==1)] <- i}
D <-"months_treated"
Y <- "fightweap_dummy"
Z <- c("block1", "block2", "block3")
controls <- c("ageover60", "age40_60", "age20_40",
 "yrs_edu", "female", "stranger", "christian",
 "minority", "cashearn_imputedhst", "noland",
 "land_sizehst", "farm_sizehst", "lndtake_dum",
 "housetake_dum", "vsmall", "small",
 "small2", "small3", "quartdummy", "cedulevel_bc",
```

```r
 "ctownhh_log_el", "cwealthindex_bc", "cviol_experienced_bc",
 "clndtake_bc", "cviol_scale_bc", "clandconf_scale_bc",
 "cwitchcraft_scale_bc", "cpalaviol_imputed_bc",
 "cprog_ldr_beliefs_bc", "cattitudes_tribe_bc",
 "crelmarry_bc", "trainee")
cl <- "district"
FE <- "district"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef    SE      t CI 2.5% CI 97.5% p.value
## Analytic 7e-04 5e-04 1.2355  -4e-04   0.0018  0.2167
## Boot.c   7e-04 6e-04 1.0471  -8e-04   0.0017  0.4120
## Boot.t   7e-04 5e-04 1.2355  -6e-04   0.0020  0.2650
##
## $est_2sls
##            Coef    SE      t CI 2.5% CI 97.5% p.value
## Analytic 9e-04 5e-04 1.9157   0e+00   0.0018  0.0554
## Boot.c   9e-04 6e-04 1.5044  -6e-04   0.0018  0.2020
## Boot.t   9e-04 5e-04 1.9157  -2e-04   0.0020  0.0950
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    5.0886    3.0000 1896.0000    0.0016
##
## $AR$ci.print
## [1] "[0.0006, 0.0022]"
##
## $AR$ci
## [1] 0.0006 0.0022
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##   F.standard    F.robust   F.cluster F.bootstrap F.effective
##    2756.3845   2472.2847    234.3492    102.3902     52.1000
##
## $rho
## [1] 0.9039
##
## $est_rf
##           Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
```

```
## block1 0.0263 0.0085  0.0020 0.0128  -0.0053    0.0451     0.094
## block2 0.0027 0.0099  0.7812 0.0131  -0.0241    0.0281     0.922
## block3 0.0085 0.0064  0.1816 0.0108  -0.0146    0.0265     0.322
##
## $est_fs
##           Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## block1 20.0361 0.7567       0 1.2037  17.8817   22.5304     0.000
## block2 12.9786 1.7805       0 2.1259   8.7558   16.8593     0.000
## block3  6.7831 1.3081       0 1.7928   3.1251   10.5196     0.002
##
## $p_iv
## [1] 3
##
## $N
## [1] 1900
##
## $N_cl
## [1] 15
##
## $df
## [1] 14
##
## $nvalues
##      fightweap_dummy months_treated block1 block2 block3
## [1,]               2             34      2      2      2
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Colantone and Stanig (2018)

Replication Summary	
Unit of analysis	region
Treatment	regional-level import shock from China
Instrument	imports from China to the United States * local industrial structure
Outcome	leave share
Model	Table1(6)

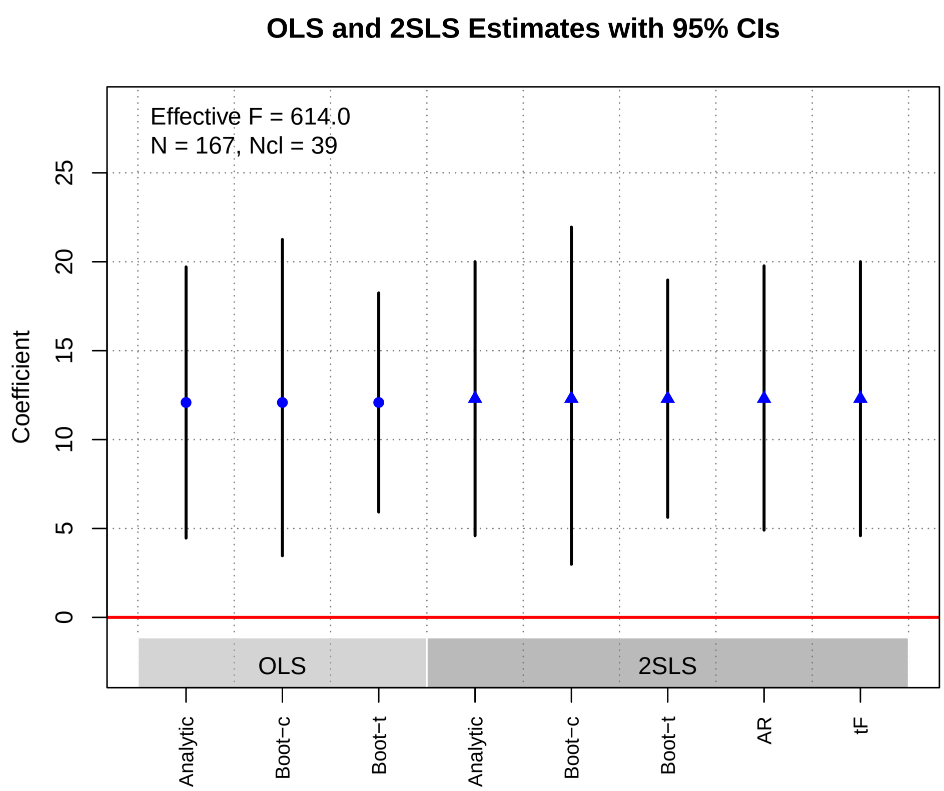
```
df<-readRDS("./data/apsr_Colantone_etal_2018.rds")
D <-'import_shock'
Y <- "leave_share"
Z <- "instrument_for_shock"
controls <- c("immigrant_share", "immigrant_arrivals")
cl <- "fix"
FE <- "nuts1"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 12.0854 3.8903 3.1066   4.4605   19.7104  0.0019
## Boot.c   12.0854 4.4866 2.6937   3.4677   21.2540  0.0040
```

```
## Boot.t   12.0854 3.8903 3.1066  5.9225  18.2484  0.0000
##
## $est_2sls
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 12.2993 3.9320 3.1280  4.5926  20.0060  0.0018
## Boot.c   12.2993 4.6321 2.6553  2.9873  21.9487  0.0040
## Boot.t   12.2993 3.9320 3.1280  5.6257  18.9730  0.0000
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##  10.5300   1.0000 165.0000   0.0014
##
## $AR$ci.print
## [1] "[4.9072, 19.7701]"
##
## $AR$ci
## [1]  4.9072 19.7701
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##   2158.0662    792.4682    613.9804    532.8092    613.9804
##
## $rho
## [1] 0.9663
##
## $tF
##        F       cF     Coef       SE        t   CI2.5%  CI97.5%  p-value
## 613.9804   1.9600  12.2993   3.9320   3.1280   4.5926  20.0060   0.0018
##
## $est_rf
##                       Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## instrument_for_shock 1.5671 0.5015  0.0018 0.6026   0.3774    2.8771     0.004
##
## $est_fs
##                       Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## instrument_for_shock 0.1274 0.0051       0 0.0055   0.1181    0.1398         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 167
```

```
##
## $N_cl
## [1] 39
##
## $df
## [1] 153
##
## $nvalues
##      leave_share import_shock instrument_for_shock
## [1,]         167          148                  148
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Croke et al. (2016)

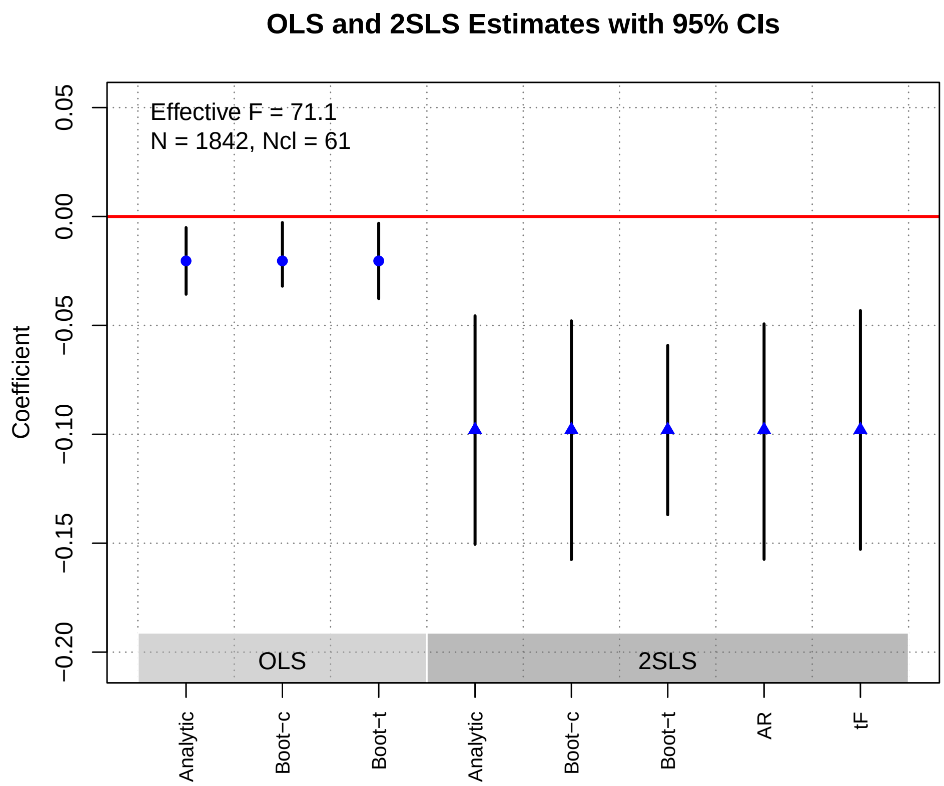
Replication Summary	
Unit of analysis	individual
Treatment	education attainment
Instrument	access to the secondary education
Outcome	political participation
Model	Table2(b1)

```r
df <-readRDS("./data/apsr_Croke_etal_2016.rds")
D <- "edu"
Y <- "part_scale"
Z <- "treatment"
controls <-NULL
cl<- "district"
FE<- "year_survey"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.0204 0.0078 -2.6133 -0.0357  -0.0051   0.009
## Boot.c   -0.0204 0.0078 -2.6111 -0.0320  -0.0028   0.012
## Boot.t   -0.0204 0.0078 -2.6133 -0.0377  -0.0031   0.020
##
## $est_2sls
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.098 0.0268 -3.6620 -0.1505  -0.0456   3e-04
## Boot.c   -0.098 0.0273 -3.5858 -0.1575  -0.0479   0e+00
## Boot.t   -0.098 0.0268 -3.6620 -0.1369  -0.0592   0e+00
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##   16.1473    1.0000 1840.0000    0.0001
##
## $AR$ci.print
## [1] "[-0.1574, -0.0493]"
##
## $AR$ci
## [1] -0.1574 -0.0493
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     79.7552     78.2588     71.1356     68.3350     71.1356
##
## $rho
## [1] 0.2041
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
```

```
## 71.1356  2.0466 -0.0980  0.0268 -3.6620 -0.1528 -0.0432  0.0005
##
## $est_rf
##              Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## treatment -0.0657 0.0164   1e-04 0.0164  -0.0973   -0.0331         0
##
## $est_fs
##             Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## treatment 0.6708 0.0795       0 0.0811   0.5239    0.8367         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 1842
##
## $N_cl
## [1] 61
##
## $df
## [1] 1835
##
## $nvalues
##      part_scale edu treatment
## [1,]          7   7         5
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Dower et al. (2018) (a)

Replication Summary	
Unit of analysis	district*year
Treatment	frequency of unrest
Instrument	religious polarization
Outcome	peasant representation
Model	Table3(1)

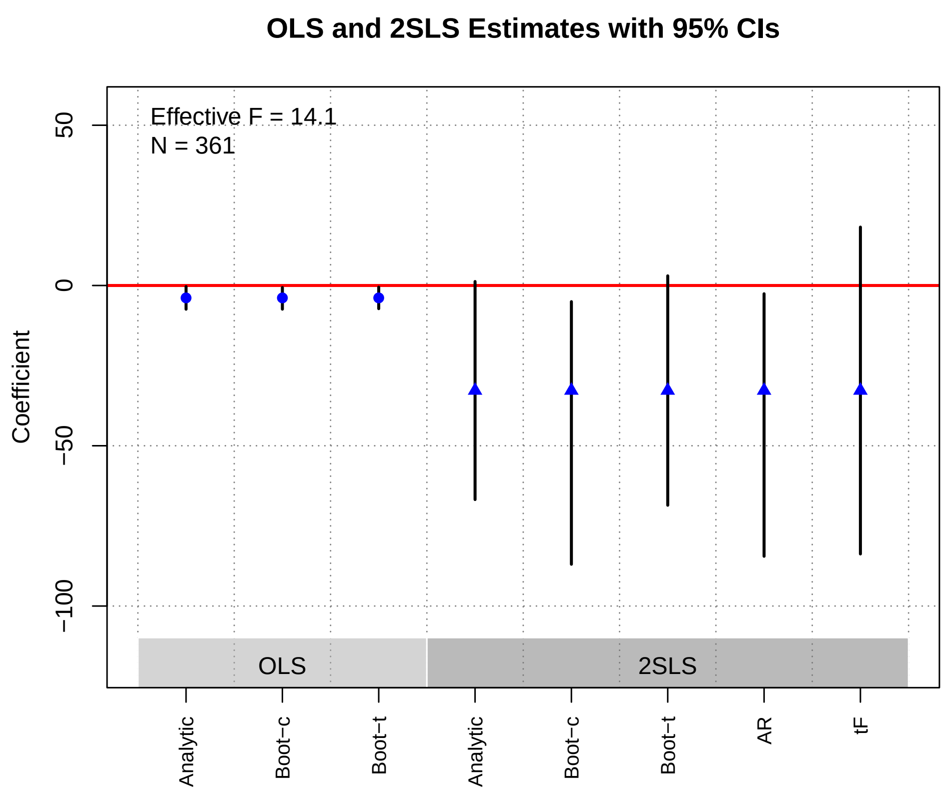
```
df <- readRDS("./data/apsr_Dower_etal_2018.rds")
D <-"afreq"
Y <-"peasantrepresentation_1864"
Z <-"religpolarf4_1870"
controls <- c("distance_moscow", "goodsoil", "lnurban", "lnpopn", "province_capital")
cl <- NULL
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##                Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -3.8696 1.8013 -2.1483 -7.4001  -0.3391  0.0317
## Boot.c   -3.8696 1.7589 -2.2000 -7.3880  -0.6414  0.0160
```

```
## Boot.t   -3.8696 1.8013 -2.1483 -7.2283  -0.5109  0.0270
##
## $est_2sls
##              Coef      SE       t  CI 2.5% CI 97.5% p.value
## Analytic -32.7701 17.3518 -1.8886 -66.7796   1.2393  0.0589
## Boot.c   -32.7701 27.2859 -1.2010 -86.9716  -5.0398  0.0160
## Boot.t   -32.7701 17.3518 -1.8886 -68.5590   3.0188  0.0650
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   4.4669   1.0000 359.0000   0.0352
##
## $AR$ci.print
## [1] "[-84.4784, -2.5780]"
##
## $AR$ci
## [1] -84.4784  -2.5780
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     12.0237     14.0828          NA     14.1902     14.0828
##
## $rho
## [1] 0.1812
##
## $tF
##        F       cF     Coef       SE        t   CI2.5%  CI97.5%  p-value
##  14.0828   2.9384 -32.7701  17.3518  -1.8886 -83.7561  18.2159   0.2078
##
## $est_rf
##                      Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## religpolarf4_1870 -3.9279 1.8715  0.0358 1.9303  -8.0377   -0.5621     0.014
##
## $est_fs
##                     Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## religpolarf4_1870 0.1199 0.0319   2e-04 0.0318   0.0604    0.1866     0.002
##
## $p_iv
## [1] 1
##
## $N
## [1] 361
```

```
##
## $N_cl
## NULL
##
## $df
## [1] 354
##
## $nvalues
##      peasantrepresentation_1864 afreq religpolarf4_1870
## [1,]                        128    12               361
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Dower et al. (2018) (b)

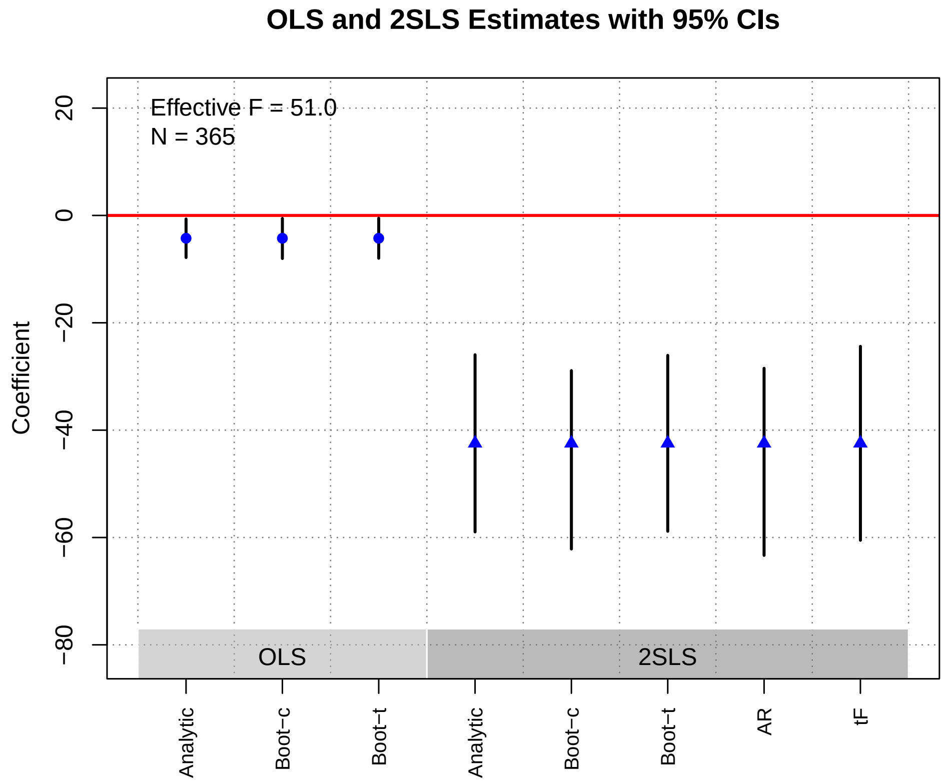
Replication Summary	
Unit of analysis	district*year
Treatment	frequency of unrest
Instrument	religious polarization
Outcome	peasant representation
Model	Table1(2)

```r
df <- readRDS("./data/apsr_Dower_etal_2018.rds")
D <-"afreq"
Y <-"peasantrepresentation_1864"
Z <-"serfperc1"
controls <- c("distance_moscow", "goodsoil", "lnurban", "lnpopn", "province_capital")
cl <- NULL
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -4.2492 1.8297 -2.3224 -7.8353  -0.6631  0.0202
## Boot.c   -4.2492 1.8887 -2.2498 -8.0244  -0.5588  0.0120
## Boot.t   -4.2492 1.8297 -2.3224 -7.9791  -0.5194  0.0250
##
## $est_2sls
##              Coef     SE       t  CI 2.5% CI 97.5% p.value
## Analytic -42.4545 8.4195 -5.0424 -58.9567 -25.9522       0
## Boot.c   -42.4545 8.6864 -4.8875 -62.1471 -28.9097       0
## Boot.t   -42.4545 8.4195 -5.0424 -58.8417 -26.0673       0
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##  52.2466   1.0000 363.0000   0.0000
##
## $AR$ci.print
## [1] "[-63.3348, -28.4781]"
##
## $AR$ci
## [1] -63.3348 -28.4781
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     47.6256     51.0176          NA     49.2694     51.0176
##
## $rho
## [1] 0.3427
##
## $tF
##        F       cF     Coef       SE        t   CI2.5%  CI97.5%  p-value
```

```
##  51.0176   2.1457 -42.4545   8.4195  -5.0424 -60.5204 -24.3885   0.0000
##
## $est_rf
##               Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## serfperc1 -11.7823 1.6414       0 1.6072 -15.0285   -8.6447         0
##
## $est_fs
##             Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## serfperc1 0.2775 0.0389       0 0.0395   0.1995    0.3545         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 365
##
## $N_cl
## NULL
##
## $df
## [1] 358
##
## $nvalues
##      peasantrepresentation_1864 afreq serfperc1
## [1,]                        128    12       361
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Gerber et al. (2010)

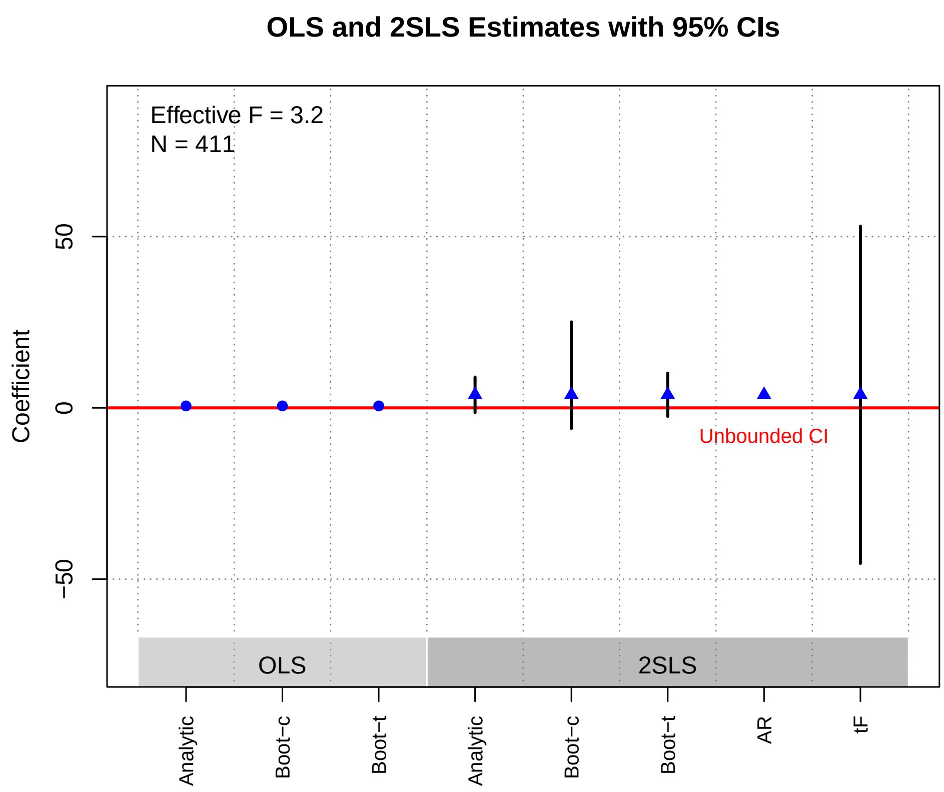
Replication Summary	
Unit of analysis	individual
Treatment	aligning party identification with latent partisanship
Instrument	being sent mail
Outcome	voting and party alignment scale
Model	Table4(1)

```
df <- readRDS("./data/apsr_Gerber_etal_2010.rds")
D <-"pt_id_with_lean"
Y <- "pt_voteevalalignindex"
Z <- "treat"
controls <- c("pre_lean_dem", "age", "age2" ,"regyear" ,
              "regyearmissing", "twonames", "combined_female",
              "voted2006", "voted2004", "voted2002", "voted2000",
              "voted1998", "voted1996", "interest", "pre_aligned_vh",
              "pre_direct_unemp", "pre_direct_econ","pre_direct_bushap",
              "pre_direct_congapp")
cl <- NULL
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.5658 0.1709 3.3105  0.2308   0.9008   9e-04
## Boot.c   0.5658 0.1722 3.2853  0.2318   0.9007   0e+00
## Boot.t   0.5658 0.1709 3.3105  0.2203   0.9112   0e+00
##
## $est_2sls
##            Coef      SE      t CI 2.5% CI 97.5% p.value
## Analytic 3.8231  2.6392 1.4486 -1.3497   8.9960  0.1475
## Boot.c   3.8231 19.2000 0.1991 -5.9904  25.1153  0.1140
## Boot.t   3.8231  2.6392 1.4486 -2.4948  10.1410  0.1610
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   3.8593   1.0000 409.0000   0.0501
##
## $AR$ci.print
## [1] "[0.0227, Inf)"
##
## $AR$ci
## [1] 0.0227    Inf
##
## $AR$bounded
## [1] FALSE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##      2.9926      3.1563          NA      3.0625      3.1563
##
## $rho
## [1] 0.0873
##
## $tF
##        F       cF     Coef       SE        t   CI2.5%  CI97.5%  p-value
##   3.1563  18.6600   3.8231   2.6392   1.4486 -45.4249  53.0712   0.8791
##
## $est_rf
##         Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## treat 0.2742 0.1429  0.0551 0.1486   -0.029    0.5664     0.068
##
## $est_fs
##         Coef     SE p.value  SE.b CI.b2.5% CI.b97.5% p.value.b
## treat 0.0717 0.0404  0.0756 0.041   -6e-04    0.1581     0.064
##
## $p_iv
```

```
## [1] 1
##
## $N
## [1] 411
##
## $N_cl
## NULL
##
## $df
## [1] 390
##
## $nvalues
##      pt_voteevalalignindex pt_id_with_lean treat
## [1,]                    10               2     2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Hager et al. (2019)

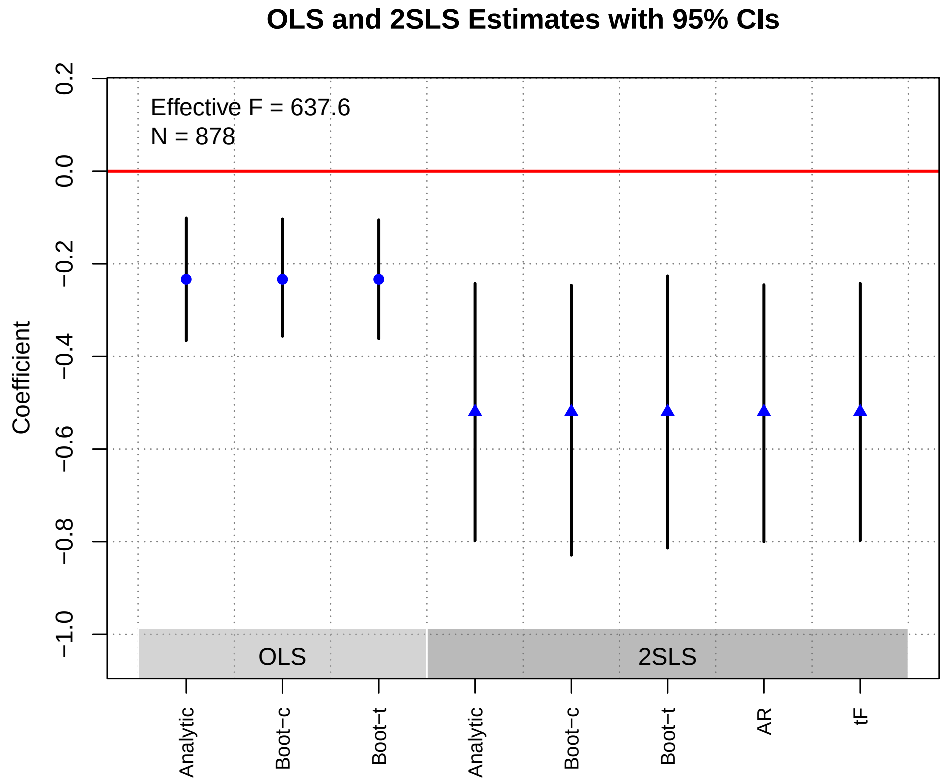
Replication Summary	
Unit of analysis	individual
Treatment	ethnic riots (destruction)
Instrument	distance to the nearest location where armored military vehicles were stolen
Outcome	prosocial behavior
Model	Figure6

```
df <- readRDS("./data/apsr_Hager_etal_2019.rds")
D <-"affected"
Y <- "pd_in_scale"
Z <-  "apc_min_distance"
controls <- NULL
cl <- NULL
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.2335 0.0675 -3.4582 -0.3658  -0.1011   5e-04
## Boot.c   -0.2335 0.0663 -3.5211 -0.3564  -0.1033   2e-03
## Boot.t   -0.2335 0.0675 -3.4582 -0.3617  -0.1052   1e-03
##
## $est_2sls
##           Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.52 0.1416 -3.6733 -0.7975  -0.2425   2e-04
## Boot.c   -0.52 0.1466 -3.5463 -0.8291  -0.2465   2e-03
## Boot.t   -0.52 0.1416 -3.6733 -0.8137  -0.2263   1e-03
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##  13.7909   1.0000 876.0000   0.0002
##
## $AR$ci.print
## [1] "[-0.8003, -0.2454]"
##
## $AR$ci
## [1] -0.8003 -0.2454
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
```

```
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##    271.8565    637.5699          NA    633.0687    637.5699
##
## $rho
## [1] 0.4867
##
## $tF
##        F       cF      Coef        SE         t    CI2.5%   CI97.5%   p-value
## 637.5699   1.9600   -0.5200    0.1416   -3.6733   -0.7975   -0.2425    0.0002
##
## $est_rf
##                    Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## apc_min_distance 0.1011 0.0272   2e-04 0.0281   0.0467    0.1576     0.002
##
## $est_fs
##                     Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## apc_min_distance -0.1943 0.0077       0 0.0077  -0.2089    -0.178         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 878
##
## $N_cl
## NULL
##
## $df
## [1] 876
##
## $nvalues
##      pd_in_scale affected apc_min_distance
## [1,]           2        2              193
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Hager and Krakowski (2022)

Replication Summary	
Unit of analysis	individual
Treatment	number of secret police officers
Instrument	number of corrupted Catholic priests
Outcome	resistance
Model	Table3(2)

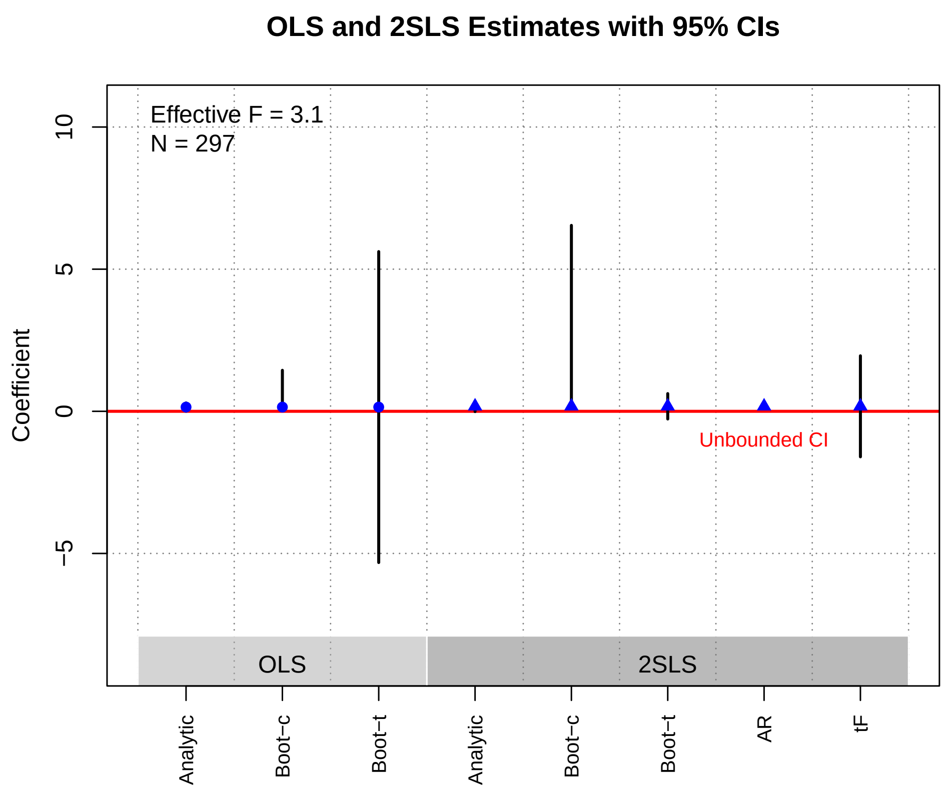
```
df <- readRDS("./data/apsr_Hager_Krakowski_2022.rds")

D <-"commanders"
Y <- "y"
Z <-  "priests_continuous"
controls <- NULL
cl <- NULL
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.1494 0.0751 1.9891  0.0022   0.2965  0.0467
```

```
## Boot.c   0.1494 0.3177 0.4701  0.0595   1.4434  0.0000
## Boot.t   0.1494 0.0751 1.9891 -5.3196   5.6183  0.5300
##
## $est_2sls
##            Coef      SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.1765  0.0952 1.8537 -0.0101   0.3632  0.0638
## Boot.c   0.1765 11.0200 0.0160  0.0847   6.5405  0.0020
## Boot.t   0.1765  0.0952 1.8537 -0.2701   0.6231  0.3730
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   8.7245   1.0000 295.0000   0.0034
##
## $AR$ci.print
## [1] "[0.0642, Inf)"
##
## $AR$ci
## [1] 0.0642    Inf
##
## $AR$bounded
## [1] FALSE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##    109.0543      3.1403          NA      3.1778      3.1403
##
## $rho
## [1] 0.5195
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
##  3.1403 18.6600  0.1765  0.0952  1.8537 -1.6005  1.9535  0.8456
##
## $est_rf
##                      Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## priests_continuous 0.4736 0.1603  0.0031 0.1726   0.2014    0.8527         0
##
## $est_fs
##                      Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## priests_continuous 2.6827 1.5139  0.0764 1.5049   0.0284    5.3683     0.002
##
## $p_iv
## [1] 1
##
## $N
```

```
## [1] 297
##
## $N_cl
## NULL
##
## $df
## [1] 295
##
## $nvalues
##       y commanders priests_continuous
## [1,] 14         12                  7
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Kapoor and Magesan (2018)

Replication Summary	
Unit of analysis	constituency*election
Treatment	number of independent candidates
Instrument	changes in entry costs
Outcome	voter turnout

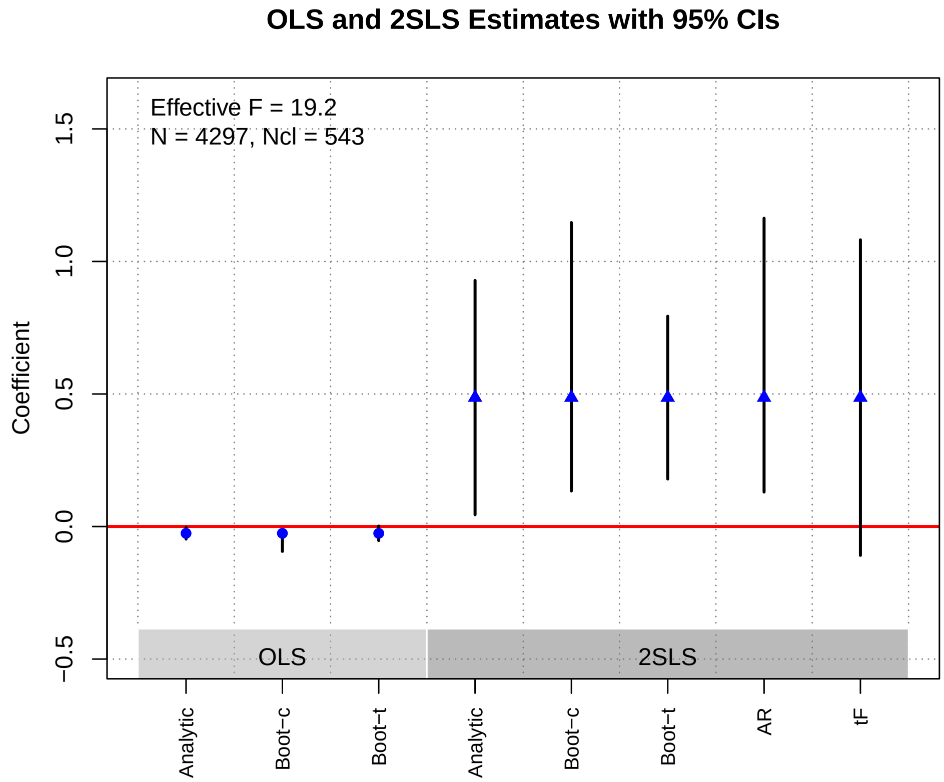
Replication Summary	
Model	Table4(b5)

```
df<-readRDS("./data/apsr_Kapoor_etal_2018.rds")
D <-'CitCand'
Y <- "Turnout"
Z <- "UnScheduledDepChange"
controls <- c("CitCandBaseTrend", "CitCandBaseTrendSq", "CitCandBaseTrendCu",
              "CitCandBaseTrendQu",  "TurnoutBaseTrend", "TurnoutBaseTrendSq",
              "TurnoutBaseTrendCu", "TurnoutBaseTrendQu", "LnElectors",
              "LagWinDist", "LagWinDistSq", "LagWinDistCu",
              "LagWinDistQu", "LagTightElection")
cl<- "constituency"
FE <- c("year","constituency")
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.0256 0.0110 -2.3216 -0.0472  -0.0040  0.0203
## Boot.c   -0.0256 0.0209 -1.2218 -0.0938  -0.0135  0.0000
## Boot.t   -0.0256 0.0110 -2.3216 -0.0530   0.0018  0.0620
##
## $est_2sls
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.4864 0.2256 2.1562  0.0443   0.9285  0.0311
## Boot.c   0.4864 0.2625 1.8531  0.1342   1.1468  0.0040
## Boot.t   0.4864 0.2256 2.1562  0.1794   0.7934  0.0010
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    7.7339    1.0000 4295.0000    0.0054
##
## $AR$ci.print
## [1] "[0.1300, 1.1631]"
##
## $AR$ci
## [1] 0.1300 1.1631
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
```

```
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     11.2301     23.7168     19.1635     18.8309     19.1635
##
## $rho
## [1] 0.0548
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 19.1635  2.6390  0.4864  0.2256  2.1562 -0.1089  1.0817  0.1093
##
## $est_rf
##                        Coef   SE p.value  SE.b CI.b2.5% CI.b97.5% p.value.b
## UnScheduledDepChange -1.277 0.46  0.0055 0.446  -2.1384   -0.4092     0.004
##
## $est_fs
##                         Coef     SE p.value  SE.b CI.b2.5% CI.b97.5% p.value.b
## UnScheduledDepChange -2.6256 0.5998       0 0.605  -3.8731   -1.5209         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 4297
##
## $N_cl
## [1] 543
##
## $df
## [1] 542
##
## $nvalues
##      Turnout CitCand UnScheduledDepChange
## [1,]    4293      68                    2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Kuipers and Sahn (2022)

Replication Summary	
Unit of analysis	municipality* year
Treatment	civil service reform
Instrument	statewide assignment mandate
Outcome	descriptive representation on an unrestricted sample
Model	Table1(2)

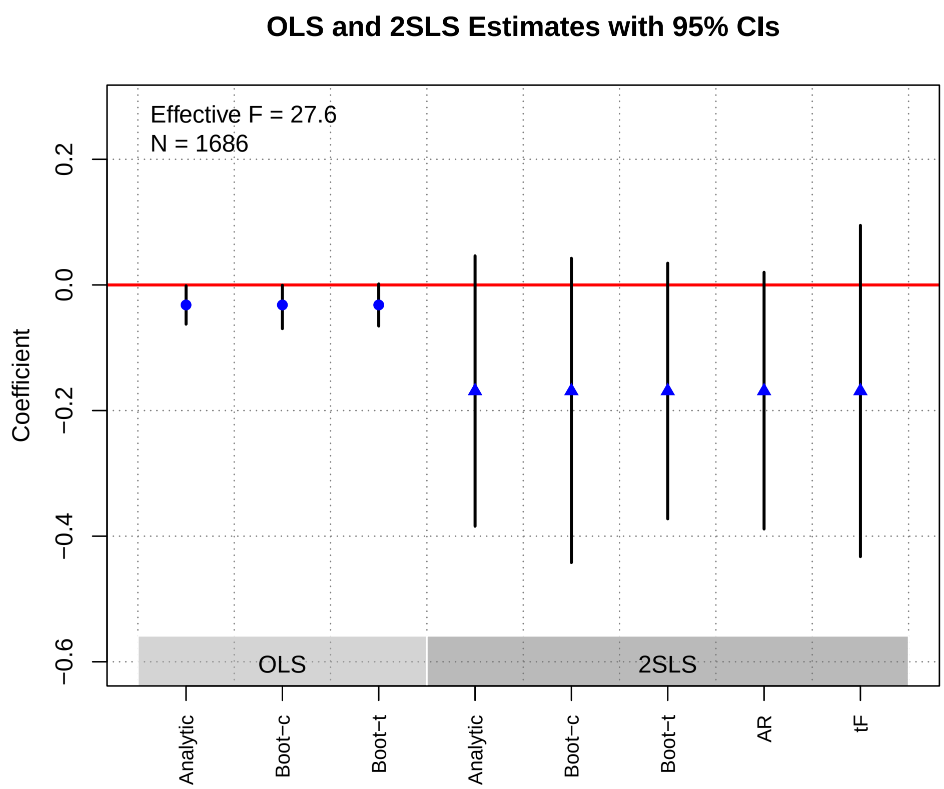
```
df <- readRDS("./data/apsr_kuipers_2022.rds")
df<-df%>%filter(occ=='blue_collar' & name=='white_x_native_born')
D <-"treat_actual"
Y <- "govt"
Z <-  "treat_assign"
controls <-"pop"
cl <- NULL
FE <- c("YEAR","city")
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.0319 0.0156 -2.0467 -0.0625  -0.0014  0.0407
```

```
## Boot.c   -0.0319 0.0171 -1.8624 -0.0696  -0.0005  0.0480
## Boot.t   -0.0319 0.0156 -2.0467 -0.0655   0.0016  0.0620
##
## $est_2sls
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.1689 0.1099 -1.5373 -0.3842   0.0464  0.1242
## Boot.c   -0.1689 0.1211 -1.3944 -0.4420   0.0424  0.1360
## Boot.t   -0.1689 0.1099 -1.5373 -0.3724   0.0346  0.1120
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    3.0769    1.0000 1684.0000    0.0796
##
## $AR$ci.print
## [1] "[-0.3886, 0.0201]"
##
## $AR$ci
## [1] -0.3886  0.0201
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     32.4157     27.5670          NA     23.1863     27.5670
##
## $rho
## [1] 0.153
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 27.5670  2.3999 -0.1689  0.1099 -1.5373 -0.4326  0.0948  0.2093
##
## $est_rf
##                 Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## treat_assign -0.0254 0.0162   0.116 0.0172  -0.0606    0.0069     0.136
##
## $est_fs
##                Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## treat_assign 0.1504 0.0286       0 0.0312   0.1015    0.2186         0
##
## $p_iv
## [1] 1
##
## $N
```

```
## [1] 1686
##
## $N_cl
## NULL
##
## $df
## [1] 1352
##
## $nvalues
##      govt treat_actual treat_assign
## [1,]  658            2            2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Laitin and Ramachandran (2016)

Replication Summary	
Unit of analysis	country
Treatment	language choice
Instrument	geographic distance from the origins of writing
Outcome	human development index

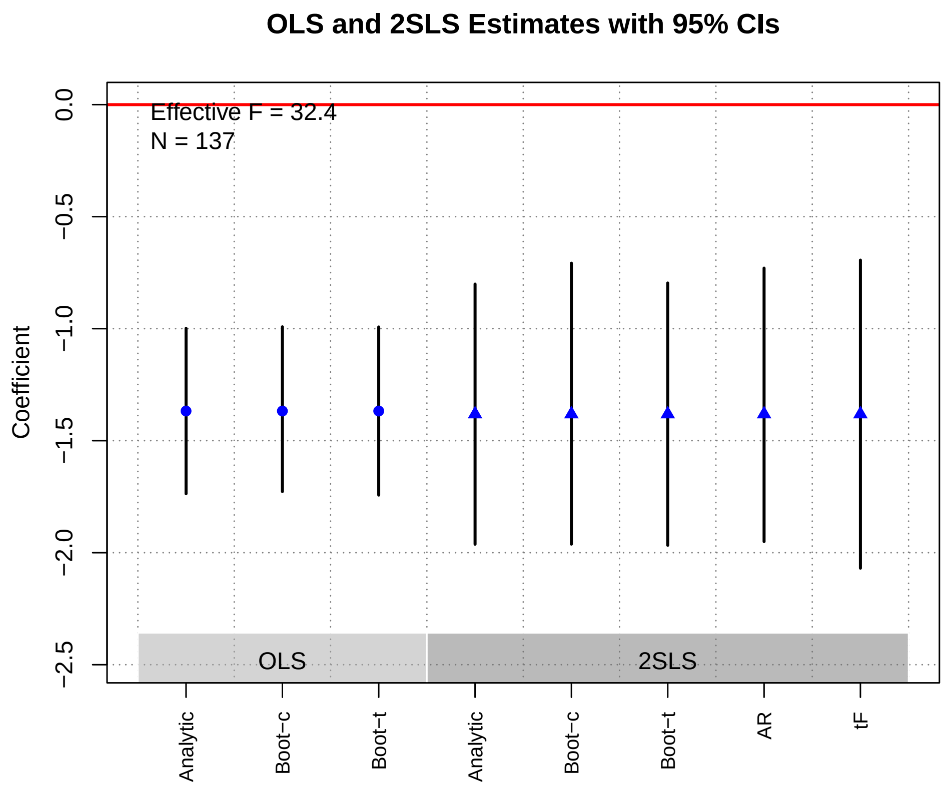
Replication Summary	
Model	Table10(10)

```
df <-readRDS("./data/apsr_Laitin_2016.rds")
D <-"avgdistance_delta50"
Y <- "zhdi_2010"
Z <- "DIST_BGNC"
controls <- c("cdf2003","ln_GDP_Indp", "edes1975",
              "America","xconst")
cl<- NULL
FE<- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -1.3676 0.1884 -7.2594 -1.7369  -0.9984       0
## Boot.c   -1.3676 0.1859 -7.3580 -1.7269  -0.9916       0
## Boot.t   -1.3676 0.1884 -7.2594 -1.7430  -0.9923       0
##
## $est_2sls
##              Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -1.3815 0.2963 -4.6618 -1.9623  -0.8007       0
## Boot.c   -1.3815 0.3092 -4.4687 -1.9618  -0.7074       0
## Boot.t   -1.3815 0.2963 -4.6618 -1.9670  -0.7960       0
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##  11.4476   1.0000 135.0000   0.0009
##
## $AR$ci.print
## [1] "[-1.9505, -0.7295]"
##
## $AR$ci
## [1] -1.9505 -0.7295
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     55.1871     32.4040          NA     32.4703     32.4040
##
```

```
## $rho
## [1] 0.5459
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 32.4040  2.3208 -1.3815  0.2963 -4.6618 -2.0692 -0.6938  0.0001
##
## $est_rf
##              Coef SE p.value SE.b CI.b2.5% CI.b97.5% p.value.b
## DIST_BGNC -1e-04  0   9e-04    0   -2e-04         0         0
##
## $est_fs
##             Coef SE p.value SE.b CI.b2.5% CI.b97.5% p.value.b
## DIST_BGNC 1e-04  0       0    0    1e-04     1e-04         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 137
##
## $N_cl
## NULL
##
## $df
## [1] 130
##
## $nvalues
##      zhdi_2010 avgdistance_delta50 DIST_BGNC
## [1,]       121                  93       134
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Meredith (2013)

Replication Summary	
Unit of analysis	down-ballot race
Treatment	Democratic governor
Instrument	governor's home county
Outcome	down-ballot Democratic candidates' vote share
Model	Table3(5)

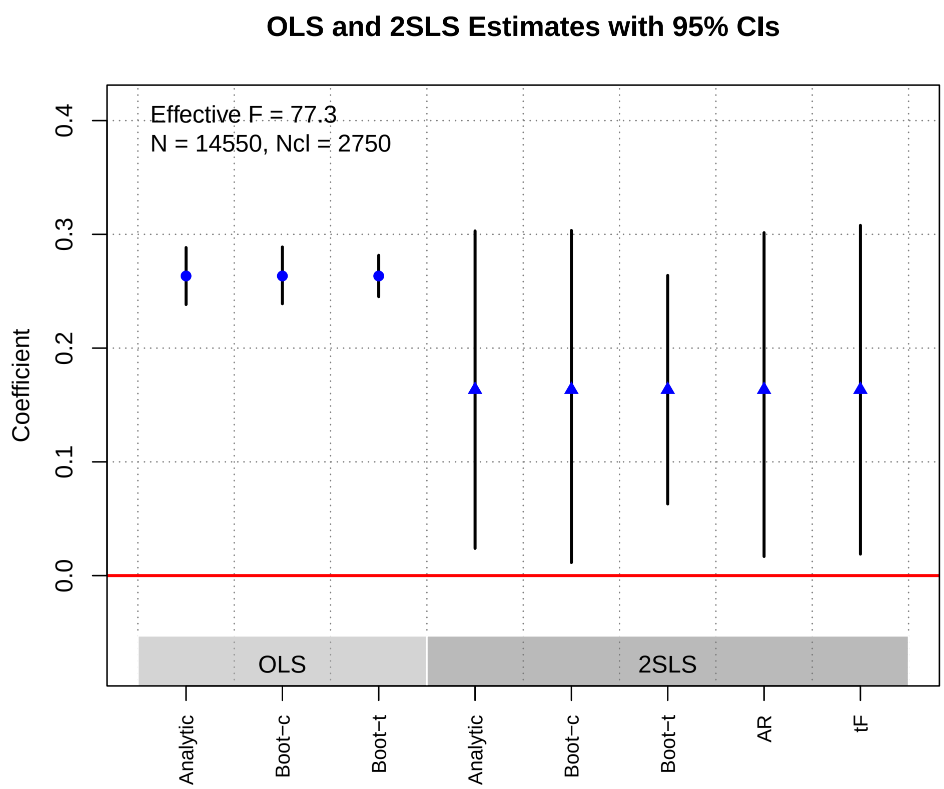
```
df <-readRDS("./data/apsr_Meredith_2013.rds")
Y <- "DemShareDB_res"
D<-"DemShareGOV_res"
Z <- "HomeGOV_res"
controls <- "HomeDB_res"
cl <- "fips"
FE<- NULL
weights<-NULL
(g <- ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic 0.2634 0.0128 20.5976  0.2383   0.2884       0
## Boot.c   0.2634 0.0130 20.3276  0.2390   0.2889       0
```

```
## Boot.t   0.2634 0.0128 20.5976  0.2452   0.2816       0
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.1634 0.0712 2.2959  0.0239   0.3030  0.0217
## Boot.c   0.1634 0.0728 2.2435  0.0115   0.3034  0.0380
## Boot.t   0.1634 0.0712 2.2959  0.0630   0.2639  0.0000
##
## $AR
## $AR$Fstat
##          F        df1        df2          p
##     4.6123     1.0000 14548.0000     0.0318
##
## $AR$ci.print
## [1] "[0.0168, 0.3015]"
##
## $AR$ci
## [1] 0.0168 0.3015
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##    284.9652    141.9189     77.2953     78.7213     77.2953
##
## $rho
## [1] 0.1386
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 77.2953  2.0300  0.1634  0.0712  2.2959  0.0189  0.3079  0.0266
##
## $est_rf
##               Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## HomeGOV_res 0.0062 0.0029  0.0317 0.0029    4e-04    0.0124     0.038
##
## $est_fs
##               Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## HomeGOV_res 0.0379 0.0043       0 0.0043     0.03    0.0465         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 14550
```

```
##
## $N_cl
## [1] 2750
##
## $df
## [1] 14547
##
## $nvalues
##      DemShareDB_res DemShareGOV_res HomeGOV_res
## [1,]          14550           14550        1466
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Nellis and Siddiqui (2018)

Replication Summary	
Unit of analysis	district*election
Treatment	the proportion of MNA seats in a district won by secularist candidates
Instrument	narrow victory by secular parties in a district
Outcome	religious violence

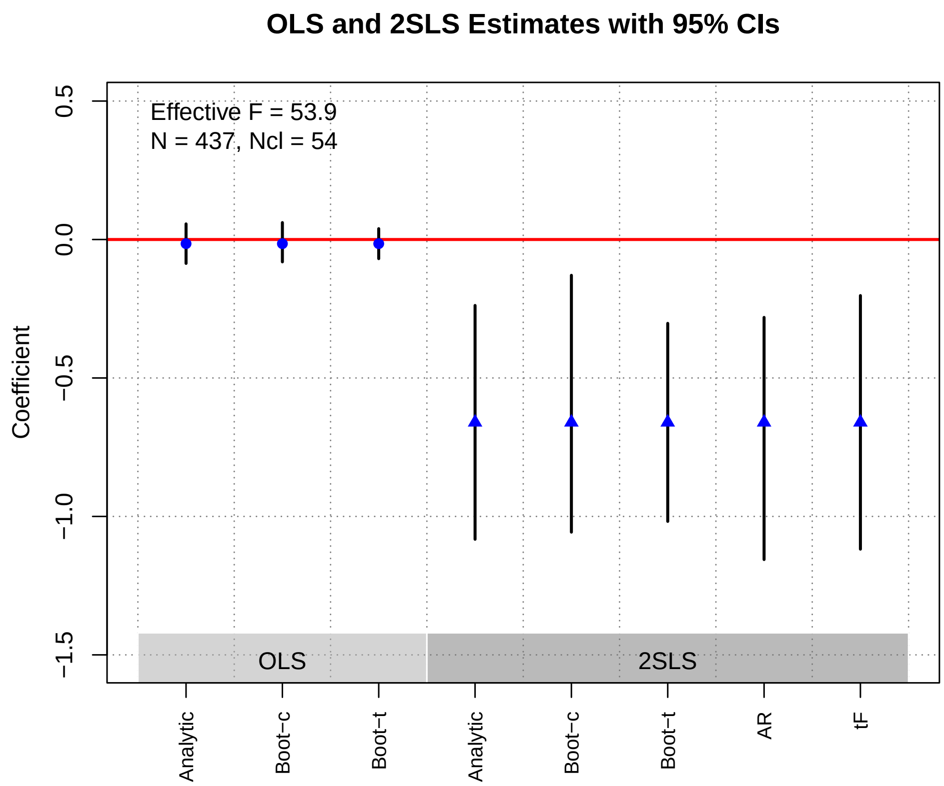
Replication Summary	
Model	Table2(1)

```r
df<-readRDS("./data/apsr_Nellis_etal_2018.rds")
D <-'secular_win'
Y <- "any_violence"
Z <- "secular_close_win"
controls <-"secular_close_race"
cl <- "cluster_var"
FE <- "pro"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.015 0.0364 -0.4107 -0.0863   0.0564  0.6813
## Boot.c   -0.015 0.0370 -0.4046 -0.0808   0.0611  0.6880
## Boot.t   -0.015 0.0364 -0.4107 -0.0691   0.0392  0.5980
##
## $est_2sls
##              Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.6603 0.2154 -3.0658 -1.0825  -0.2382  0.0022
## Boot.c   -0.6603 0.2478 -2.6651 -1.0567  -0.1293  0.0260
## Boot.t   -0.6603 0.2154 -3.0658 -1.0179  -0.3028  0.0110
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##  12.2950   1.0000 435.0000   0.0005
##
## $AR$ci.print
## [1] "[-1.1557, -0.2813]"
##
## $AR$ci
## [1] -1.1557 -0.2813
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##   F.standard    F.robust   F.cluster F.bootstrap F.effective
##      22.0208     60.0400     53.9103     40.6712     53.9103
##
```

```
## $rho
## [1] 0.2207
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 53.9103  2.1258 -0.6603  0.2154 -3.0658 -1.1182 -0.2025  0.0047
##
## $est_rf
##                      Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## secular_close_win -0.5965 0.1711   5e-04 0.192  -0.8629   -0.1252     0.026
##
## $est_fs
##                     Coef    SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## secular_close_win 0.9034 0.123       0 0.1417   0.6301    1.1773         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 437
##
## $N_cl
## [1] 54
##
## $df
## [1] 430
##
## $nvalues
##      any_violence secular_win secular_close_win
## [1,]            2          26                17
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Ritter and Conrad (2016)

Replication Summary	
Unit of analysis	province in 54 African countries*day
Treatment	mobilized dissent
Instrument	rainfall
Outcome	repression
Model	Table1(3b)

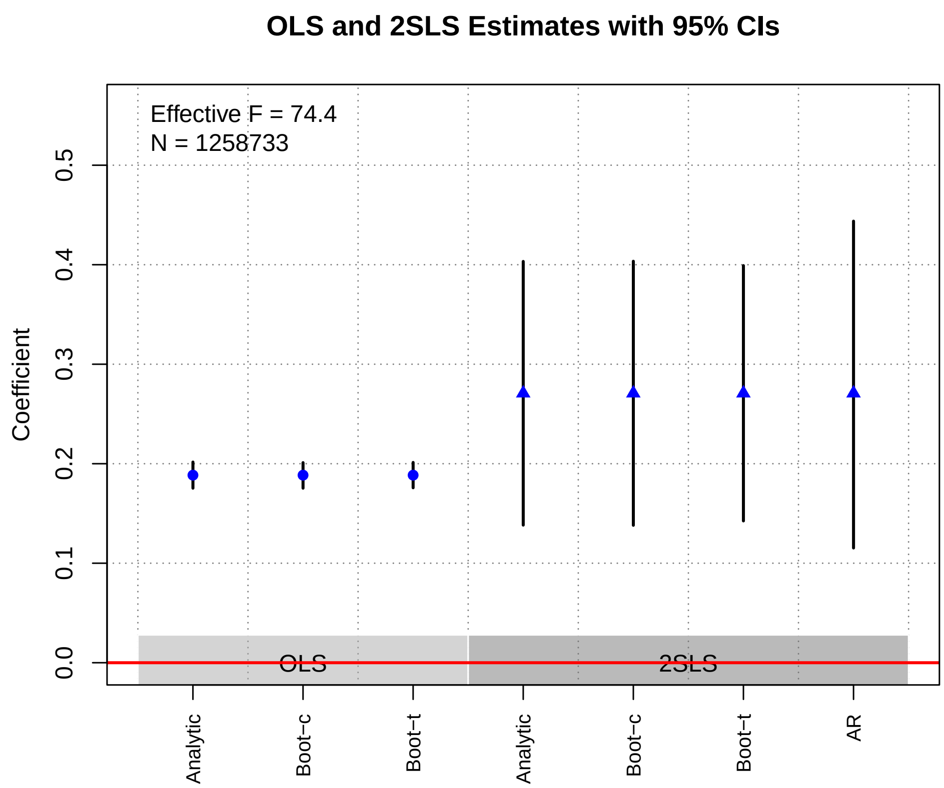
```
df <- readRDS("./data/apsr_Ritter_etal_2016.rds")
D <- "dissentcount"
Y <- "represscount"
Z <- c("lograin", "rainannualpct")
controls <-"urban_mean"
cl<- NULL
FE<- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic 0.1885 0.0067 28.0525  0.1754   0.2017       0
## Boot.c   0.1885 0.0067 28.1560  0.1754   0.2011       0
```

```
## Boot.t   0.1885 0.0067 28.0525  0.1758   0.2013       0
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.2708 0.0676 4.0058  0.1383   0.4033   1e-04
## Boot.c   0.2708 0.0678 3.9960  0.1381   0.4035   0e+00
## Boot.t   0.2708 0.0676 4.0058  0.1425   0.3991   0e+00
##
## $AR
## $AR$Fstat
##           F         df1         df2           p
## 8.36210e+00 2.00000e+00 1.25873e+06 2.00000e-04
##
## $AR$ci.print
## [1] "[0.1153, 0.4438]"
##
## $AR$ci
## [1] 0.1153 0.4438
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     58.3505     73.6819          NA     79.5130     74.3587
##
## $rho
## [1] 0.0096
##
## $est_rf
##                   Coef     SE p.value  SE.b CI.b2.5% CI.b97.5% p.value.b
## lograin         0.0001 0.0000  0.0000 0.000   0.0001    0.0002     0.000
## rainannualpct -0.0092 0.0059  0.1199 0.006  -0.0201    0.0043     0.144
##
## $est_fs
##                   Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## lograin         0.0005 0.0000   0e+00 0.0000   0.0004    0.0006         0
## rainannualpct -0.0250 0.0065   1e-04 0.0066  -0.0374   -0.0118         0
##
## $p_iv
## [1] 2
##
## $N
## [1] 1258733
##
## $N_cl
```

```
## NULL
##
## $df
## [1] 1258730
##
## $nvalues
##      represscount dissentcount lograin rainannualpct
## [1,]            3            5  390194        593785
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



AJPS

Barth et al. (2015)

Replication Summary	
Unit of analysis	country*year
Treatment	wage inequality
Instrument	adjusted bargaining coverage; effective number of union confederations

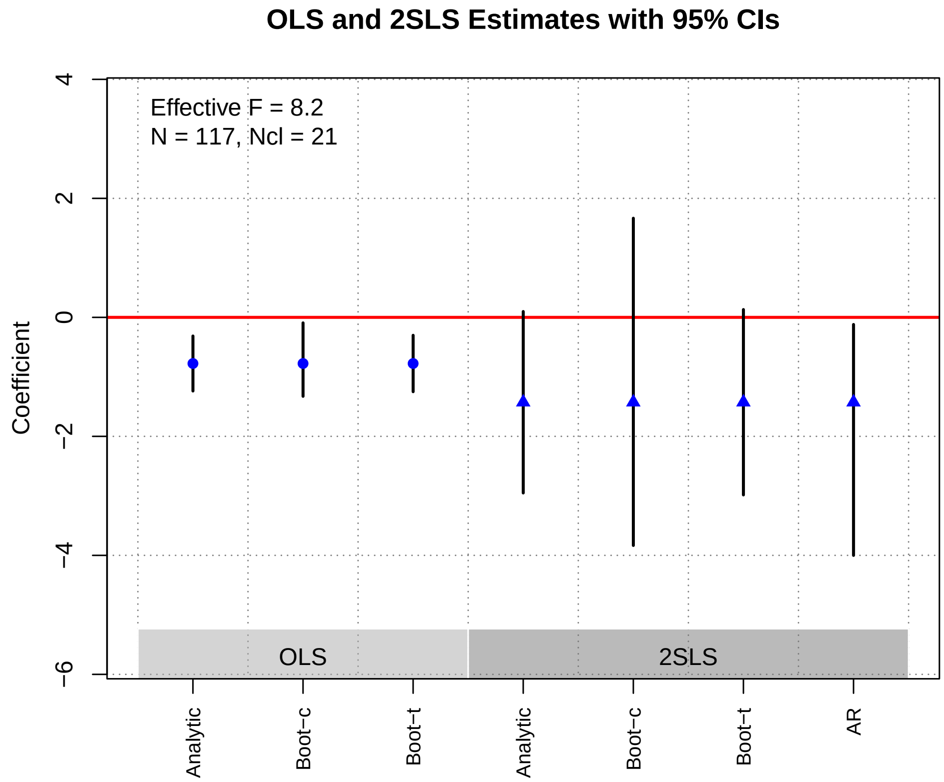
Replication Summary	
Outcome	welfare support
Model	Table4(1)

```
df<- readRDS("./data/ajps_Barth_2015.rds")
D <-"ld9d1"
Y <- "welfareleft"
Z <- c("l2ip_adjcov5", "l2ip_enucfs")
controls <- c("lgdpgr", "lelderly", "llntexp", "lud", "ludsq",
              "lechp", "lnet", "lannual", "ltrend", "ltrendsq")
cl <- FE <- "countrynumber"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.7755 0.2358 -3.2886 -1.2376  -0.3133   0.001
## Boot.c   -0.7755 0.3112 -2.4915 -1.3269  -0.0925   0.028
## Boot.t   -0.7755 0.2358 -3.2886 -1.2495  -0.3015   0.005
##
## $est_2sls
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -1.4265 0.7779 -1.8339 -2.9511   0.0981  0.0667
## Boot.c   -1.4265 1.5508 -0.9198 -3.8336   1.6661  0.2860
## Boot.t   -1.4265 0.7779 -1.8339 -2.9841   0.1311  0.0720
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   3.6053   2.0000 114.0000   0.0303
##
## $AR$ci.print
## [1] "[-4.0005, -0.1197]"
##
## $AR$ci
## [1] -4.0005 -0.1197
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##   F.standard    F.robust   F.cluster F.bootstrap F.effective
##       9.7741     15.0268     11.5754      3.3331      8.1611
##
```

```
## $rho
## [1] 0.4345
##
## $est_rf
##                  Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## l2ip_adjcov5 0.0184 0.0124  0.1377 0.0202  -0.0298    0.0500     0.352
## l2ip_enucfs  0.1687 0.2420  0.4858 0.3724  -0.7636    0.7268     0.706
##
## $est_fs
##                  Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## l2ip_adjcov5 -0.0096 0.0046  0.0383 0.0069  -0.0271   -0.0007     0.042
## l2ip_enucfs  -0.1542 0.0777  0.0473 0.0933  -0.2877    0.0774     0.152
##
## $p_iv
## [1] 2
##
## $N
## [1] 117
##
## $N_cl
## [1] 21
##
## $df
## [1] 20
##
## $nvalues
##      welfareleft ld9d1 l2ip_adjcov5 l2ip_enucfs
## [1,]         117   117          106         112
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Blair et al. (2022)

Replication Summary	
Unit of analysis	UN peacekeeping operations event level
Treatment	fragmentation of any given PKO mandate
Instrument	average fragmentation of all ongoing PKO mandates
Outcome	process performance
Model	TableD7(3)

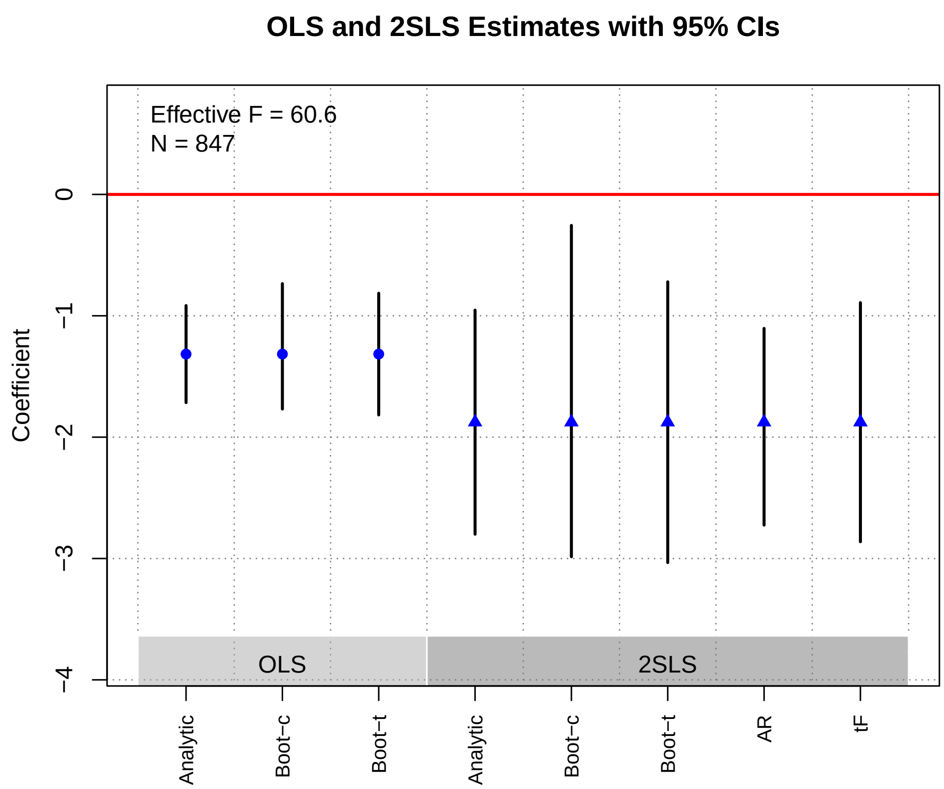
```
df <-readRDS("./data/ajps_Blair_2022.rds")
df<-as.data.frame(df)
D<-"L_avg"
Y <- "sh_perfassist_pb"
Z <- "L_fract_assistv3"
  controls <- c("L_experman_assist_pbv3","L_numtask_assist_pbv3","L_lntot",
                "L_deployment","L_lnpop","L_lngdp","L_ucdpconflictspell","L_polity")
cl <- NULL
FE <- c("date3","iso3n")
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##                Coef      SE        t CI 2.5% CI 97.5% p.value
```

```
## Analytic -1.3155 0.2040 -6.4481 -1.7153  -0.9156       0
## Boot.c   -1.3155 0.2571 -5.1168 -1.7683  -0.7348       0
## Boot.t   -1.3155 0.2040 -6.4481 -1.8169  -0.8141       0
##
## $est_2sls
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -1.8768 0.4711 -3.9841 -2.8001  -0.9535  0.0001
## Boot.c   -1.8768 0.6978 -2.6897 -2.9859  -0.2552  0.0180
## Boot.t   -1.8768 0.4711 -3.9841 -3.0335  -0.7201  0.0030
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##  20.4937   1.0000 845.0000   0.0000
##
## $AR$ci.print
## [1] "[-2.7247, -1.1042]"
##
## $AR$ci
## [1] -2.7247 -1.1042
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##    186.0679     60.6442          NA     24.7580     60.6442
##
## $rho
## [1] 0.4793
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 60.6442  2.0913 -1.8768  0.4711 -3.9841 -2.8619 -0.8917  0.0002
##
## $est_rf
##                   Coef    SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## L_fract_assistv3 1.805 0.464   1e-04 0.7674   0.2216    3.3257     0.018
##
## $est_fs
##                     Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## L_fract_assistv3 -0.9617 0.1235       0 0.1933  -1.4964   -0.7159         0
##
## $p_iv
## [1] 1
##
```

```
## $N
## [1] 847
##
## $N_cl
## NULL
##
## $df
## [1] 624
##
## $nvalues
##      sh_perfassist_pb L_avg L_fract_assistv3
## [1,]               56    55              222
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Carnegie and Marinov (2017)

Replication Summary	
Unit of analysis	country*year
Treatment	foreign aid
Instrument	being a former colony of one of the Council members

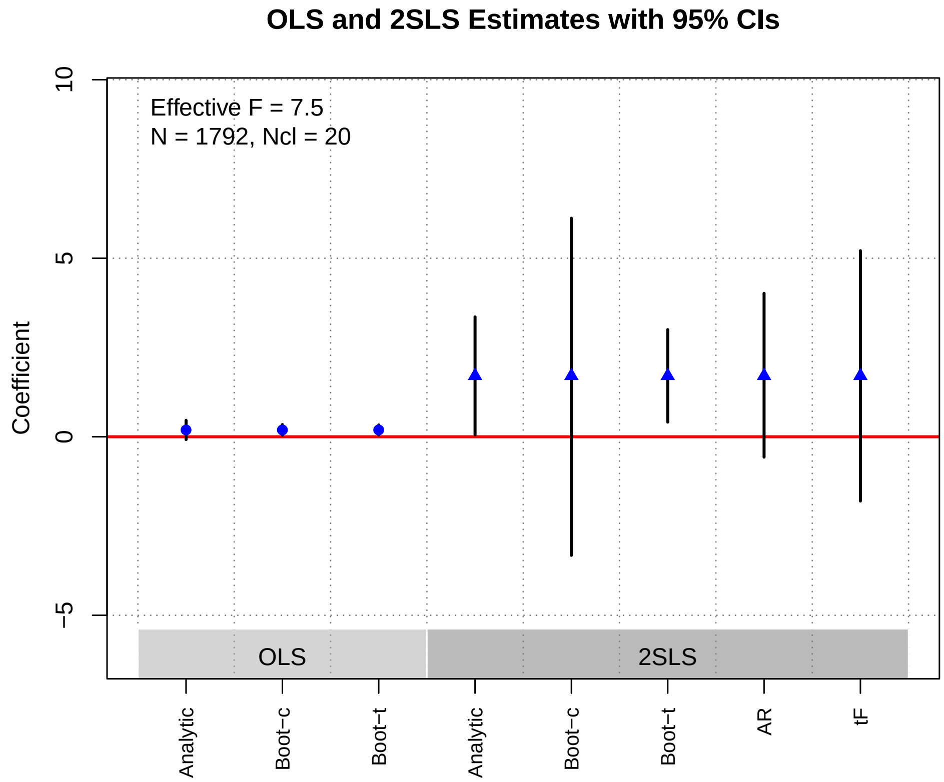
Replication Summary	
Outcome	CIRI Human Empowerment index
Model	Table1(2)

```r
df<-readRDS("./data/ajps_Carnegie_etal_2017.rds")
D <-"EV"
Y <- "new_empinxavg"
Z <- "l2CPcol2"
controls <- c( "covloggdp", "covloggdpCF", "covloggdpC",
              "covdemregionF", "covdemregion", "coviNY_GDP_PETR_RT_ZSF",
              "coviNY_GDP_PETR_RT_ZS", "covwvs_relF", "covwvs_rel",
              "covwdi_imp", "covwdi_fdiF", "covwdi_fdi",
              "covwdi_expF", "covwdi_exp", "covihme_ayemF", "covihme_ayem")
cl<-c("year","ccode")
FE <- c("year","ccode")
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.1903 0.1376 1.3831 -0.0794   0.4601  0.1666
## Boot.c   0.1903 0.0763 2.4932  0.0448   0.3424  0.0040
## Boot.t   0.1903 0.1376 1.3831  0.0485   0.3322  0.0180
##
## $est_2sls
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 1.7054 0.8436 2.0217  0.0520   3.3589  0.0432
## Boot.c   1.7054 6.4778 0.2633 -3.3230   6.1199  0.1880
## Boot.t   1.7054 0.8436 2.0217  0.4095   3.0014  0.0250
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    2.7312    1.0000 1790.0000    0.0986
##
## $AR$ci.print
## [1] "[-0.5722, 4.0169]"
##
## $AR$ci
## [1] -0.5722  4.0169
##
## $AR$bounded
## [1] TRUE
##
##
```

```
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##      4.5101      4.5766      7.5007      4.0541      7.5007
##
## $rho
## [1] 0.0523
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
##  7.5007  4.1570  1.7054  0.8436  2.0217 -1.8014  5.2123  0.3405
##
## $est_rf
##            Coef   SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## l2CPcol2 0.2632 0.16  0.0998 0.1908  -0.0555    0.6777     0.136
##
## $est_fs
##            Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## l2CPcol2 0.1543 0.0564  0.0062 0.0767  -0.0146    0.2974     0.066
##
## $p_iv
## [1] 1
##
## $N
## [1] 1792
##
## $N_cl
## [1] 20
##
## $df
## [1] 19
##
## $nvalues
##      new_empinxavg   EV l2CPcol2
## [1,]            57 1601        2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Chong et al. (2019)

Replication Summary	
Unit of analysis	household
Treatment	actual proportion of households treated in the locality
Instrument	treatment assignment in get-out-to-vote campaigns
Outcome	voted in 2013 presidential election
Model	Table4(1)

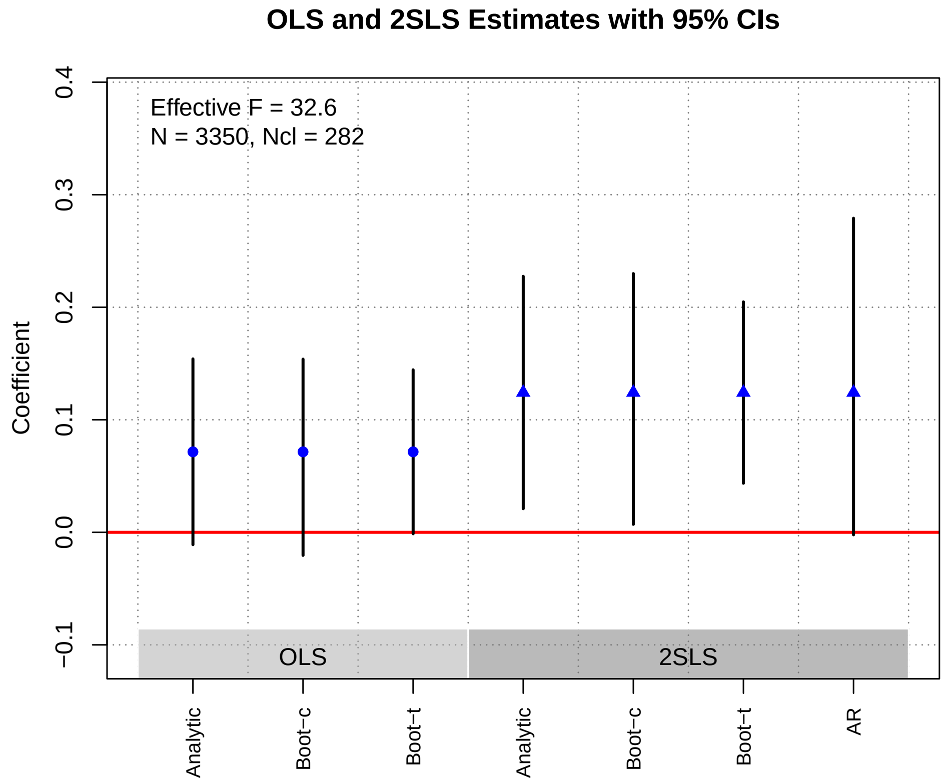
```
df <-readRDS("./data/ajps_Chong_etal_2019.rds")
D <-"ratio_treat"
Y <- "elecc_presid2013"
Z <- c("D2D30", "D2D40", "D2D50")
controls <-c("age", "married", "children", "num_children",
             "employed", "languag", "yrseduc", "bornloc",
             "hh_asset_index", "log_pop", "mujeres_perc",
             "pob_0_14_perc", "pob_15_64_perc", "pob_65mas_perc",
             "analfabetos_perc", "asiste_escuela_perc",
             "TASA_women", "TASA_men", "electricidad_perc",
             "agua_perc", "desague_perc", "basura_perc",
             "fono_fijo_perc", "fono_cel_perc", "ocupantes",
             "Rural",  "distancia2_final", "db_age",
             "db_married", "db_children", "db_num_children",
             "db_employed", "db_languag", "db_yrseduc",
```

```r
              "db_bornloc", "db_hh_asset_index", "db_log_pop",
              "db_mujeres_perc", "db_pob_0_14_perc",
              "db_pob_15_64_perc", "db_pob_65mas_perc",
              "db_analfabetos_perc", "db_asiste_escuela_perc",
              "db_TASA_women", "db_TASA_men", "db_electricidad_perc",
              "db_agua_perc", "db_desague_perc", "db_basura_perc",
              "db_fono_fijo_perc", "db_fono_cel_perc",
              "db_ocupantes", "db_Rural", "db_distancia2_final",
              "dpto1", "elecc_presid2008", "db_elecc_presid2008")
cl <- "loc"
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0715 0.0421 1.6984 -0.0110   0.1541  0.0894
## Boot.c   0.0715 0.0440 1.6248 -0.0205   0.1539  0.0940
## Boot.t   0.0715 0.0421 1.6984 -0.0013   0.1444  0.0540
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.1242 0.0527 2.3584  0.0210   0.2275  0.0184
## Boot.c   0.1242 0.0552 2.2507  0.0071   0.2299  0.0400
## Boot.t   0.1242 0.0527 2.3584  0.0436   0.2048  0.0020
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    2.5349    3.0000 3346.0000    0.0551
##
## $AR$ci.print
## [1] "[-0.0022, 0.2791]"
##
## $AR$ci
## [1] -0.0022  0.2791
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##   F.standard     F.robust    F.cluster F.bootstrap F.effective
##    1163.8658     270.5690      37.7653     34.0492     32.5611
##
## $rho
```

```
## [1] 0.7163
##
## $est_rf
##         Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## D2D30 0.0194 0.0333  0.5611 0.0348  -0.0529    0.0829     0.614
## D2D40 0.0651 0.0243  0.0075 0.0265   0.0121    0.1138     0.024
## D2D50 0.0190 0.0277  0.4940 0.0304  -0.0423    0.0728     0.518
##
## $est_fs
##         Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## D2D30 0.2996 0.0434       0 0.0447   0.2200    0.3849         0
## D2D40 0.3946 0.0754       0 0.0775   0.2579    0.5590         0
## D2D50 0.2663 0.0438       0 0.0479   0.2017    0.3815         0
##
## $p_iv
## [1] 3
##
## $N
## [1] 3350
##
## $N_cl
## [1] 282
##
## $df
## [1] 3316
##
## $nvalues
##      elecc_presid2013 ratio_treat D2D30 D2D40 D2D50
## [1,]                2          56     2     2     2
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Colantone and Stanig (2018)

Replication Summary	
Unit of analysis	region*year
Treatment	regional import shock from China
Instrument	Chinese imports to the United States
Outcome	Economic nationalism
Model	Table1(1)

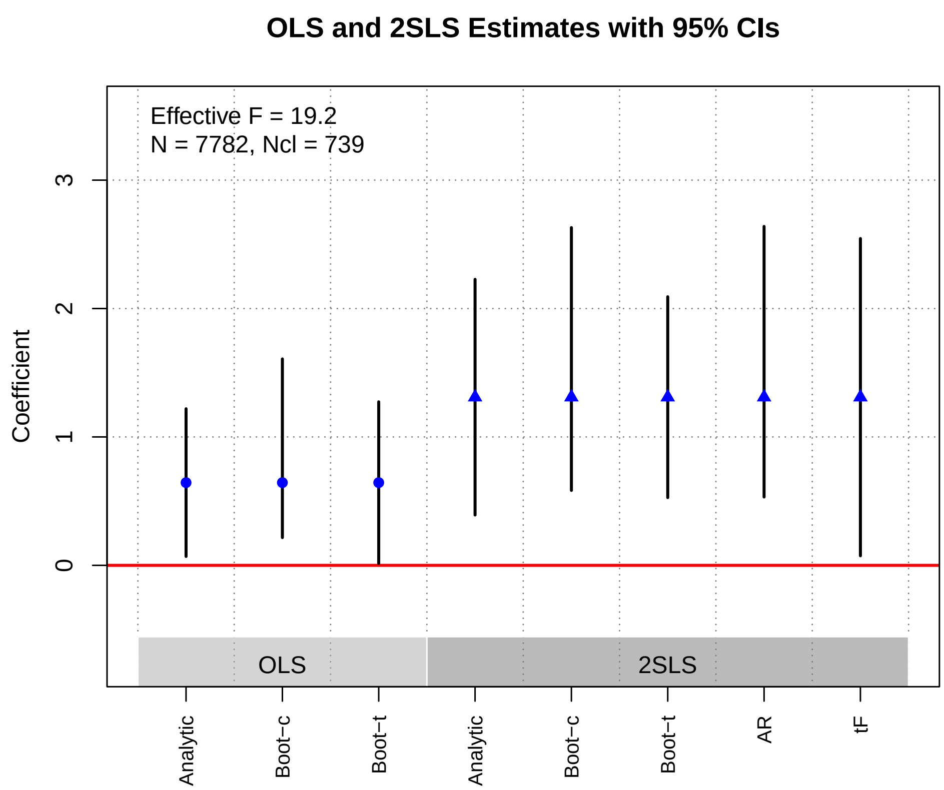
```
df <-readRDS("./data/ajps_Colantone_etal_2018.rds")
D <-"import_shock"
Y <- "median_nationalism"
Z <- "instrument_for_shock"
controls <- NULL
cl <- "nuts2_year"
FE <- "fix_effect"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.6442 0.2934 2.1955  0.0691    1.2193  0.0281
## Boot.c   0.6442 0.3612 1.7833  0.2162    1.6073  0.0000
```

```
## Boot.t   0.6442 0.2934 2.1955  0.0151   1.2733  0.0460
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 1.3096 0.4682 2.7970  0.3919   2.2273  0.0052
## Boot.c   1.3096 0.5396 2.4269  0.5836   2.6305  0.0020
## Boot.t   1.3096 0.4682 2.7970  0.5275   2.0917  0.0030
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##   10.9563    1.0000 7780.0000    0.0009
##
## $AR$ci.print
## [1] "[0.5323, 2.6393]"
##
## $AR$ci
## [1] 0.5323 2.6393
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##   1810.3678     42.8350     19.1709     12.0799     19.1709
##
## $rho
## [1] 0.4358
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 19.1709  2.6386  1.3096  0.4682  2.7970  0.0741  2.5450  0.0377
##
## $est_rf
##                        Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## instrument_for_shock 0.0514 0.0156   0.001 0.0196   0.0265    0.1039     0.002
##
## $est_fs
##                        Coef    SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## instrument_for_shock 0.0392 0.009       0 0.0113   0.0263    0.0692         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 7782
```

```
##
## $N_cl
## [1] 739
##
## $df
## [1] 7724
##
## $nvalues
##      median_nationalism import_shock instrument_for_shock
## [1,]                167          739                  739
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Coppock and Green (2016)

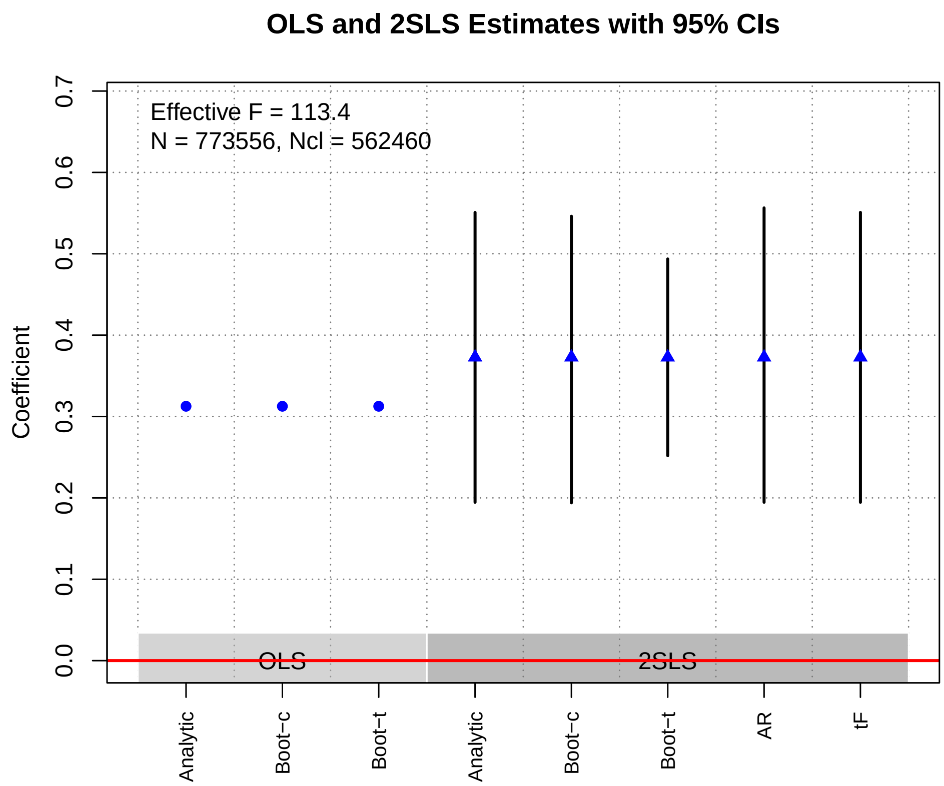
Replication Summary	
Unit of analysis	individual
Treatment	voting in November 2007 municipal elections
Instrument	mailing showing 2005 Vote
Outcome	voting in the 2008 presidential primary
Model	Table2(2)

```r
df<-readRDS("./data/ajps_Coppock_etal_2016.rds")
D <-"og2007"
Y <- "JAN2008"
Z <- "treat2"
controls <- NULL
cl <- "hh"
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE        t CI 2.5% CI 97.5% p.value
## Analytic 0.3126 0.0014 229.6550  0.3099   0.3152       0
## Boot.c   0.3126 0.0014 222.8556  0.3099   0.3155       0
## Boot.t   0.3126 0.0014 229.6550  0.3106   0.3146       0
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.3728 0.0909 4.1013  0.1946   0.5509       0
## Boot.c   0.3728 0.0911 4.0925  0.1939   0.5462       0
## Boot.t   0.3728 0.0909 4.1013  0.2519   0.4937       0
##
## $AR
## $AR$Fstat
##           F         df1         df2           p
##     15.4540      1.0000 773554.0000      0.0001
##
## $AR$ci.print
## [1] "[0.1946, 0.5564]"
##
## $AR$ci
## [1] 0.1946 0.5564
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##   F.standard    F.robust   F.cluster F.bootstrap F.effective
##     165.8659    151.8337    113.3680    107.4874    113.3680
##
## $rho
## [1] 0.0146
##
## $tF
##         F       cF     Coef       SE        t   CI2.5%  CI97.5%  p-value
```

```
## 113.3680   1.9600   0.3728   0.0909   4.1013   0.1946   0.5509   0.0000
##
## $est_rf
##          Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## treat2 0.0187 0.0048   1e-04 0.0047    0.009    0.0276         0
##
## $est_fs
##          Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## treat2 0.0502 0.0047       0 0.0048   0.0402    0.0596         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 773556
##
## $N_cl
## [1] 562460
##
## $df
## [1] 773554
##
## $nvalues
##      JAN2008 og2007 treat2
## [1,]       2      2      2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



De La O (2013)

Replication Summary	
Unit of analysis	village
Treatment	early coverage of Conditional Cash Transfer
Instrument	random assignment to early coverage
Outcome	incumbent party's vote share
Model	Table3(b1)

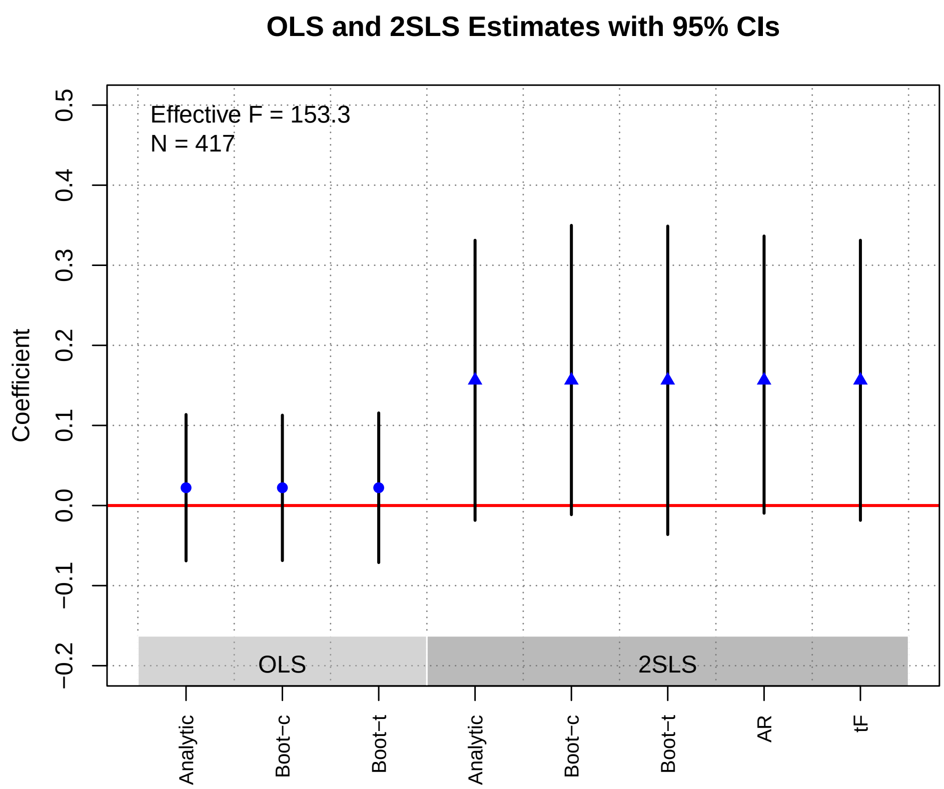
```
df <- readRDS("./data/ajps_De_La_O_2013.rds")
D <-"early_progresa_p"
Y <- "t2000"
Z <- "treatment"
controls <- c("avgpoverty","pobtot1994", "votos_totales1994",
              "pri1994", "pan1994", "prd1994")
cl <- NULL
FE <- "villages"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0222 0.0466 0.4771 -0.0691   0.1136  0.6333
```

```
## Boot.c   0.0222 0.0470 0.4737 -0.0687   0.1128  0.7060
## Boot.t   0.0222 0.0466 0.4771 -0.0712   0.1156  0.6450
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.1563 0.0892 1.7521 -0.0185   0.3312  0.0798
## Boot.c   0.1563 0.0925 1.6906 -0.0114   0.3498  0.0780
## Boot.t   0.1563 0.0892 1.7521 -0.0362   0.3489  0.0990
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   3.3846   1.0000 415.0000   0.0665
##
## $AR$ci.print
## [1] "[-0.0096, 0.3365]"
##
## $AR$ci
## [1] -0.0096  0.3365
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##    177.1916    153.2854          NA    149.7375    153.2854
##
## $rho
## [1] 0.556
##
## $tF
##        F       cF     Coef       SE        t   CI2.5%  CI97.5%  p-value
## 153.2854   1.9600   0.1563   0.0892   1.7521  -0.0185   0.3312   0.0798
##
## $est_rf
##             Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## treatment 0.0532 0.0296  0.0723 0.0302  -0.0039    0.1118     0.078
##
## $est_fs
##             Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## treatment 0.3401 0.0275       0 0.0278   0.2874    0.3958         0
##
## $p_iv
## [1] 1
##
## $N
```

```
## [1] 417
##
## $N_cl
## NULL
##
## $df
## [1] 396
##
## $nvalues
##      t2000 early_progresa_p treatment
## [1,]   407              251         2
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Goldstein and You (2017)

Replication Summary	
Unit of analysis	city
Treatment	lobbying spending
Instrument	direct flight to Washington, DC
Outcome	total earmarks or grants awarded

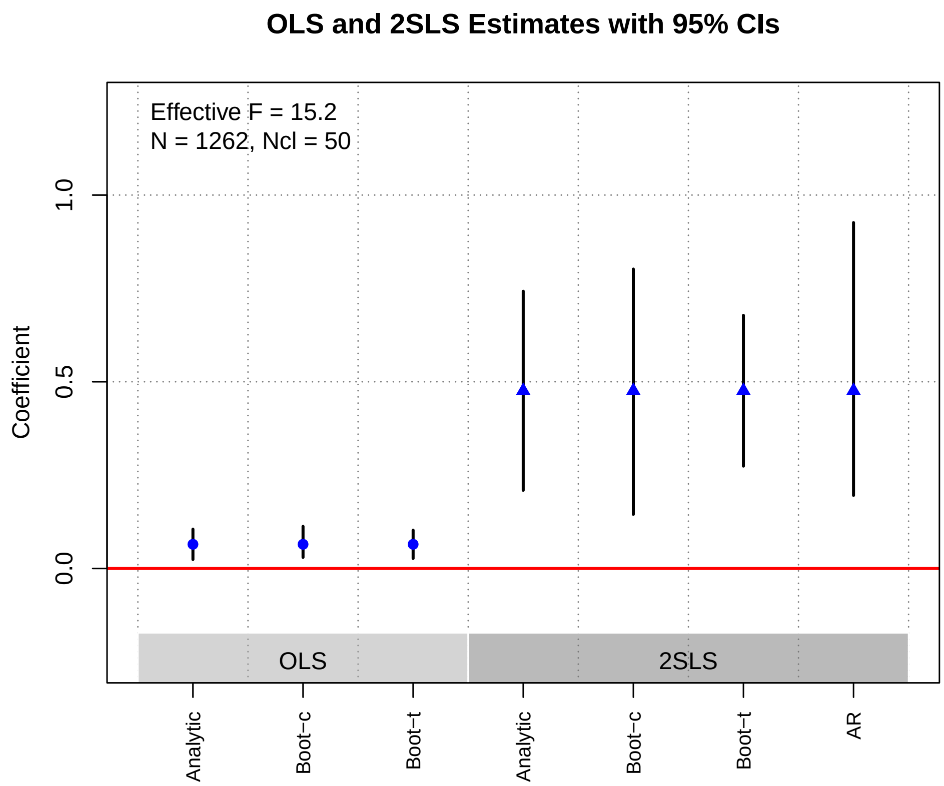
Replication Summary	
Model	Table4(4)

```r
df <- readRDS("./data/ajps_Goldstein_etal_2017.rds")
df <- as.data.frame(df)
Y <-"ln_recovery"
D <-"ln_citylob"
Z <- c("direct_flight_dc", "diverge2_r")
controls <- c("pop_r", "land_r", "water_r", "senior_r", "student_r", "ethnic_r",
              "mincome_r", "unemp_r", "poverty_r", "gini_r", "city_propertytaxshare_r",
              "city_intgovrevenueshare_r", "city_airexp_r", "houdem_r", "ln_countylob")
cl <- "state2"
FE <- "state2"
weights <- NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl, weights=weights, cores = cores, parallel = TRUE))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0648 0.0208 3.1171  0.0240   0.1055  0.0018
## Boot.c   0.0648 0.0215 3.0082  0.0297   0.1129  0.0000
## Boot.t   0.0648 0.0208 3.1171  0.0268   0.1027  0.0040
##
## $est_2sls
##           Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.476 0.1361 3.4987  0.2094   0.7427  0.0005
## Boot.c   0.476 0.1677 2.8384  0.1450   0.8020  0.0140
## Boot.t   0.476 0.1361 3.4987  0.2742   0.6779  0.0000
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    8.2957    2.0000 1259.0000    0.0003
##
## $AR$ci.print
## [1] "[0.1958, 0.9263]"
##
## $AR$ci
## [1] 0.1958 0.9263
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
```

```
##     16.6195     13.7688     15.7426     15.2361     15.1587
##
## $rho
## [1] 0.1645
##
## $est_rf
##                     Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## direct_flight_dc 1.2403 0.5428  0.0223 0.6325  -0.3281    2.2105     0.108
## diverge2_r       0.3010 0.1688  0.0745 0.1818  -0.0340    0.6604     0.076
##
## $est_fs
##                     Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## direct_flight_dc 2.6658 0.7247   2e-04 0.7530   1.0819    4.0075     0.002
## diverge2_r       0.6070 0.2164   5e-03 0.2254   0.1854    1.0687     0.010
##
## $p_iv
## [1] 2
##
## $N
## [1] 1262
##
## $N_cl
## [1] 50
##
## $df
## [1] 49
##
## $nvalues
##      ln_recovery ln_citylob direct_flight_dc diverge2_r
## [1,]        1196        135                2       1262
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Hager and Hilbig (2019) a

Replication Summary	
Unit of analysis	city
Treatment	equiTable inheritance customs
Instrument	mean elevation
Outcome	female representation
Model	Table3(1)

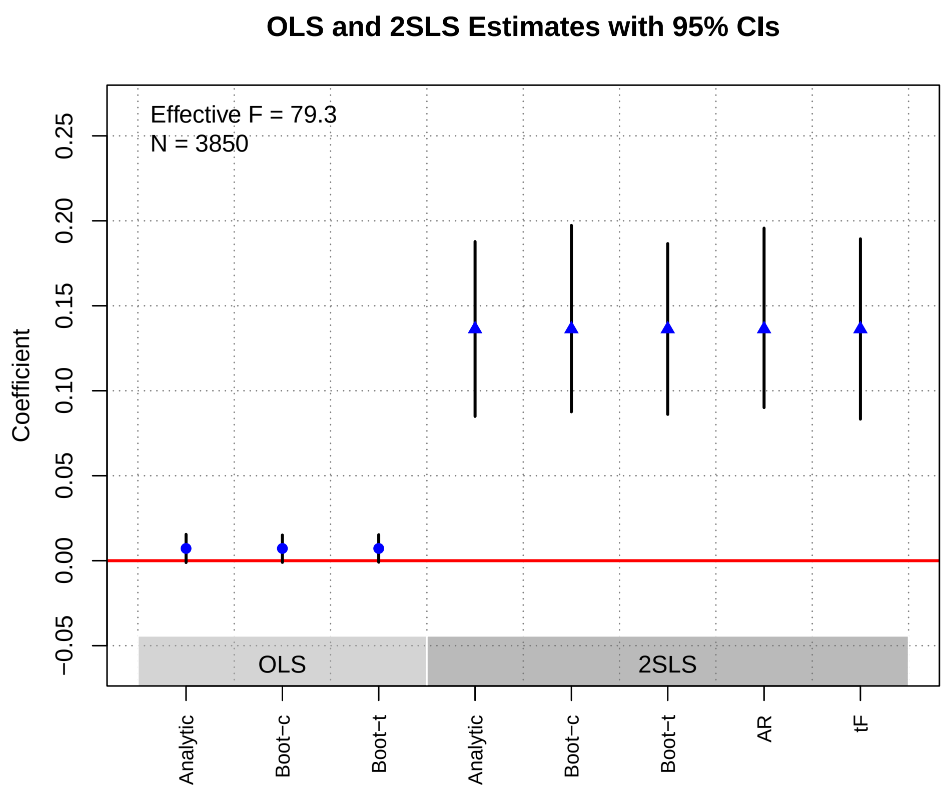
```
df<-readRDS("./data/ajps_Hager_etal_2019.rds")
D <-"fair_dic"
Y <- "gem_women_share"
Z <- "elev_mean"
controls <- c("lon", "lat", "childlabor_mean_1898",
              "support_expenses_total_capita","gem_council",
              "gem_pop_density","pop_tot")
cl<- NULL
FE<- c("state2","law_cat2")
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef      SE       t CI 2.5% CI 97.5% p.value
```

```
## Analytic 0.0072 0.0042 1.7010 -0.0011   0.0155  0.0889
## Boot.c   0.0072 0.0041 1.7334 -0.0010   0.0151  0.0860
## Boot.t   0.0072 0.0042 1.7010 -0.0009   0.0153  0.0820
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.1363 0.0262 5.1939  0.0849   0.1878       0
## Boot.c   0.1363 0.0275 4.9546  0.0876   0.1973       0
## Boot.t   0.1363 0.0262 5.1939  0.0861   0.1866       0
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##   38.9099    1.0000 3848.0000    0.0000
##
## $AR$ci.print
## [1] "[0.0901, 0.1957]"
##
## $AR$ci
## [1] 0.0901 0.1957
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##    122.1930     79.2985          NA     76.5626     79.2985
##
## $rho
## [1] 0.1758
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 79.2985  2.0200  0.1363  0.0262  5.1939  0.0833  0.1894  0.0000
##
## $est_rf
##              Coef SE p.value SE.b CI.b2.5% CI.b97.5% p.value.b
## elev_mean -1e-04  0       0    0   -2e-04    -1e-04         0
##
## $est_fs
##              Coef    SE p.value  SE.b CI.b2.5% CI.b97.5% p.value.b
## elev_mean -9e-04 1e-04       0 1e-04  -0.0011    -7e-04         0
##
## $p_iv
## [1] 1
##
```

```
## $N
## [1] 3850
##
## $N_cl
## NULL
##
## $df
## [1] 3831
##
## $nvalues
##      gem_women_share fair_dic elev_mean
## [1,]             230        2      3850
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Hager and Hilbig (2019) b

Replication Summary	
Unit of analysis	city
Treatment	equiTable inheritance customs
Instrument	distance to rivers

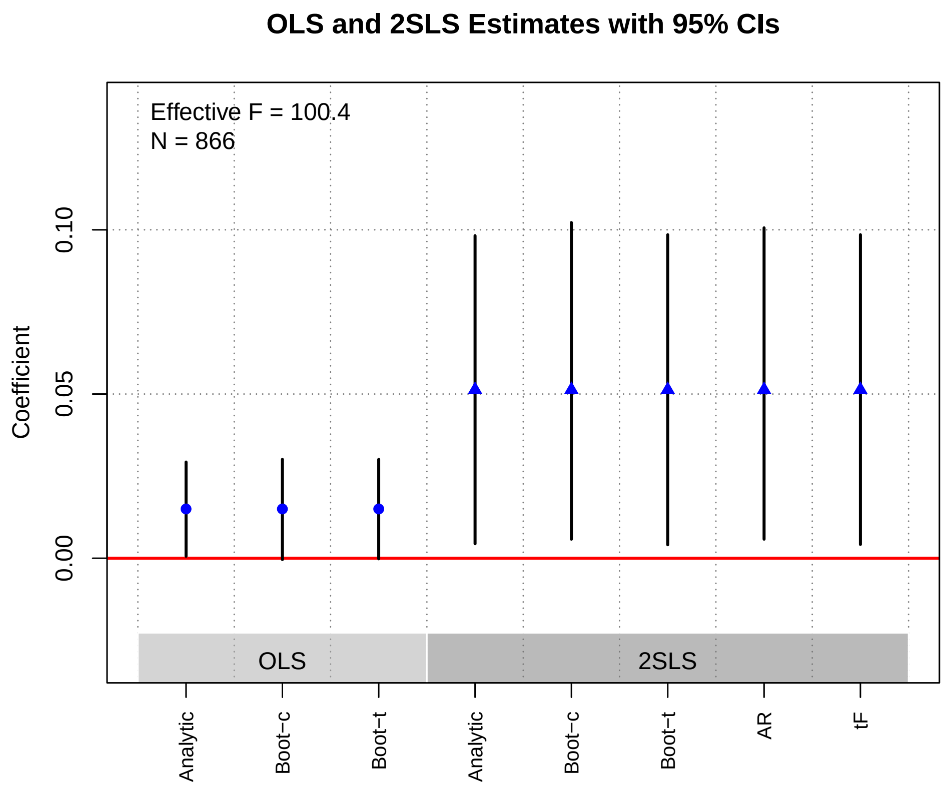
Replication Summary	
Outcome	female representation
Model	Table3(2)

```r
df<-readRDS("./data/ajps_Hager_etal_2019.rds")
D <-"fair_dic"
Y <- "gem_women_share"
Z <-"river_dist_min"
controls <- c("lon", "lat", "childlabor_mean_1898",
              "support_expenses_total_capita","gem_council",
              "gem_pop_density","pop_tot")
cl<- NULL
FE<- c("law_cat2")
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.015 0.0073 2.0379   6e-04   0.0293  0.0416
## Boot.c   0.015 0.0077 1.9395  -4e-04   0.0301  0.0540
## Boot.t   0.015 0.0073 2.0379  -2e-04   0.0301  0.0520
##
## $est_2sls
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0513 0.0239 2.1441  0.0044   0.0982   0.032
## Boot.c   0.0513 0.0244 2.1036  0.0058   0.1022   0.024
## Boot.t   0.0513 0.0239 2.1441  0.0041   0.0985   0.035
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   4.8070   1.0000 864.0000   0.0286
##
## $AR$ci.print
## [1] "[0.0058, 0.1006]"
##
## $AR$ci
## [1] 0.0058 0.1006
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
```

```
##     99.1676    100.3609          NA    102.1481    100.3609
##
## $rho
## [1] 0.3222
##
## $tF
##        F       cF     Coef       SE        t    CI2.5%  CI97.5%  p-value
## 100.3609   1.9700   0.0513   0.0239   2.1441   0.0042   0.0985   0.0329
##
## $est_rf
##                  Coef    SE p.value  SE.b CI.b2.5% CI.b97.5% p.value.b
## river_dist_min -5e-04 2e-04  0.0291 2e-04   -0.001    -1e-04     0.024
##
## $est_fs
##                   Coef    SE p.value  SE.b CI.b2.5% CI.b97.5% p.value.b
## river_dist_min -0.0105 0.001       0 0.001  -0.0125   -0.0083         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 866
##
## $N_cl
## NULL
##
## $df
## [1] 856
##
## $nvalues
##      gem_women_share fair_dic river_dist_min
## [1,]             110        2            866
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Hong et al. (2022)

Replication Summary	
Unit of analysis	township
Treatment	NVM subsidy per voter
Instrument	Terrain elevation slope
Outcome	Park's vote share in 2012
Model	Table3(3)

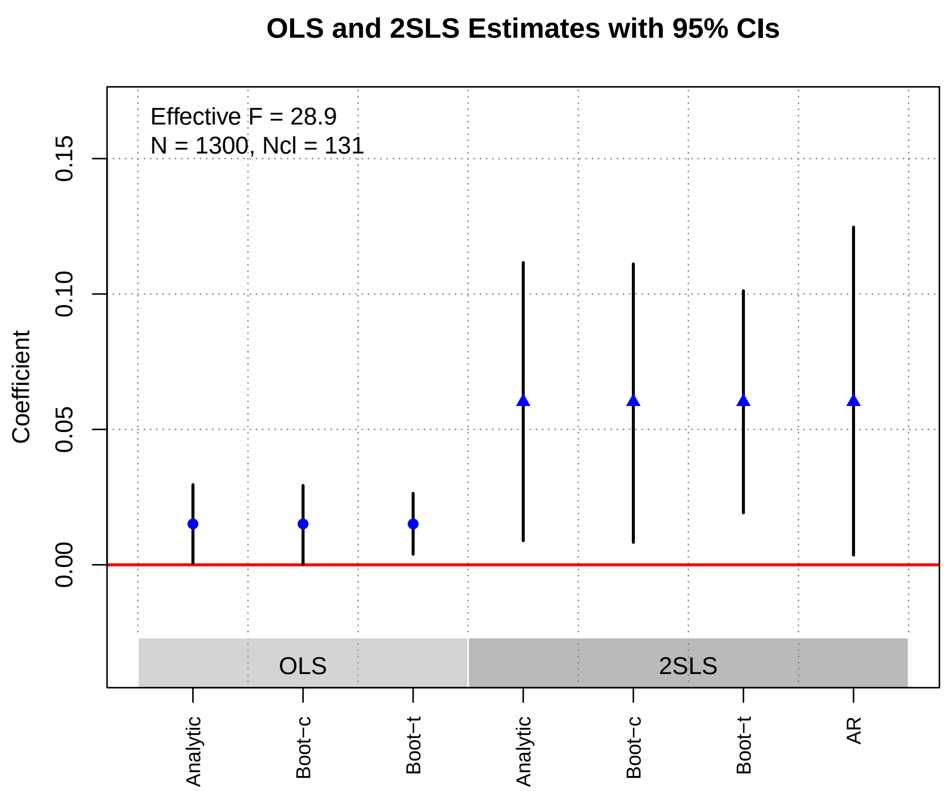
```
df <-readRDS("./data/ajps_Hong_etal_2022.rds")
df<-as.data.frame(df)
D<-"total_Lamount_1974_1978_perelect"
Y <- "E18ConsSh"
Z <- c("te_median1", "ts_median1")
controls <- c("area_1970","demo_female_share_1966","demo_age_15plus_1966",
              "demo_illiterate_1966","demo_pop_ch_1970_1966","E17ConsSh","eup")
cl <- "CTY_cd"
FE <- "CTY_cd"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef      SE       t CI 2.5% CI 97.5% p.value
```

```
## Analytic 0.0151 0.0074 2.0600  0.0007   0.0296  0.0394
## Boot.c   0.0151 0.0075 2.0188  0.0002   0.0293  0.0480
## Boot.t   0.0151 0.0074 2.0600  0.0039   0.0264  0.0080
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0602 0.0262 2.2980  0.0089   0.1116  0.0216
## Boot.c   0.0602 0.0269 2.2431  0.0083   0.1111  0.0160
## Boot.t   0.0602 0.0262 2.2980  0.0192   0.1012  0.0030
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    3.2888    2.0000 1297.0000    0.0376
##
## $AR$ci.print
## [1] "[0.0036, 0.1247]"
##
## $AR$ci
## [1] 0.0036 0.1247
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     34.7064     29.0832     28.2296     28.0519     28.8604
##
## $rho
## [1] 0.2376
##
## $est_rf
##               Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## te_median1 -0.0036 0.0233  0.8774 0.0226  -0.0470    0.0430     0.774
## ts_median1  0.0020 0.0010  0.0509 0.0010   0.0002    0.0041     0.028
##
## $est_fs
##              Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## te_median1 0.3276 0.1352  0.0154 0.1331   0.0808    0.6003     0.018
## ts_median1 0.0171 0.0061  0.0050 0.0060   0.0056    0.0293     0.004
##
## $p_iv
## [1] 2
##
## $N
## [1] 1300
```

```
##
## $N_cl
## [1] 131
##
## $df
## [1] 130
##
## $nvalues
##      E18ConsSh total_Lamount_1974_1978_perelect te_median1 ts_median1
## [1,]      1292                             1285       1300       1232
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Kim (2019)

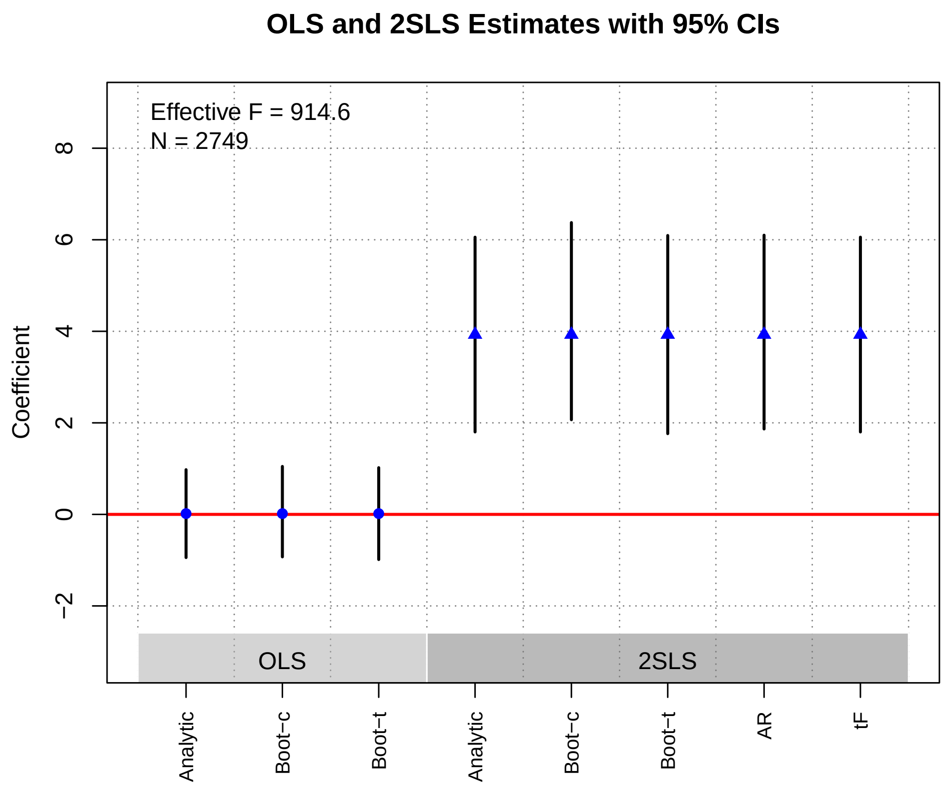
Replication Summary	
Unit of analysis	municipality*year
Treatment	Democratic institutions
Instrument	population threshold
Outcome	women political engagement
Model	Table2(1)

```r
df<- readRDS("./data/ajps_Kim_2019.rds")
D <-"direct"
Y <- "wm_turnout"
Z <-  "new"
controls <- c("left", "wm_voters", "enep")
cl <- NULL
FE <- "year"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##           Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.017 0.4897 0.0346 -0.9429   0.9768  0.9724
## Boot.c   0.017 0.5130 0.0331 -0.9283   1.0475  0.9500
## Boot.t   0.017 0.4897 0.0346 -0.9865   1.0204  0.9750
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 3.9287 1.0855 3.6192  1.8011   6.0563   3e-04
## Boot.c   3.9287 1.1010 3.5684  2.0681   6.3751   0e+00
## Boot.t   3.9287 1.0855 3.6192  1.7641   6.0932   0e+00
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##   14.3152    1.0000 2747.0000    0.0002
##
## $AR$ci.print
## [1] "[1.8662, 6.0997]"
##
## $AR$ci
## [1] 1.8662 6.0997
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##   1007.3382    914.6461          NA    957.7521    914.6461
##
## $rho
## [1] 0.5186
##
## $tF
##        F       cF     Coef        SE         t   CI2.5%   CI97.5%   p-value
```

```
## 914.6461   1.9600   3.9287   1.0855   3.6192   1.8011   6.0563   0.0003
##
## $est_rf
##      Coef    SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## new 1.949 0.516   2e-04 0.5172   1.0259    3.0977         0
##
## $est_fs
##       Coef     SE p.value  SE.b CI.b2.5% CI.b97.5% p.value.b
## new 0.4961 0.0164       0 0.016   0.4619    0.5238         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 2749
##
## $N_cl
## NULL
##
## $df
## [1] 2738
##
## $nvalues
##      wm_turnout direct new
## [1,]       2606      2   2
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Kocher et al. (2011)

Replication Summary	
Unit of analysis	hamlet (smallest population unit)
Treatment	aerial bombing
Instrument	past insurgent control
Outcome	changes in local control
Model	Table5(5B)

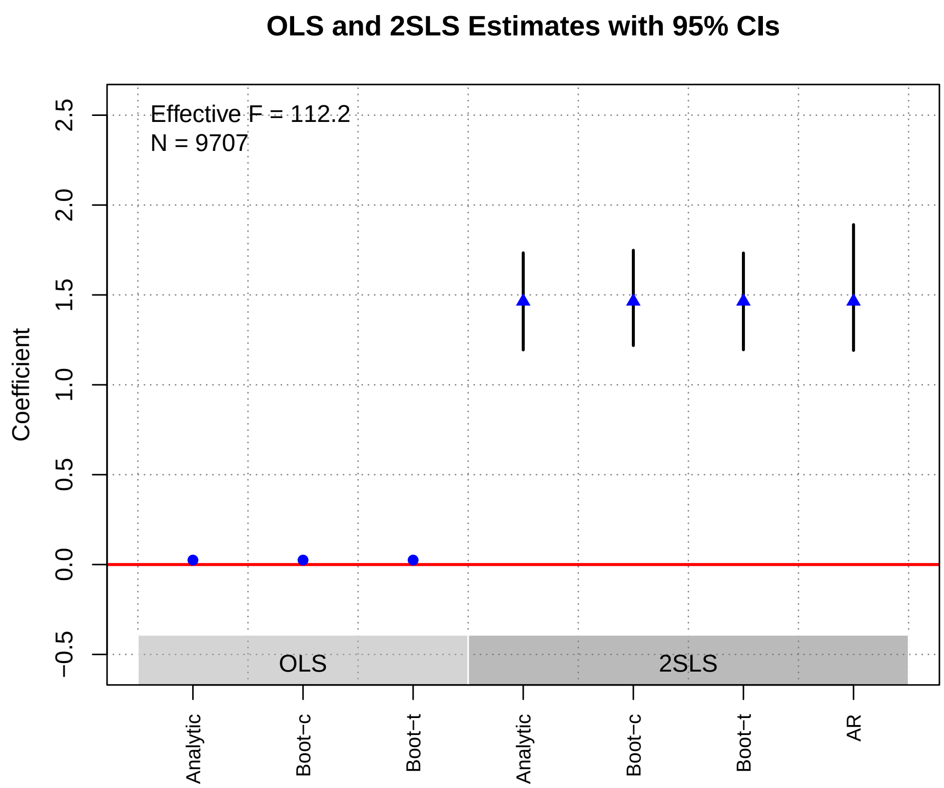
```
df<-readRDS("./data/ajps_Kocher_etal_2011.rds")
D <-"bombed_969"
Y<- "mod2a_1adec"
Z <- c("mod2a_1ajul", "mod2a_1aaug")
controls <- c("mod2a_1asep", "score", "ln_dist", "std", "lnhpop")
cl<- NULL
FE <-NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0249 0.0042 5.8926  0.0166   0.0332       0
## Boot.c   0.0249 0.0043 5.7797  0.0175   0.0342       0
```

```
## Boot.t   0.0249 0.0042 5.8926  0.0163   0.0335       0
##
## $est_2sls
##           Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic 1.464 0.1377 10.6345  1.1942   1.7339       0
## Boot.c   1.464 0.1391 10.5284  1.2186   1.7482       0
## Boot.t   1.464 0.1377 10.6345  1.1950   1.7330       0
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##  681.5407    2.0000 9704.0000    0.0000
##
## $AR$ci.print
## [1] "[1.1914, 1.8908]"
##
## $AR$ci
## [1] 1.1914 1.8908
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     44.1703     59.8861          NA     59.9371    112.1923
##
## $rho
## [1] 0.095
##
## $est_rf
##               Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## mod2a_1ajul 0.2562 0.0123       0 0.0125   0.2319    0.2799         0
## mod2a_1aaug 0.1830 0.0134       0 0.0139   0.1573    0.2119         0
##
## $est_fs
##               Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## mod2a_1ajul 0.1681 0.0284       0 0.0283   0.1104    0.2192         0
## mod2a_1aaug 0.1328 0.0311       0 0.0325   0.0731    0.1994         0
##
## $p_iv
## [1] 2
##
## $N
## [1] 9707
##
## $N_cl
```

```
## NULL
##
## $df
## [1] 9700
##
## $nvalues
##      mod2a_1adec bombed_969 mod2a_1ajul mod2a_1aaug
## [1,]           5         35           5           5
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Lelkes et al. (2017)

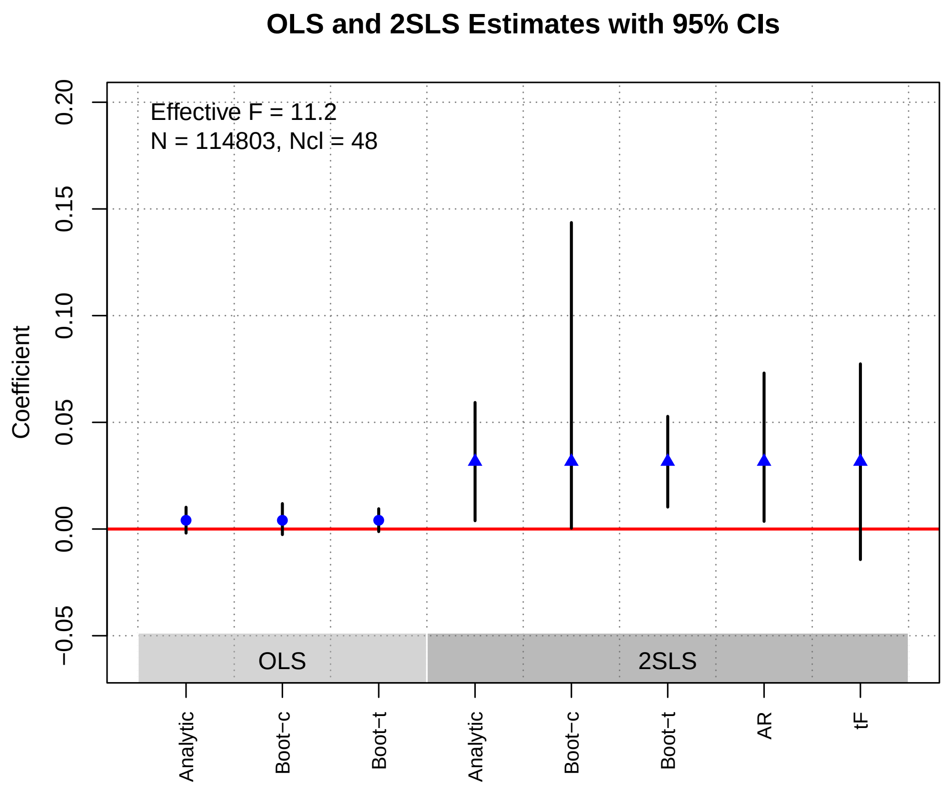
Replication Summary	
Unit of analysis	state*year
Treatment	number of broadband Internet providers
Instrument	state-level ROW index
Outcome	affective polarization
Model	Table1(3)

```r
df<-readRDS("./data/ajps_Lelkes_2017.rds")
D <-"D"
Y <- "outcome"
Z <- "Total_log"
controls <- c("region", "percent_black", "percent_white",
              "percent_male", "lowed", "unemploymentrate",
              "density", "HHINC_log")
cl<- "state"
FE <- "year"
weights=NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0041 0.0031 1.3481 -0.0019   0.0102  0.1776
## Boot.c   0.0041 0.0037 1.1150 -0.0026   0.0119  0.2900
## Boot.t   0.0041 0.0031 1.3481 -0.0012   0.0095  0.1270
##
## $est_2sls
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0316 0.0141 2.2364  0.0039   0.0593  0.0253
## Boot.c   0.0316 0.0972 0.3250  0.0004   0.1436  0.0500
## Boot.t   0.0316 0.0141 2.2364  0.0103   0.0528  0.0090
##
## $AR
## $AR$Fstat
##           F         df1         df2           p
##      4.6542      1.0000 114801.0000      0.0310
##
## $AR$ci.print
## [1] "[0.0036, 0.0731]"
##
## $AR$ci
## [1] 0.0036 0.0731
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##   9525.8467   8161.7346     11.1632      7.4715     11.1632
##
## $rho
## [1] 0.2768
##
```

```
## $tF
##       F      cF     Coef       SE        t   CI2.5% CI97.5% p-value
## 11.1632  3.2489  0.0316  0.0141  2.2364 -0.0143  0.0774  0.1773
##
## $est_rf
##             Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## Total_log 0.0033 0.0015   0.031 0.0019    4e-04    0.0083     0.028
##
## $est_fs
##             Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## Total_log 0.1042 0.0312   8e-04 0.0381   0.0138    0.1677     0.026
##
## $p_iv
## [1] 1
##
## $N
## [1] 114803
##
## $N_cl
## [1] 48
##
## $df
## [1] 114790
##
## $nvalues
##      outcome    D Total_log
## [1,]    2423 1438        43
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



López-Moctezuma et al. (2020)

Replication Summary	
Unit of analysis	individual
Treatment	town-hall meetings
Instrument	assignment to treatment
Outcome	voting behavior
Model	figure3(2)

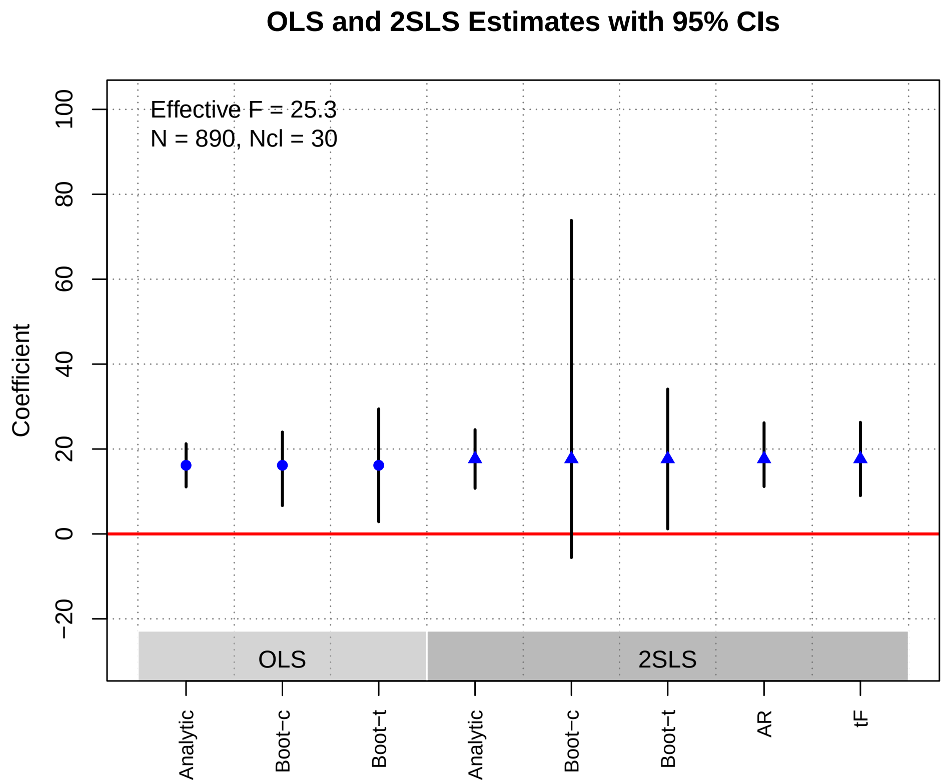
```
df <-readRDS("./data/ajps_Moctezuma_etal_2020.rds")
df<-as.data.frame(df)
D<-"treatment"
Y <- "vote"
Z <- "assignment"
  controls <- NULL
cl <- "barangay"
FE <- "city"
weights<-"weight.att"
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 16.1643 2.5956 6.2275 11.0769  21.2517   0.000
```

```
## Boot.c   16.1643 4.3183 3.7432  6.6772  24.0026   0.008
## Boot.t   16.1643 2.5956 6.2275  2.8757  29.4529   0.036
##
## $est_2sls
##             Coef       SE      t CI 2.5% CI 97.5% p.value
## Analytic 17.6531   3.5231 5.0106 10.7478  24.5584  0.0000
## Boot.c   17.6531 174.8439 0.1010 -5.5604  73.8547  0.0681
## Boot.t   17.6531   3.5231 5.0106  1.1865  34.1196  0.0420
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##  18.6344   1.0000 888.0000   0.0000
##
## $AR$ci.print
## [1] "[11.1705, 26.1790]"
##
## $AR$ci
## [1] 11.1705 26.1790
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##   1663.9064    521.4034     25.2694      5.2999     25.2694
##
## $rho
## [1] 0.8089
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 25.2694  2.4519 17.6531  3.5231  5.0106  9.0146 26.2915  0.0001
##
## $est_rf
##               Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## assignment 13.2179 3.0776       0 6.2669   0.7688   26.3833      0.04
##
## $est_fs
##              Coef    SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## assignment 0.7488 0.149       0 0.3252  -0.0529         1    0.0601
##
## $p_iv
## [1] 1
##
## $N
```

```
## [1] 890
##
## $N_cl
## [1] 30
##
## $df
## [1] 879
##
## $nvalues
##      vote treatment assignment
## [1,]    2         2          2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



McClendon (2014)

Replication Summary	
Unit of analysis	individual
Treatment	reading social esteem promising email
Instrument	assignment to treatment
Outcome	participation in LGBTQ events

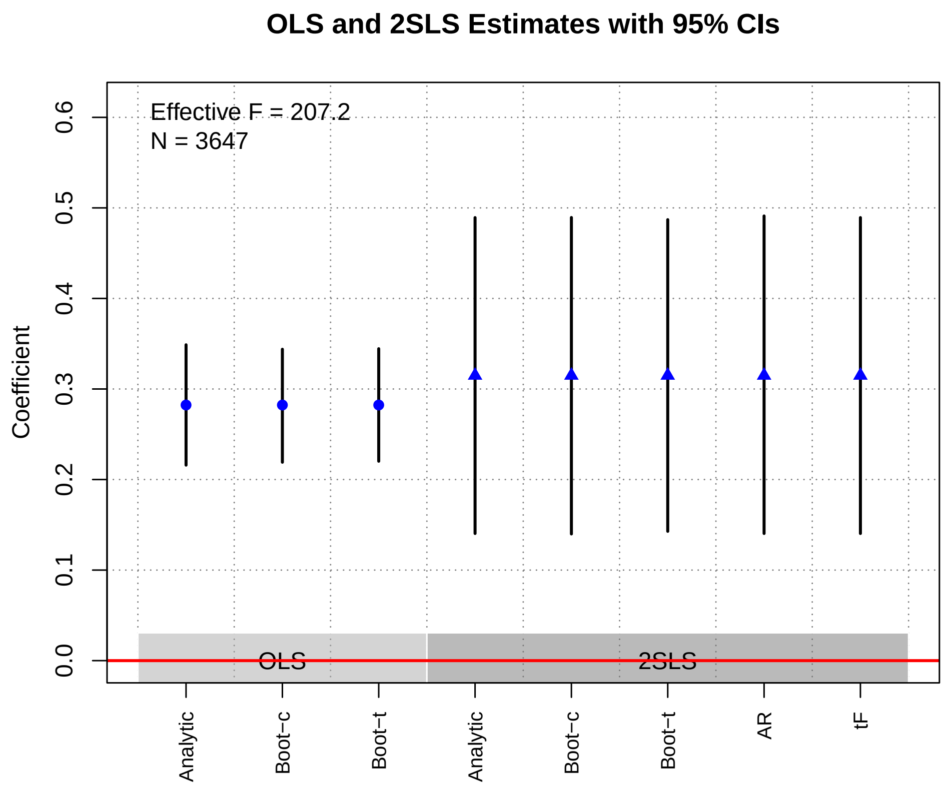
Replication Summary	
Model	Table2(1)

```r
df <- readRDS("./data/ajps_McClendon_2014.rds")
D<-"openedesteem"
Y<- "intended"
Z <- "esteem"
controls <- NULL
cl<- NULL
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.2823 0.0339 8.3291  0.2159   0.3488       0
## Boot.c   0.2823 0.0331 8.5274  0.2191   0.3439       0
## Boot.t   0.2823 0.0339 8.3291  0.2202   0.3445       0
##
## $est_2sls
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.3149 0.0890 3.5376  0.1404   0.4893   4e-04
## Boot.c   0.3149 0.0901 3.4944  0.1399   0.4894   0e+00
## Boot.t   0.3149 0.0890 3.5376  0.1428   0.4870   0e+00
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##   11.9462    1.0000 3645.0000    0.0006
##
## $AR$ci.print
## [1] "[0.1404, 0.4911]"
##
## $AR$ci
## [1] 0.1404 0.4911
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##   F.standard    F.robust   F.cluster F.bootstrap F.effective
##     103.7604    207.1798          NA    220.5915    207.1798
##
## $rho
```

```
## [1] 0.1664
##
## $tF
##        F       cF     Coef       SE        t   CI2.5%  CI97.5%  p-value
## 207.1798   1.9600   0.3149   0.0890   3.5376   0.1404   0.4893   0.0004
##
## $est_rf
##          Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## esteem 0.0247 0.0072   5e-04 0.0072   0.0106    0.0381         0
##
## $est_fs
##          Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## esteem 0.0786 0.0055       0 0.0053   0.0679    0.0882         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 3647
##
## $N_cl
## NULL
##
## $df
## [1] 3645
##
## $nvalues
##      intended openedesteem esteem
## [1,]        2            2      2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Rueda (2017)

Replication Summary	
Unit of analysis	city
Treatment	actual polling place size.
Instrument	the size of the polling station
Outcome	citizens' reports of electoral manipulation
Model	Table5(1)

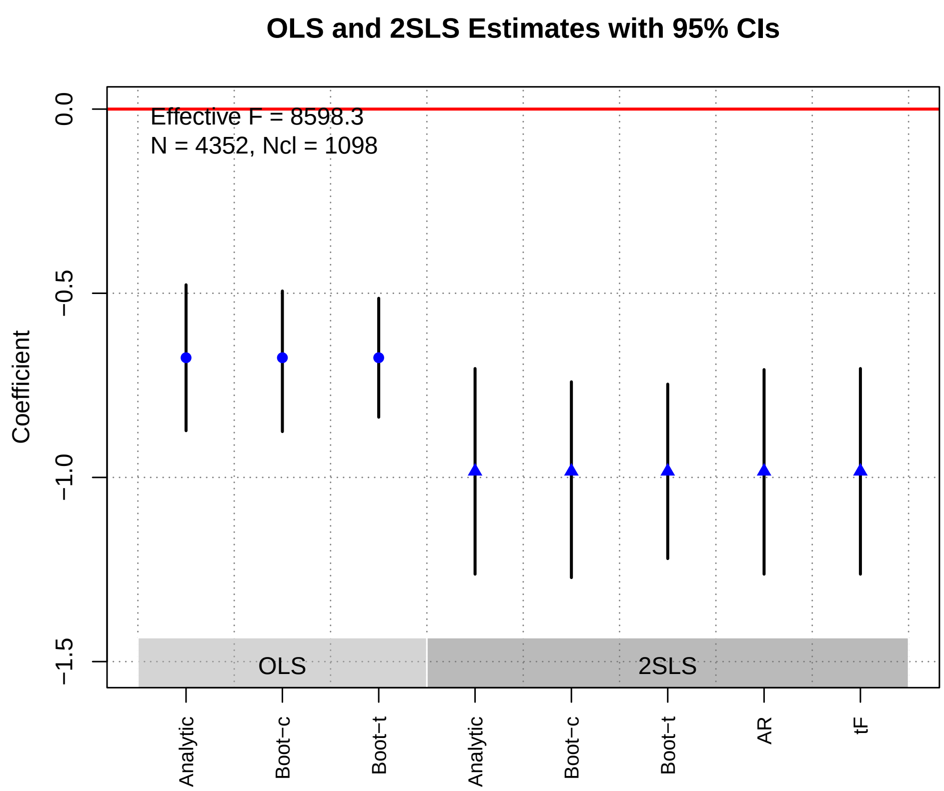
```
df <- readRDS("./data/ajps_Rueda_2017.rds")
D <-"lm_pob_mesa"
Y <- "e_vote_buying"
Z <- "lz_pob_mesa_f"
controls <- c("lpopulation", "lpotencial")
cl <- "muni_code"
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.675 0.1011 -6.6803 -0.8731  -0.4770       0
## Boot.c   -0.675 0.0977 -6.9069 -0.8755  -0.4939       0
```

```
## Boot.t   -0.675 0.1011 -6.6803 -0.8365  -0.5136       0
##
## $est_2sls
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.9835 0.1424 -6.9071 -1.2626  -0.7044       0
## Boot.c   -0.9835 0.1396 -7.0448 -1.2719  -0.7404       0
## Boot.t   -0.9835 0.1424 -6.9071 -1.2203  -0.7467       0
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##   48.4768    1.0000 4350.0000    0.0000
##
## $AR$ci.print
## [1] "[-1.2626, -0.7073]"
##
## $AR$ci
## [1] -1.2626 -0.7073
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##    3106.387    3108.591    8598.326    8236.037    8598.326
##
## $rho
## [1] 0.6455
##
## $tF
##         F        cF      Coef        SE         t    CI2.5%   CI97.5%   p-value
## 8598.3264    1.9600   -0.9835    0.1424   -6.9071   -1.2626   -0.7044    0.0000
##
## $est_rf
##                  Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## lz_pob_mesa_f -0.7826 0.1124       0 0.1098  -1.0094   -0.5889         0
##
## $est_fs
##                 Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## lz_pob_mesa_f 0.7957 0.0086       0 0.0088   0.7779    0.8127         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 4352
```

```
##
## $N_cl
## [1] 1098
##
## $df
## [1] 4348
##
## $nvalues
##      e_vote_buying lm_pob_mesa lz_pob_mesa_f
## [1,]            16        4118          3860
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Sexton et al. (2019)

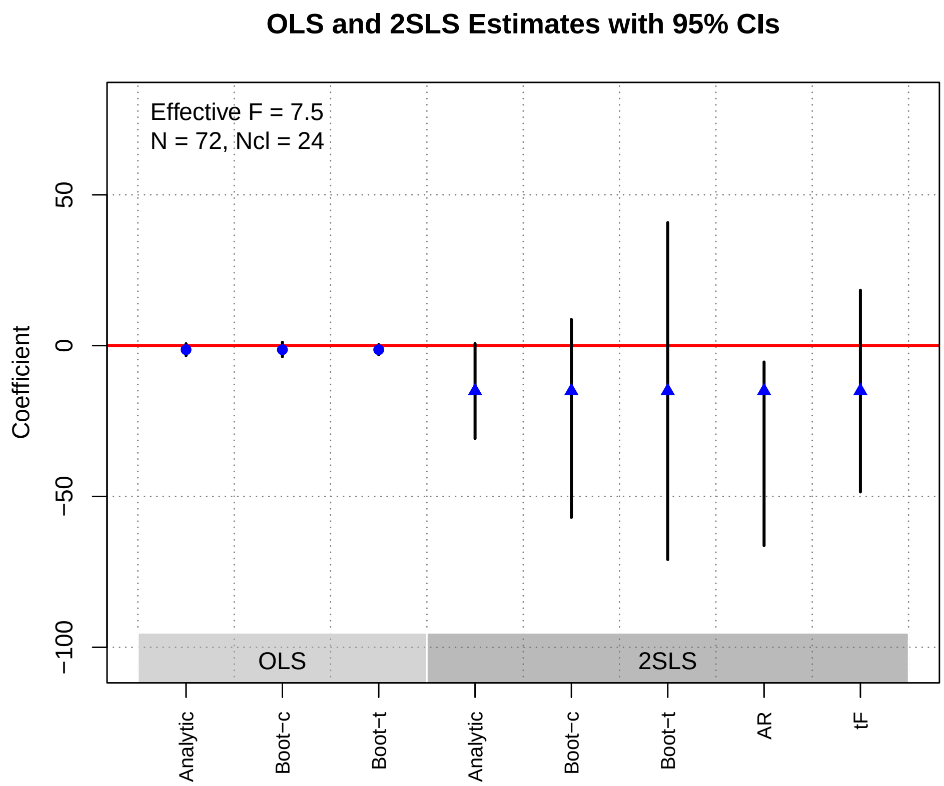
Replication Summary	
Unit of analysis	department*year
Treatment	health budget
Instrument	soldier fatalities
Outcome	health social service
Model	Table3(1)

```r
df <-readRDS("./data/ajps_Sexton_etal_2019.rds")
D<-"socialservice_b"
Y <- "Finfant_mortality"
Z <- "Lgk_budget"
controls <- c("Lgk_prebudget", "ln_pbi_pc", "execution_nohealth")
cl <- "deptcode"
FE <- c("year","deptcode")
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -1.3472 1.0152 -1.3270 -3.3371   0.6426  0.1845
## Boot.c   -1.3472 1.1861 -1.1358 -3.6612   1.1256  0.2594
## Boot.t   -1.3472 1.0152 -1.3270 -3.0556   0.3611  0.1145
##
## $est_2sls
##               Coef      SE       t  CI 2.5% CI 97.5% p.value
## Analytic -15.0645  8.0376 -1.8743 -30.8181   0.6892  0.0609
## Boot.c   -15.0645 55.4253 -0.2718 -56.9465   8.6700  0.1945
## Boot.t   -15.0645  8.0376 -1.8743 -70.9153  40.7864  0.1824
##
## $AR
## $AR$Fstat
##       F     df1     df2       p
## 18.0386  1.0000 70.0000  0.0001
##
## $AR$ci.print
## [1] "[-66.3101, -5.4194]"
##
## $AR$ci
## [1] -66.3101  -5.4194
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##      1.0172      2.5692      7.4923      2.8813      7.4923
##
## $rho
## [1] 0.1538
##
## $tF
##        F       cF     Coef       SE         t   CI2.5%   CI97.5%   p-value
```

```
##   7.4923   4.1607 -15.0645   8.0376  -1.8743 -48.5065  18.3775   0.3773
##
## $est_rf
##              Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## Lgk_budget 4.3552 1.0481       0 1.9528  -1.3625    6.0525     0.156
##
## $est_fs
##               Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## Lgk_budget -0.2891 0.1056  0.0062 0.1703   -0.673    -0.011    0.0466
##
## $p_iv
## [1] 1
##
## $N
## [1] 72
##
## $N_cl
## [1] 24
##
## $df
## [1] 23
##
## $nvalues
##      Finfant_mortality socialservice_b Lgk_budget
## [1,]                39              72          6
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Spenkuch and Tillmann (2018)

Replication Summary	
Unit of analysis	electoral district
Treatment	religion of voters living in the same areas more than three and a half centuries later
Instrument	individual princes' decisions concerning whether to adopt Protestantism
Outcome	Nazi vote share
Model	Table2(B1)

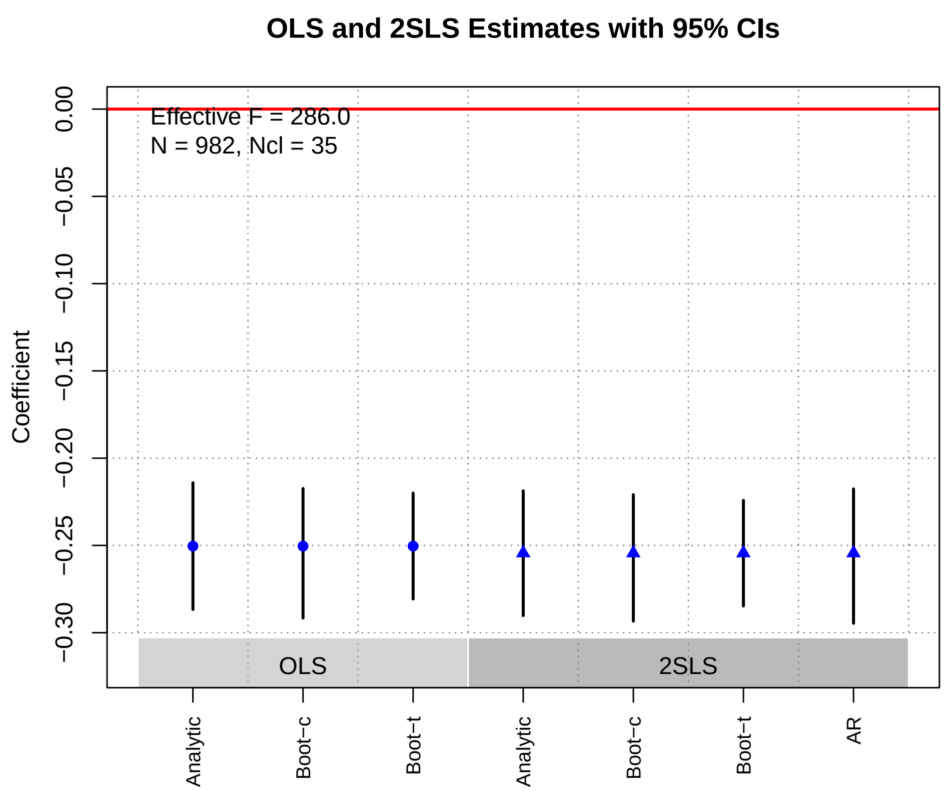
```
df <-readRDS("./data/ajps_Spenkuch_etal_2018.rds")
D <-"r_1925C_kath"
Y <- "r_NSDAP_NOV1932_p"
Z <- c("r_kath1624", "r_gem1624")
controls <- c("r_1925C_juden", "r_1925C_others",
              "r_M1925C_juden","r_M1925C_others")
cl <- 'WKNR'
FE <- NULL
weights="r_wahlberechtigte_NOV1932"
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##               Coef      SE         t CI 2.5% CI 97.5% p.value
```

```
## Analytic -0.2504 0.0185 -13.5112 -0.2867  -0.2141       0
## Boot.c   -0.2504 0.0191 -13.1177 -0.2916  -0.2174       0
## Boot.t   -0.2504 0.0185 -13.5112 -0.2807  -0.2200       0
##
## $est_2sls
##             Coef     SE        t CI 2.5% CI 97.5% p.value
## Analytic -0.2544 0.0182 -13.9439 -0.2902  -0.2187       0
## Boot.c   -0.2544 0.0187 -13.6037 -0.2934  -0.2209       0
## Boot.t   -0.2544 0.0182 -13.9439 -0.2847  -0.2242       0
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##  89.3425   2.0000 979.0000   0.0000
##
## $AR$ci.print
## [1] "[-0.2946, -0.2176]"
##
## $AR$ci
## [1] -0.2946 -0.2176
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##   1215.3547    726.7058    212.7390    203.7997    286.0263
##
## $rho
## [1] 0.8446
##
## $est_rf
##                Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## r_kath1624 -17.2028 1.2929       0 1.2952 -19.7304  -14.7653         0
## r_gem1624   -9.1477 1.5382       0 1.6801 -13.0491   -6.4079         0
##
## $est_fs
##               Coef    SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## r_kath1624 66.6657 3.232       0 3.3021  59.4406   72.9125         0
## r_gem1624  39.2697 4.320       0 4.6904  31.2145   50.1767         0
##
## $p_iv
## [1] 2
##
## $N
## [1] 982
```

```
##
## $N_cl
## [1] 35
##
## $df
## [1] 978
##
## $nvalues
##      r_NSDAP_NOV1932_p r_1925C_kath r_kath1624 r_gem1624
## [1,]               982          977          2         2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Stokes (2016)

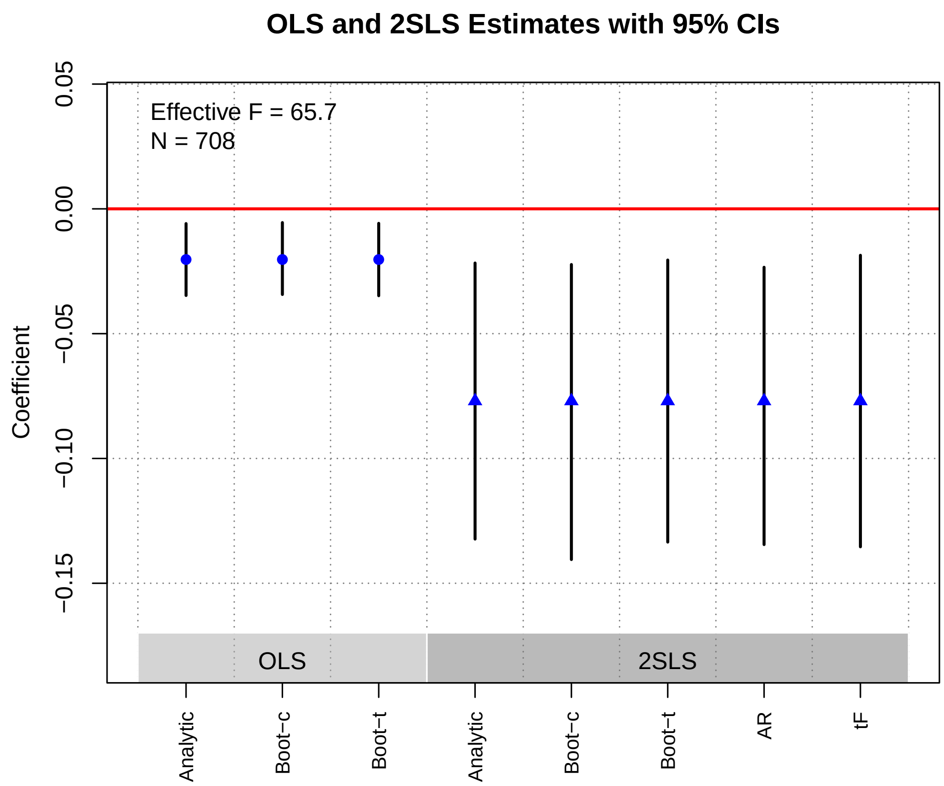
Replication Summary	
Unit of analysis	precinct
Treatment	turbine location
Instrument	wind speed
Outcome	vote turnout
Model	Table2(2)

```r
df<-readRDS("./data/ajps_Stokes_2016.rds")
D <-"prop_3km"
Y <- "chng_lib"
Z <- "avg_pwr_log"
controls <- c("mindistlake", "mindistlake_sq", "longitude",
              "long_sq", "latitude", "lat_sq", "long_lat")
cl <- NULL
FE <- "ed_id"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.0203 0.0073 -2.7638 -0.0347  -0.0059  0.0057
## Boot.c   -0.0203 0.0074 -2.7526 -0.0343  -0.0055  0.0080
## Boot.t   -0.0203 0.0073 -2.7638 -0.0348  -0.0058  0.0060
##
## $est_2sls
##            Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.077 0.0282 -2.7289 -0.1323  -0.0217  0.0064
## Boot.c   -0.077 0.0306 -2.5134 -0.1405  -0.0223  0.0020
## Boot.t   -0.077 0.0282 -2.7289 -0.1335  -0.0205  0.0060
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   7.6582   1.0000 706.0000   0.0058
##
## $AR$ci.print
## [1] "[-0.1345, -0.0234]"
##
## $AR$ci
## [1] -0.1345 -0.0234
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     67.9032     65.7306          NA     59.4844     65.7306
##
## $rho
## [1] 0.3025
##
## $tF
```

```
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 65.7306  2.0693 -0.0770  0.0282 -2.7289 -0.1354 -0.0186  0.0097
##
## $est_rf
##                Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## avg_pwr_log -0.0585 0.0216  0.0069 0.0222  -0.1029   -0.0158     0.002
##
## $est_fs
##               Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## avg_pwr_log 0.7602 0.0938       0 0.0986   0.5588    0.9438         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 708
##
## $N_cl
## NULL
##
## $df
## [1] 674
##
## $nvalues
##      chng_lib prop_3km avg_pwr_log
## [1,]      708        2         708
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Tajima (2013)

Replication Summary	
Unit of analysis	village and urban neighborhood
Treatment	distance to police posts (as a proxy for exposure to military intervention)
Instrument	distance to health station
Outcome	incidence of communal violence
Model	Table1(4)

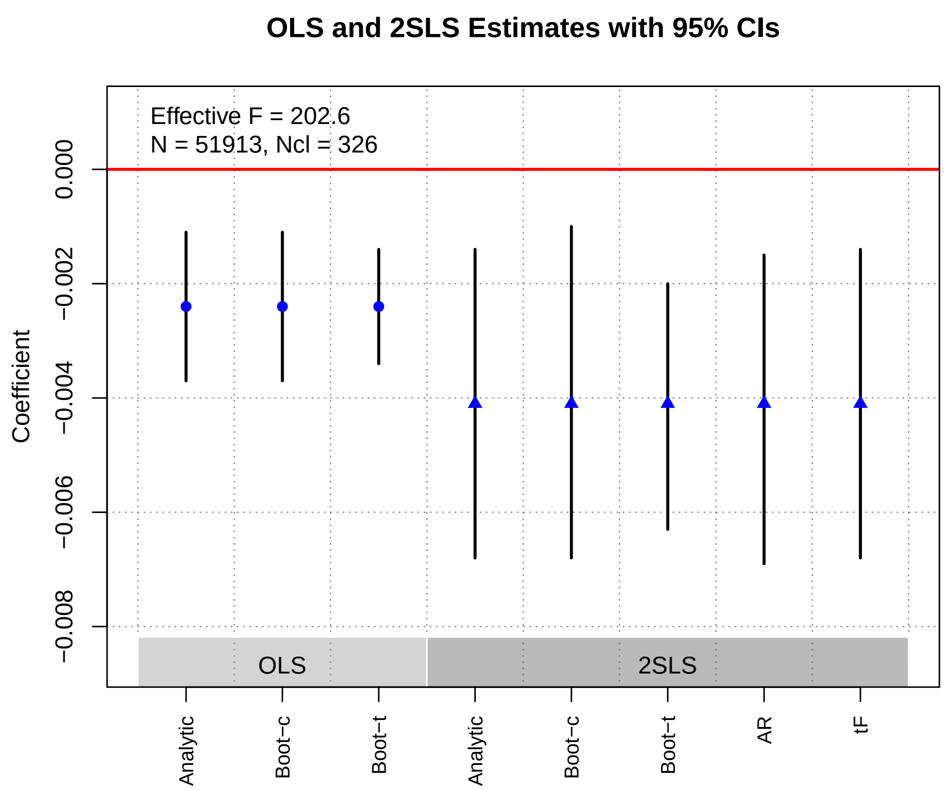
```
df<-readRDS("./data/ajps_Tajima_2013.rds")
D <-"z2_distpospol"
Y <- "horiz2"
Z <- "z2_dispuskes"
controls <- c("flat", "z2_altitude","urban", "natres", "z2_logvillpop", "z2_logdensvil",
              "z2_povrateksvil", "z2_fgtksvild", "z2_covyredvil", "z2_npwperhh",
              "z2_ethfractvil","z2_ethfractsd", "z2_ethfractd", "z2_relfractvil",
              "z2_relfractsd", "z2_relfractd", "z2_ethclustsd", "z2_ethclustvd",
              "z2_relclustsd", "z2_relclustvd", "z2_wgcovegvil", "z2_wgcovegsd",
              "z2_wgcovegd", "z2_wgcovrgvil", "z2_wgcovrgsd", "z2_wgcovrgd",
              "natdis","javanese_off_java", "islam", "split_kab03", "split_vil03")
cl <- 'kabid03'
FE <- 'prop'
weights<-"probit_touse_wts03"
```

```r
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef    SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.0024 6e-04 -3.7223 -0.0037  -0.0011   2e-04
## Boot.c   -0.0024 7e-04 -3.6202 -0.0037  -0.0011   0e+00
## Boot.t   -0.0024 6e-04 -3.7223 -0.0034  -0.0014   0e+00
##
## $est_2sls
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.0041 0.0014 -3.0103 -0.0068  -0.0014  0.0026
## Boot.c   -0.0041 0.0015 -2.7998 -0.0068  -0.0010  0.0100
## Boot.t   -0.0041 0.0014 -3.0103 -0.0063  -0.0020  0.0000
##
## $AR
## $AR$Fstat
##          F        df1        df2          p
##     9.0632     1.0000 51911.0000     0.0026
##
## $AR$ci.print
## [1] "[-0.0069, -0.0015]"
##
## $AR$ci
## [1] -0.0069 -0.0015
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##  13363.7649   1529.0807    202.6374    199.9925    202.6374
##
## $rho
## [1] 0.4527
##
## $tF
##        F       cF     Coef       SE        t   CI2.5%  CI97.5%  p-value
## 202.6374   1.9600  -0.0041   0.0014  -3.0103  -0.0068  -0.0014   0.0026
##
## $est_rf
##                 Coef    SE p.value  SE.b CI.b2.5% CI.b97.5% p.value.b
## z2_dispuskes -0.0019 6e-04  0.0026 7e-04   -0.003    -5e-04      0.01
##
## $est_fs
##               Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
```

```
## z2_dispuskes 0.447 0.0314       0 0.0316    0.382    0.5049         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 51913
##
## $N_cl
## [1] 326
##
## $df
## [1] 51853
##
## $nvalues
##      horiz2 z2_distpospol z2_dispuskes
## [1,]      2           101          101
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Trounstine (2016)

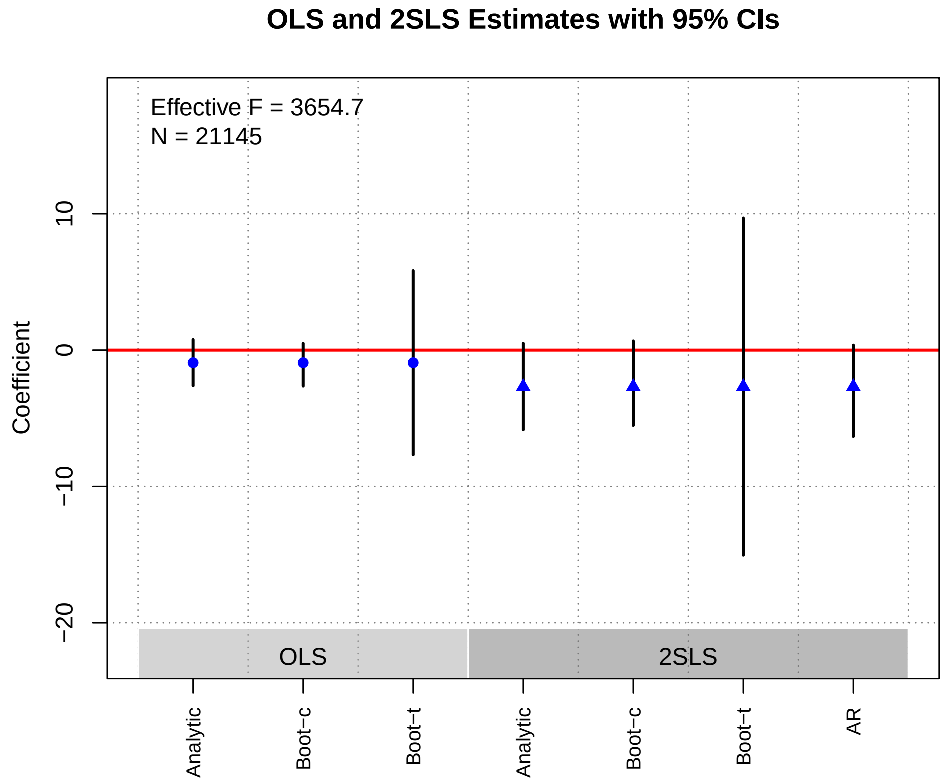
Replication Summary	
Unit of analysis	city*year
Treatment	racial segregation
Instrument	the number of waterways in a city; logged population
Outcome	direct general expenditures
Model	Table5(1)

```r
df<-readRDS("./data/ajps_Trounstine_2016.rds")
D <-"H_citytract_NHW_i"
Y <- "dgepercap_cpi"
Z <- c("total_rivs_all", "logpop")
controls <- c("dgepercap_cpilag","diversityinterp","pctblkpopinterp",
              "pctasianpopinterp","pctlatinopopinterp","medincinterp",
              "pctlocalgovworker_100","pctrentersinterp","pctover65",
              "pctcollegegradinterp","northeast","south","midwest",
              "y5", "y6", "y7", "y8", "y9")
cl <- NULL
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.9265 0.8648 -1.0713 -2.6214   0.7685   0.284
## Boot.c   -0.9265 0.8979 -1.0319 -2.6413   0.4910   0.448
## Boot.t   -0.9265 0.8648 -1.0713 -7.6790   5.8260   0.517
##
## $est_2sls
##             Coef     SE       t  CI 2.5% CI 97.5% p.value
## Analytic -2.6757 1.6174 -1.6543  -5.8458   0.4944  0.0981
## Boot.c   -2.6757 1.7255 -1.5507  -5.5237   0.6731  0.1960
## Boot.t   -2.6757 1.6174 -1.6543 -15.0400   9.6886  0.2910
##
## $AR
## $AR$Fstat
##         F        df1        df2          p
##     2.3548     2.0000 21142.0000     0.0949
##
## $AR$ci.print
## [1] "[-6.3310, 0.3650]"
##
## $AR$ci
## [1] -6.331  0.365
##
## $AR$bounded
```

```
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##    3883.651    2506.495          NA    2486.003    3654.705
##
## $rho
## [1] 0.5185
##
## $est_rf
##                  Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## total_rivs_all -0.0081 0.0229  0.7217 0.0239  -0.0580    0.0263     0.834
## logpop         -0.0855 0.0407  0.0355 0.0441  -0.1568    0.0071     0.090
##
## $est_fs
##                  Coef    SE p.value  SE.b CI.b2.5% CI.b97.5% p.value.b
## total_rivs_all 0.0054 3e-04       0 3e-04   0.0048    0.0060         0
## logpop         0.0291 5e-04       0 5e-04   0.0282    0.0301         0
##
## $p_iv
## [1] 2
##
## $N
## [1] 21145
##
## $N_cl
## NULL
##
## $df
## [1] 21125
##
## $nvalues
##      dgepercap_cpi H_citytract_NHW_i total_rivs_all logpop
## [1,]         21129             15395             22  16223
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Vernby (2013)

Replication Summary	
Unit of analysis	municipality*term
Treatment	share of noncitizens in the electorate
Instrument	immigration Inflow 1940–1950; Immigration Inflow 1960–1967
Outcome	municipal education and social spending
Model	Table3(2)

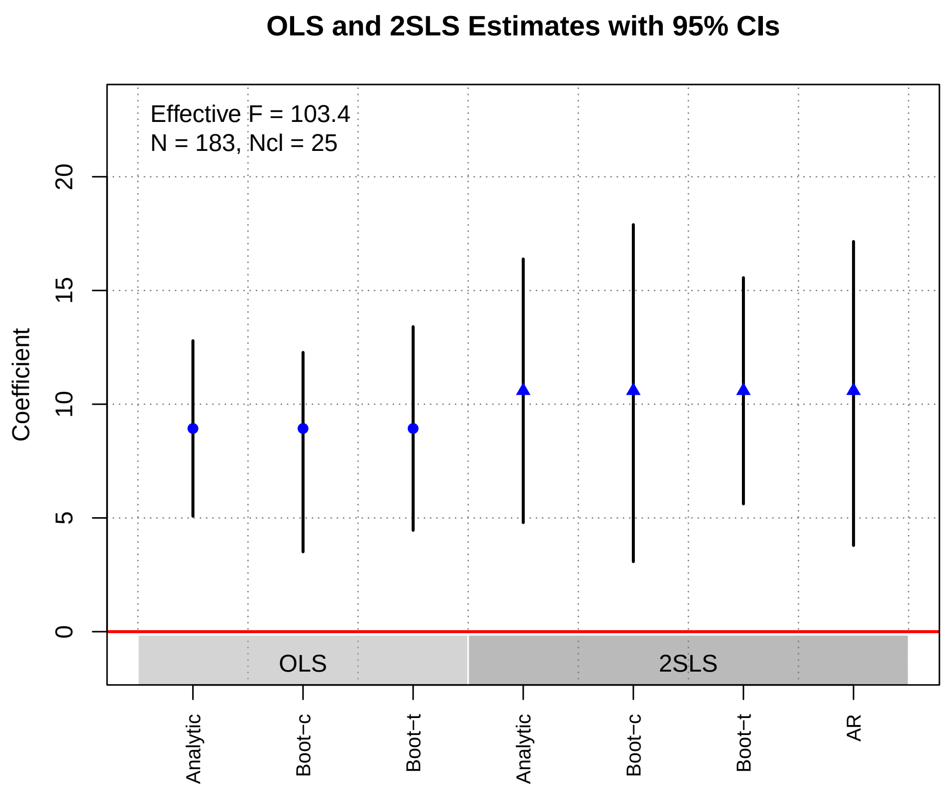
```
df<-readRDS("./data/ajps_Vernby_2013.rds")
D <-"noncitvotsh"
Y <- "Y"
Z <- c("inv1950", "inv1967")
controls <- c("Taxbase2", "L_Taxbase2", "manu", "L_manu", "pop", "L_pop")
cl <- "lan"
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 8.9328 1.9684 4.5382  5.0748  12.7908   0.000
## Boot.c   8.9328 2.2974 3.8882  3.5122  12.2771   0.000
```

```
## Boot.t   8.9328 1.9684 4.5382  4.4582  13.4075   0.001
##
## $est_2sls
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 10.5903 2.9560 3.5827  4.7965  16.3840  0.0003
## Boot.c   10.5903 3.9307 2.6943  3.0796  17.8935  0.0180
## Boot.t   10.5903 2.9560 3.5827  5.6177  15.5628  0.0020
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   5.7276   2.0000 180.0000   0.0039
##
## $AR$ci.print
## [1] "[3.7915, 17.1525]"
##
## $AR$ci
## [1]  3.7915 17.1525
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     66.2203     49.5670     79.6400     29.5799    103.3586
##
## $rho
## [1] 0.6574
##
## $est_rf
##            Coef     SE p.value    SE.b CI.b2.5% CI.b97.5% p.value.b
## inv1950  2.5029 9.0396  0.7819 11.4807 -22.8924   23.3371     0.852
## inv1967 10.0729 7.2288  0.1635  9.0319  -8.6462   27.4462     0.230
##
## $est_fs
##           Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## inv1950 0.7234 0.3444  0.0357 0.4074  -0.0407    1.4843     0.076
## inv1967 0.4665 0.2984  0.1180 0.3204  -0.2627    0.9727     0.186
##
## $p_iv
## [1] 2
##
## $N
## [1] 183
##
## $N_cl
```

```
## [1] 25
##
## $df
## [1] 175
##
## $nvalues
##          Y noncitvotsh inv1950 inv1967
## [1,] 183         183      25      25
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Wood and Grose (2022)

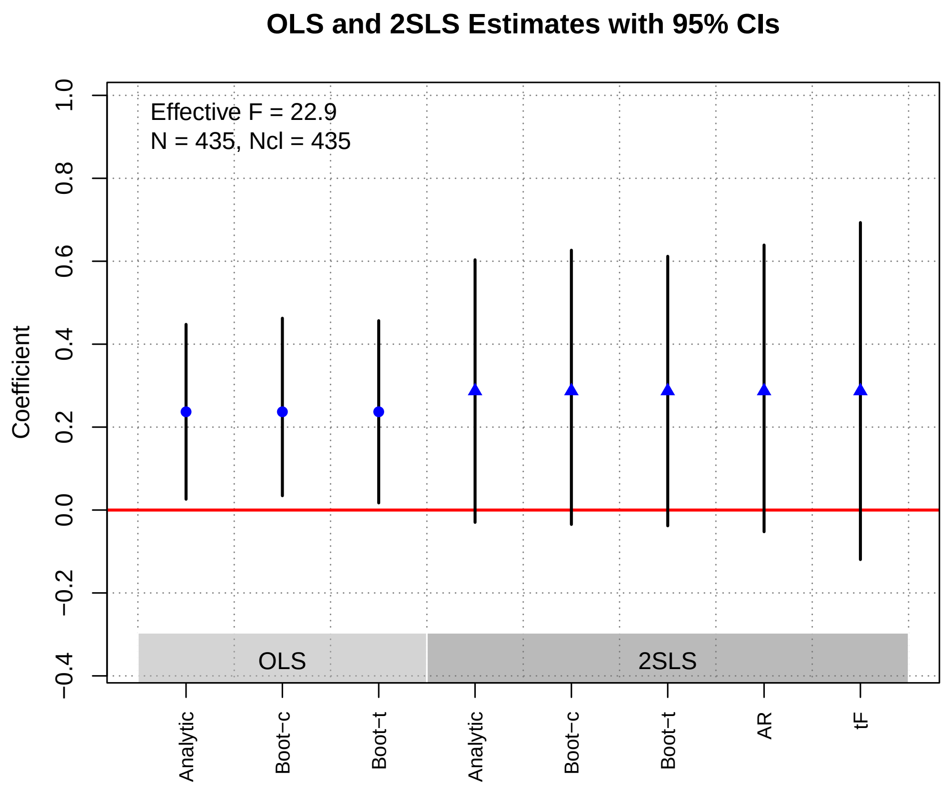
Replication Summary	
Unit of analysis	House member/district
Treatment	incumbent found to have campaign finance violations
Instrument	audit
Outcome	legislator Retired
Model	Table2(1)

```r
df <-readRDS("./data/ajps_Wood_grose_2022.rds")
## preprocess to generate xwhat and xhat in Stata
D<-"findings"
Y <- "retire__or_resign"
Z <- "audited"
controls <-c("xwhat","south")
cl <- "stcd"
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.2369 0.1076 2.2022  0.0261   0.4477  0.0276
## Boot.c   0.2369 0.1098 2.1579  0.0345   0.4626  0.0120
## Boot.t   0.2369 0.1076 2.2022  0.0172   0.4566  0.0440
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.2869 0.1615 1.7764 -0.0297   0.6035  0.0757
## Boot.c   0.2869 0.1702 1.6862 -0.0347   0.6266  0.0840
## Boot.t   0.2869 0.1615 1.7764 -0.0380   0.6119  0.0790
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   2.8595   1.0000 433.0000   0.0916
##
## $AR$ci.print
## [1] "[-0.0523, 0.6390]"
##
## $AR$ci
## [1] -0.0523  0.6390
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##   F.standard    F.robust   F.cluster F.bootstrap F.effective
##     220.6007     22.8647     22.8647     23.0601     22.8647
##
## $rho
## [1] 0.5819
##
## $tF
```

```
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 22.8647  2.5155  0.2869  0.1615  1.7764 -0.1194  0.6932  0.1663
##
## $est_rf
##           Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## audited 0.1377 0.0816  0.0916 0.0826  -0.0141      0.31     0.084
##
## $est_fs
##         Coef     SE p.value SE.b CI.b2.5% CI.b97.5% p.value.b
## audited 0.48 0.1004       0  0.1     0.28    0.6667         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 435
##
## $N_cl
## [1] 435
##
## $df
## [1] 431
##
## $nvalues
##      retire__or_resign findings audited
## [1,]                 2        2       2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Zhu (2017)

Replication Summary	
Unit of analysis	province*period
Treatment	MNC activity
Instrument	weighted geographic closeness
Outcome	corruption
Model	Table1(1)

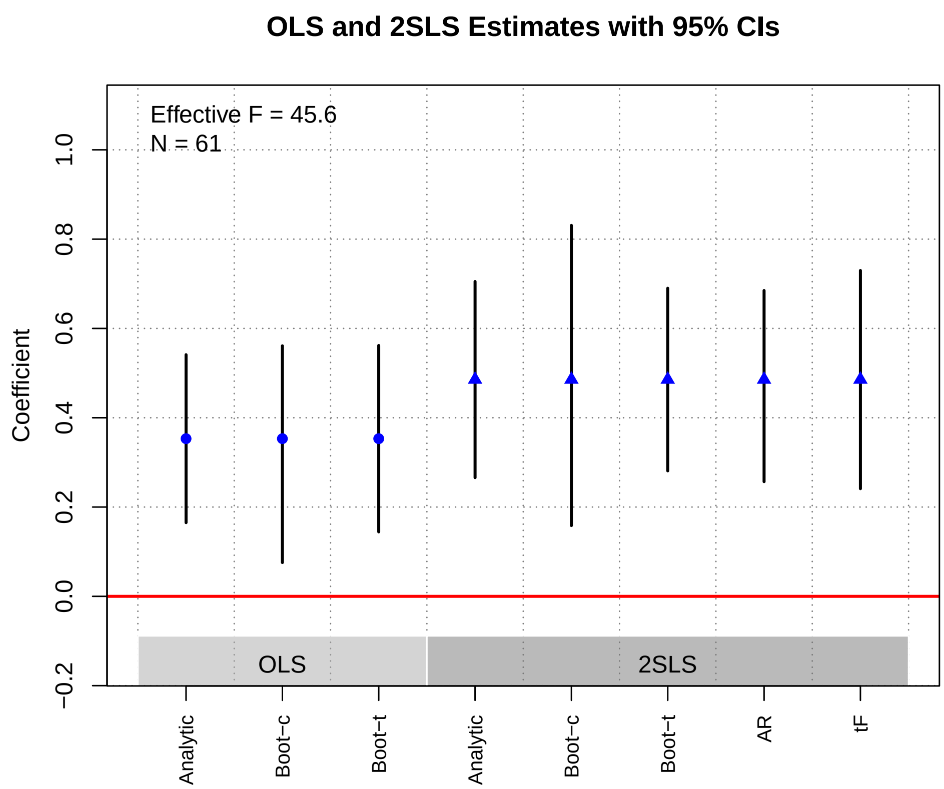
```
df <- readRDS("./data/ajps_Zhu_2017.rds")
D <-"MNC"
Y <- "corruption1"
Z <- "lwdist"
controls <- c("lgdpcap6978", "gdp6978", "population", "lgovtexp9302",
              "pubempratio", "leduc", "pwratio", "female", "time")
cl <- NULL
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.3531 0.0960 3.6788  0.1650   0.5412  0.0002
```

```
## Boot.c   0.3531 0.1246 2.8342  0.0757   0.5611  0.0120
## Boot.t   0.3531 0.0960 3.6788  0.1443   0.5619  0.0030
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.4855 0.1121 4.3317  0.2658   0.7052   0.000
## Boot.c   0.4855 0.1684 2.8832  0.1585   0.8308   0.010
## Boot.t   0.4855 0.1121 4.3317  0.2810   0.6900   0.001
##
## $AR
## $AR$Fstat
##       F     df1     df2       p
## 12.7838  1.0000 59.0000  0.0007
##
## $AR$ci.print
## [1] "[0.2568, 0.6850]"
##
## $AR$ci
## [1] 0.2568 0.6850
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     45.9155     45.5515          NA     26.0904     45.5515
##
## $rho
## [1] 0.6919
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 45.5515  2.1802  0.4855  0.1121  4.3317  0.2411  0.7298  0.0001
##
## $est_rf
##         Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## lwdist 0.559 0.1698   0.001 0.2371   0.1489    1.1397      0.01
##
## $est_fs
##          Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## lwdist 1.1514 0.1706       0 0.2254   0.7817    1.7008         0
##
## $p_iv
## [1] 1
##
## $N
```

```
## [1] 61
##
## $N_cl
## NULL
##
## $df
## [1] 50
##
## $nvalues
##      corruption1 MNC lwdist
## [1,]          61  61     61
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



JOP

Acharya et al. (2016)

Replication Summary	
Unit of analysis	county

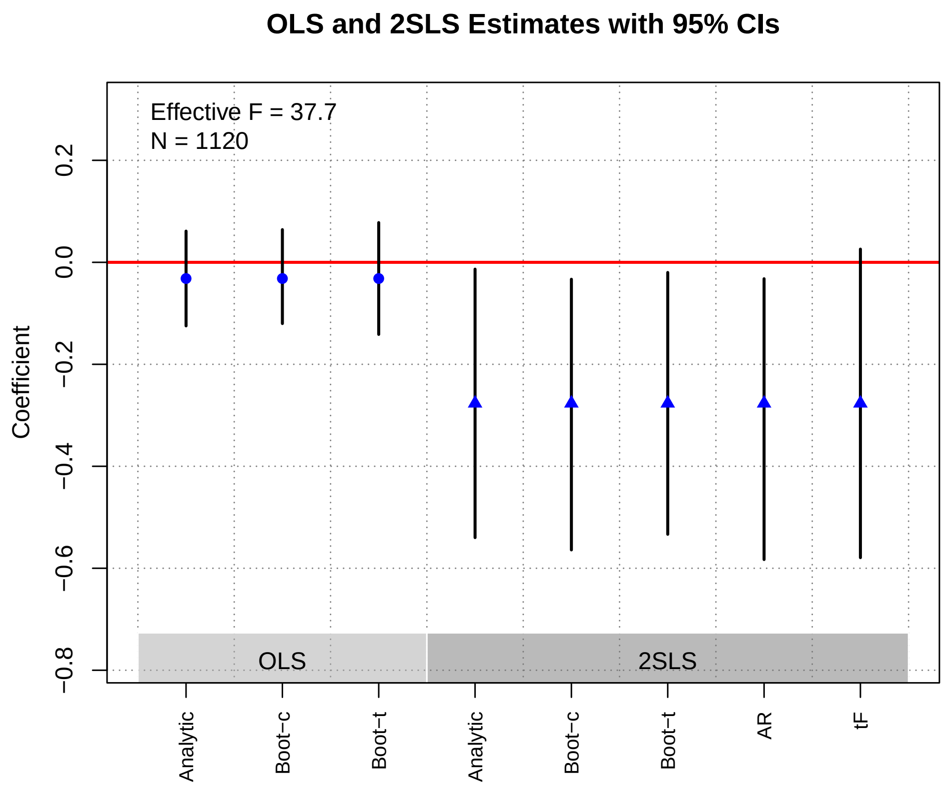
Replication Summary	
Treatment	slave proportion in 1860
Instrument	measures of the environmental suitability for growing cotton
Outcome	proportion Democrat
Model	Table2(2)

```
df<-readRDS("./data/jop_Acharya_etal_2016.rds")
Y <- "dem"
D <-"pslave1860"
Z <- "cottonsuit"
controls <- c("x2", "rugged", "latitude", "x2", "longitude", "x3","x4", "water1860")
cl <- NULL
FE <- 'code'
weights<-"sample.size"
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.0318 0.0474 -0.6701 -0.1247   0.0612  0.5028
## Boot.c   -0.0318 0.0481 -0.6608 -0.1201   0.0641  0.5400
## Boot.t   -0.0318 0.0474 -0.6701 -0.1414   0.0779  0.5520
##
## $est_2sls
##              Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.2766 0.1343 -2.0596 -0.5399  -0.0134  0.0394
## Boot.c   -0.2766 0.1412 -1.9594 -0.5640  -0.0332  0.0220
## Boot.t   -0.2766 0.1343 -2.0596 -0.5334  -0.0199  0.0410
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    4.8310    1.0000 1118.0000    0.0282
##
## $AR$ci.print
## [1] "[-0.5829, -0.0322]"
##
## $AR$ci
## [1] -0.5829 -0.0322
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
```

```
##    106.4957     37.6527          NA     36.0973     37.6527
##
## $rho
## [1] 0.2973
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 37.6527  2.2528 -0.2766  0.1343 -2.0596 -0.5792  0.0259  0.0731
##
## $est_rf
##               Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## cottonsuit -0.1128 0.0518  0.0294 0.0525  -0.2149   -0.0149     0.022
##
## $est_fs
##              Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## cottonsuit 0.4079 0.0665       0 0.0679   0.2797    0.5417         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 1120
##
## $N_cl
## NULL
##
## $df
## [1] 1098
##
## $nvalues
##      dem pslave1860 cottonsuit
## [1,] 911       1077       1120
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Alt et al. (2016)

Replication Summary	
Unit of analysis	individual
Treatment	unemployment expectations
Instrument	assignment to receiving an aggregate unemployment forecast
Outcome	vote intention
Model	Table2(1)

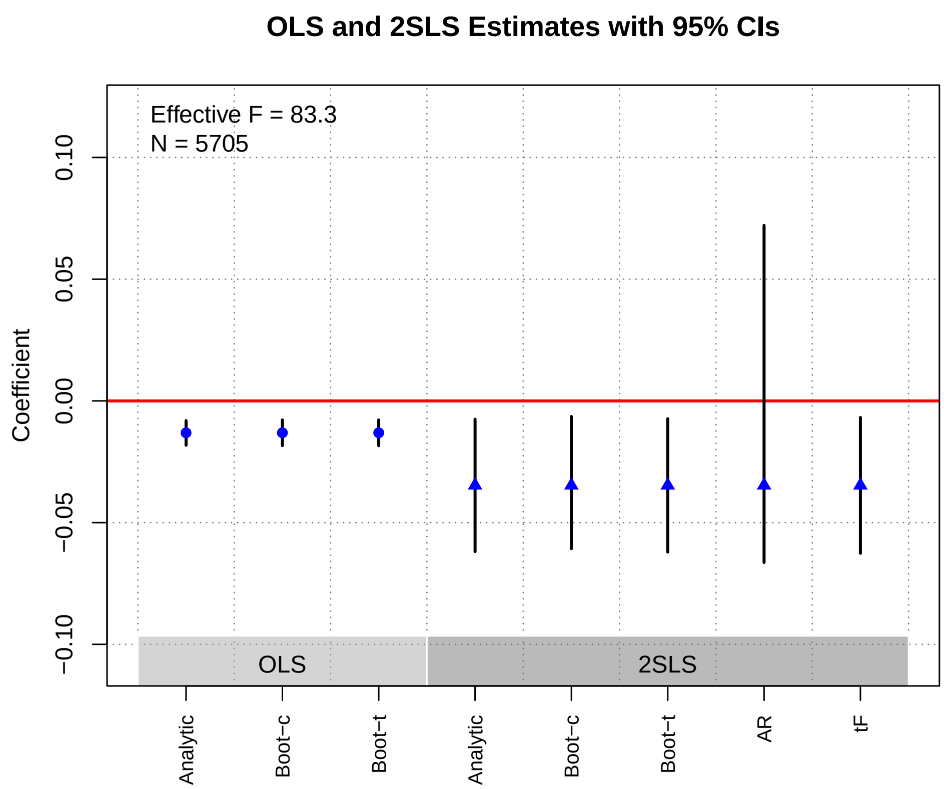
```
df<- readRDS("./data/jop_Alt_etal_2015.rds")
D <- "urate_fut"
Y <- "gov"
Z <- "treatment"
controls <- "urate_now"
cl <- NULL
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##                Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.0131 0.0026 -5.0845 -0.0182  -0.0081       0
```

```
## Boot.c   -0.0131 0.0027 -4.8875 -0.0184  -0.0078       0
## Boot.t   -0.0131 0.0026 -5.0845 -0.0184  -0.0078       0
##
## $est_2sls
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.0347 0.0139 -2.5022 -0.0619  -0.0075  0.0123
## Boot.c   -0.0347 0.0141 -2.4706 -0.0607  -0.0064  0.0140
## Boot.t   -0.0347 0.0139 -2.5022 -0.0621  -0.0073  0.0140
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    0.0017    1.0000 5703.0000    0.9671
##
## $AR$ci.print
## [1] "[-0.0664, 0.0721]"
##
## $AR$ci
## [1] -0.0664  0.0721
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     60.1863     68.9098          NA     66.3239     83.3152
##
## $rho
## [1] 0.0801
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 83.3152  2.0100 -0.0347  0.0139 -2.5022 -0.0626 -0.0068  0.0147
##
## $est_rf
##            Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## treatment 0.027 0.0243  0.2661 0.0227  -0.0161    0.0725     0.218
##
## $est_fs
##              Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## treatment -0.9354 0.1169       0 0.1149  -1.1587   -0.7251         0
##
## $p_iv
## [1] 1
##
## $N
```

```
## [1] 5705
##
## $N_cl
## NULL
##
## $df
## [1] 5702
##
## $nvalues
##      gov urate_fut treatment
## [1,]   2        88         8
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Arias and Stasavage (2019)

Replication Summary	
Unit of analysis	country*year
Treatment	government expenditures
Instrument	trade shock × UK bond yield
Outcome	regular leader turnover

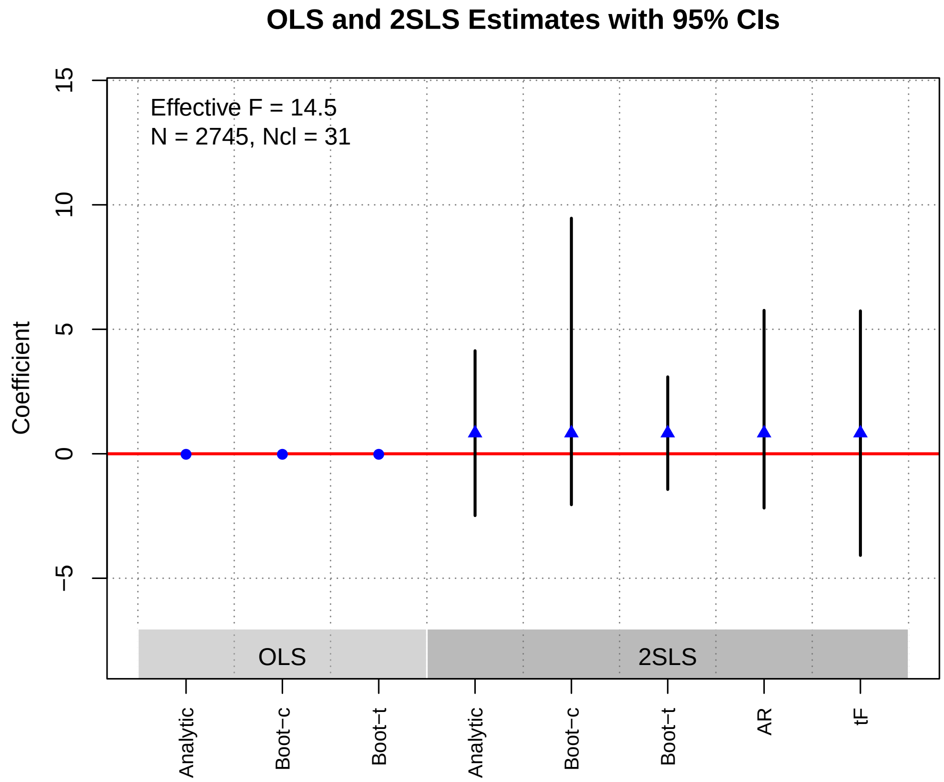
Replication Summary	
Model	Table3(2)

```r
# Variables are already residualized against controls, fixed effects, and unit-specific trends
df<-readRDS("./data/jop_Arias_etal_2019.rds")
Y <- "regular_res"
D <- "dexpenditures_res"
Z <- "interact_res"
controls <- NULL
cl<-c("ccode","year")
FE<-NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.0215 0.0359 -0.5975 -0.0919   0.0490  0.5502
## Boot.c   -0.0215 0.0406 -0.5295 -0.0965   0.0648  0.5577
## Boot.t   -0.0215 0.0359 -0.5975 -0.0754   0.0324  0.4518
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.8282 1.6891 0.4903 -2.4824   4.1389  0.6239
## Boot.c   0.8282 7.5899 0.1091 -2.0460   9.4617  0.4654
## Boot.t   0.8282 1.6891 0.4903 -1.4325   3.0890  0.4067
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    0.2643    1.0000 2743.0000    0.6073
##
## $AR$ci.print
## [1] "[-2.1784, 5.7604]"
##
## $AR$ci
## [1] -2.1784  5.7604
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##      3.0429      3.4739     14.4763      7.2085     14.4763
##
```

```
## $rho
## [1] 0.0333
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 14.4763  2.9071  0.8282  1.6891  0.4903 -4.0822  5.7387  0.7410
##
## $est_rf
##               Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## interact_res 0.276 0.5369  0.6072 0.4798  -0.4606    1.4838    0.4361
##
## $est_fs
##                Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## interact_res 0.3332 0.0876   1e-04 0.1241   0.0522    0.5505    0.0294
##
## $p_iv
## [1] 1
##
## $N
## [1] 2745
##
## $N_cl
## [1] 31
##
## $df
## [1] 2743
##
## $nvalues
##      regular_res dexpenditures_res interact_res
## [1,]        2745              2745         2745
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Bhavnani and Lee (2018)

Replication Summary	
Unit of analysis	district*period
Treatment	bureaucrats' embeddedness
Instrument	early-career job assignment
Outcome	proportion of villages with high schools
Model	Table1(4)

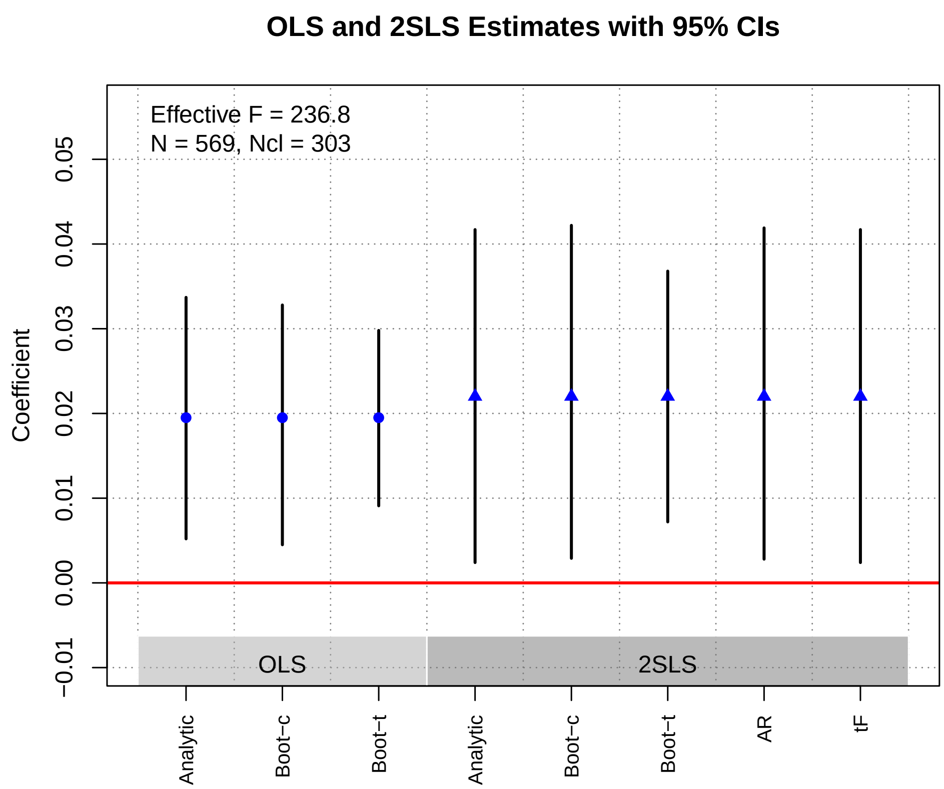
```
df <-readRDS("./data/jop_Bhavnani_etal_2018.rds")
D <- "ALLlocal"
Y <- "Phigh"
Z <- "EXALLlocal"
controls <- c("ALLbachdivi", "lnnewpop", "lnnvill", "p_rural", "p_work",
              "p_aglab", "p_sc", "p_st", "lnmurderpc", "stategov", "natgov")
cl <- "distcode71"
FE<- c('distcode71',"year")
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0195 0.0073 2.6753  0.0052   0.0337  0.0075
```

```
## Boot.c   0.0195 0.0072 2.6965  0.0045   0.0328  0.0160
## Boot.t   0.0195 0.0073 2.6753  0.0091   0.0298  0.0000
##
## $est_2sls
##           Coef   SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.022 0.01 2.1986  0.0024   0.0417  0.0279
## Boot.c   0.022 0.01 2.1935  0.0029   0.0422  0.0260
## Boot.t   0.022 0.01 2.1986  0.0072   0.0368  0.0060
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   5.0041   1.0000 567.0000   0.0257
##
## $AR$ci.print
## [1] "[0.0028, 0.0419]"
##
## $AR$ci
## [1] 0.0028 0.0419
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##    243.2947    215.8574    236.8206    231.3242    236.8206
##
## $rho
## [1] 0.7002
##
## $tF
##        F       cF     Coef       SE        t   CI2.5%  CI97.5%  p-value
## 236.8206   1.9600   0.0220   0.0100   2.1986   0.0024   0.0417   0.0279
##
## $est_rf
##              Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## EXALLlocal 0.0121 0.0055  0.0267 0.0055   0.0016    0.0225     0.026
##
## $est_fs
##              Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## EXALLlocal 0.5504 0.0358       0 0.0362   0.4863     0.622         0
##
## $p_iv
## [1] 1
##
## $N
```

```
## [1] 569
##
## $N_cl
## [1] 303
##
## $df
## [1] 253
##
## $nvalues
##      Phigh ALLlocal EXALLlocal
## [1,]   567      493        318
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Charron and Lapuente (2013)

Replication Summary	
Unit of analysis	region
Treatment	clientelism
Instrument	consolidation of clientelistic networks in regions where rulers have historically less constraints to their decisions

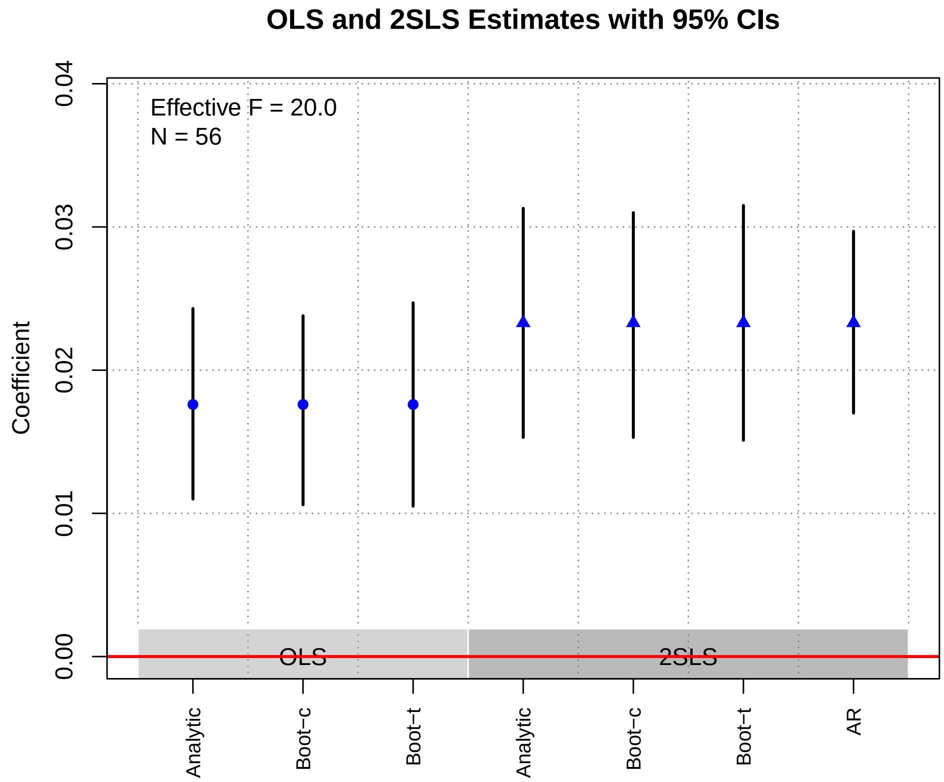
Replication Summary	
Outcome	quality of governments
Model	Table3(2a)

```
df<-readRDS("./data/jop_Charron_etal_2013.rds")
D <- "pc_all4_tol"
Y <- "eqi"
Z <- c("pc_institutions","literacy1880")
controls <- c("logpop", "capitalregion", "ger", "it", "uk","urb_1860_1850_30")
cl <- NULL
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0176 0.0034 5.1860  0.0110   0.0243       0
## Boot.c   0.0176 0.0034 5.2259  0.0106   0.0238       0
## Boot.t   0.0176 0.0034 5.1860  0.0105   0.0247       0
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0233 0.0041 5.7196  0.0153   0.0313       0
## Boot.c   0.0233 0.0040 5.8340  0.0153   0.0310       0
## Boot.t   0.0233 0.0041 5.7196  0.0151   0.0315       0
##
## $AR
## $AR$Fstat
##       F     df1     df2       p
## 18.2062  2.0000 53.0000  0.0000
##
## $AR$ci.print
## [1] "[0.0170, 0.0297]"
##
## $AR$ci
## [1] 0.0170 0.0297
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     37.2005     31.2712          NA     32.7521     19.9514
##
```

```
## $rho
## [1] 0.7828
##
## $est_rf
##                    Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## pc_institutions 0.1941 0.0765  0.0111 0.0780   0.0555    0.3558     0.014
## literacy1880    0.0204 0.0043  0.0000 0.0051   0.0091    0.0292     0.000
##
## $est_fs
##                    Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## pc_institutions 12.1093 2.3469   0e+00 2.4240   7.6679   17.2989     0.000
## literacy1880     0.5348 0.1319   1e-04 0.1554   0.1644    0.7945     0.008
##
## $p_iv
## [1] 2
##
## $N
## [1] 56
##
## $N_cl
## NULL
##
## $df
## [1] 48
##
## $nvalues
##      eqi pc_all4_tol pc_institutions literacy1880
## [1,]  56          44              14           38
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Charron et al. (2017)

Replication Summary	
Unit of analysis	region
Treatment	more developed bureaucracy
Instrument	proportion of Protestant residents in a region; aggregate literacy in 1880
Outcome	percent of single bidders in procurement contracts
Model	Table5(4)

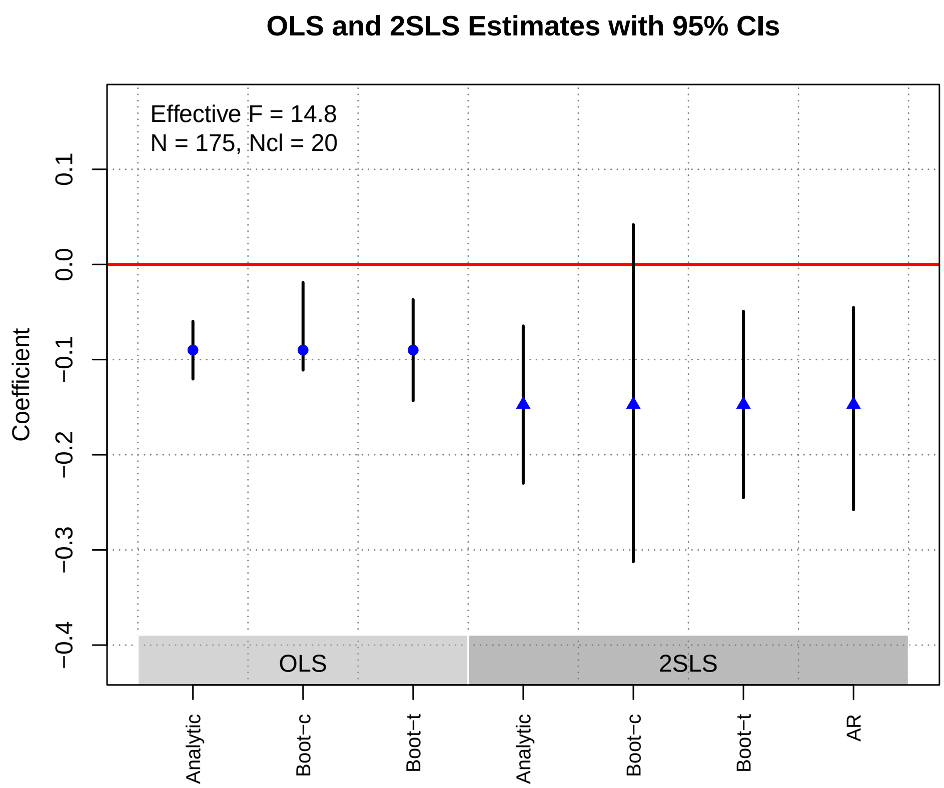
```
df <- readRDS("./data/jop_Charron_etal_2017.rds")
D <- "pubmerit"
Y <- "lcri_euc1_r"
Z <- c("litrate_1880", 'pctprot')
controls <- c("logpopdens", "logppp11", "trust", "pctwomenparl")
cl <- "country"
FE <- NULL
weights<-"eu_popweights"
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.09 0.0155 -5.8068 -0.1204  -0.0597   0.000
## Boot.c   -0.09 0.0242 -3.7254 -0.1110  -0.0190   0.008
```

```
## Boot.t   -0.09 0.0155 -5.8068 -0.1432  -0.0369   0.009
##
## $est_2sls
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.1472 0.0422 -3.4919 -0.2299  -0.0646  0.0005
## Boot.c   -0.1472 0.0944 -1.5590 -0.3123   0.0418  0.1100
## Boot.t   -0.1472 0.0422 -3.4919 -0.2452  -0.0492  0.0140
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   5.5325   2.0000 172.0000   0.0047
##
## $AR$ci.print
## [1] "[-0.2577, -0.0452]"
##
## $AR$ci
## [1] -0.2577 -0.0452
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     27.8775     23.2292     36.2651      5.7608     14.8219
##
## $rho
## [1] 0.4992
##
## $est_rf
##                 Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## litrate_1880 -0.0009 0.0005  0.0767 0.0006  -0.0019    0.0005     0.220
## pctprot      -0.1769 0.1131  0.1177 0.1442  -0.4389    0.1203     0.326
##
## $est_fs
##                Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## litrate_1880 0.0060 0.0025  0.0184 0.0029   0.0000    0.0115     0.050
## pctprot      1.1959 0.3235  0.0002 0.5047   0.0079    1.9726     0.048
##
## $p_iv
## [1] 2
##
## $N
## [1] 175
##
## $N_cl
```

```
## [1] 20
##
## $df
## [1] 169
##
## $nvalues
##      lcri_euc1_r pubmerit litrate_1880 pctprot
## [1,]         173      173           78     131
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Cirone and Van Coppenolle (2018)

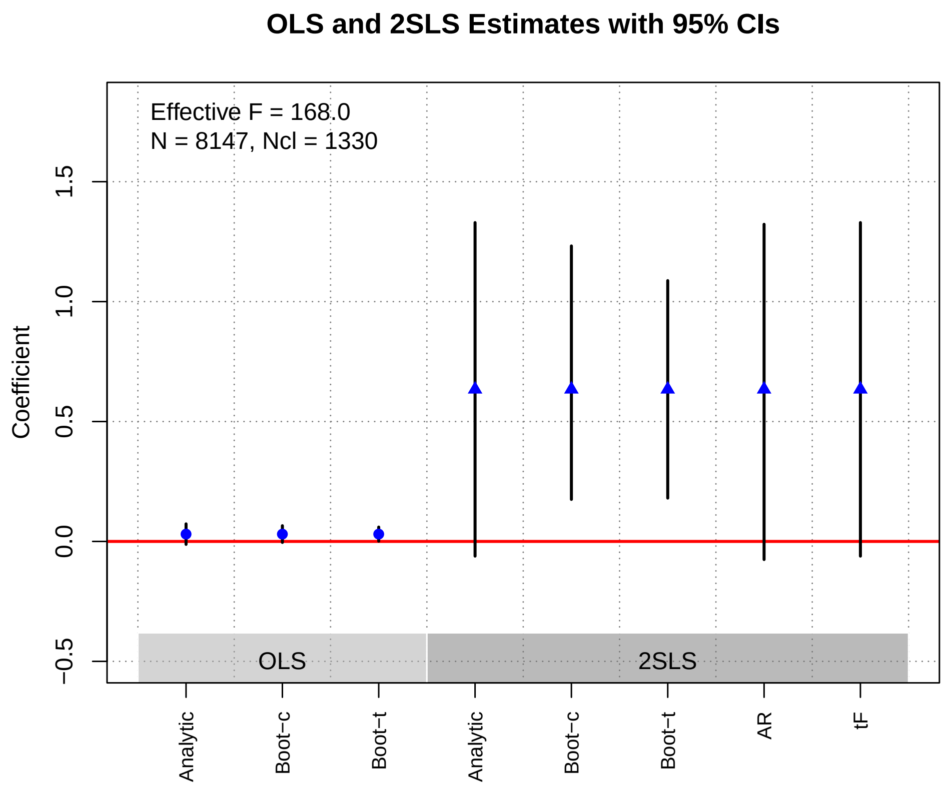
Replication Summary	
Unit of analysis	deputy*year
Treatment	budget committee service
Instrument	random assignment of budget incumbents to bureaux
Outcome	legislator sponsorship on a budget bill
Model	Table2(2)

```r
df<- readRDS("./data/jop_Cirone_etal_2018.rds")
D <- "budget"
Y <- "F1to5billbudgetdummy"
Z <- "bureauotherbudgetincumbent"
controls <- c("budgetincumbent", "cummyears", "cummyears2",
              "age", "age2", "permargin", "permargin2",
              "inscrits", "inscrits2", "proprietaire",
              "lib_all", "civil", "paris")
cl <- c("id","year")
FE <- "year"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0305 0.0218 1.3957 -0.0123   0.0733  0.1628
## Boot.c   0.0305 0.0178 1.7126 -0.0042   0.0656  0.0800
## Boot.t   0.0305 0.0218 1.3957  0.0010   0.0599  0.0410
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.6341 0.3548 1.7872 -0.0613   1.3295  0.0739
## Boot.c   0.6341 0.2689 2.3583  0.1752   1.2321  0.0080
## Boot.t   0.6341 0.3548 1.7872  0.1807   1.0875  0.0070
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    3.0669    1.0000 8145.0000    0.0799
##
## $AR$ci.print
## [1] "[-0.0755, 1.3224]"
##
## $AR$ci
## [1] -0.0755  1.3224
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     32.1302     34.2557    168.0023     34.3754    168.0023
##
## $rho
## [1] 0.0628
```

```
##
## $tF
##         F       cF     Coef       SE        t   CI2.5%  CI97.5%  p-value
## 168.0023   1.9600   0.6341   0.3548   1.7872  -0.0613   1.3295   0.0739
##
## $est_rf
##                                Coef    SE p.value  SE.b CI.b2.5% CI.b97.5%
## bureauotherbudgetincumbent -0.0052 0.003  0.0801 0.002  -0.0091   -0.0015
##                            p.value.b
## bureauotherbudgetincumbent     0.008
##
## $est_fs
##                                Coef    SE p.value   SE.b CI.b2.5% CI.b97.5%
## bureauotherbudgetincumbent -0.0083 6e-04       0 0.0014   -0.011   -0.0056
##                            p.value.b
## bureauotherbudgetincumbent         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 8147
##
## $N_cl
## [1] 1330
##
## $df
## [1] 13
##
## $nvalues
##      F1to5billbudgetdummy budget bureauotherbudgetincumbent
## [1,]                    2      2                          9
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Dietrich and Wright (2015)

Replication Summary	
Unit of analysis	transition
Treatment	economic aid
Instrument	constructed Z
Outcome	transitions to multipartyism
Model	Table1(2)

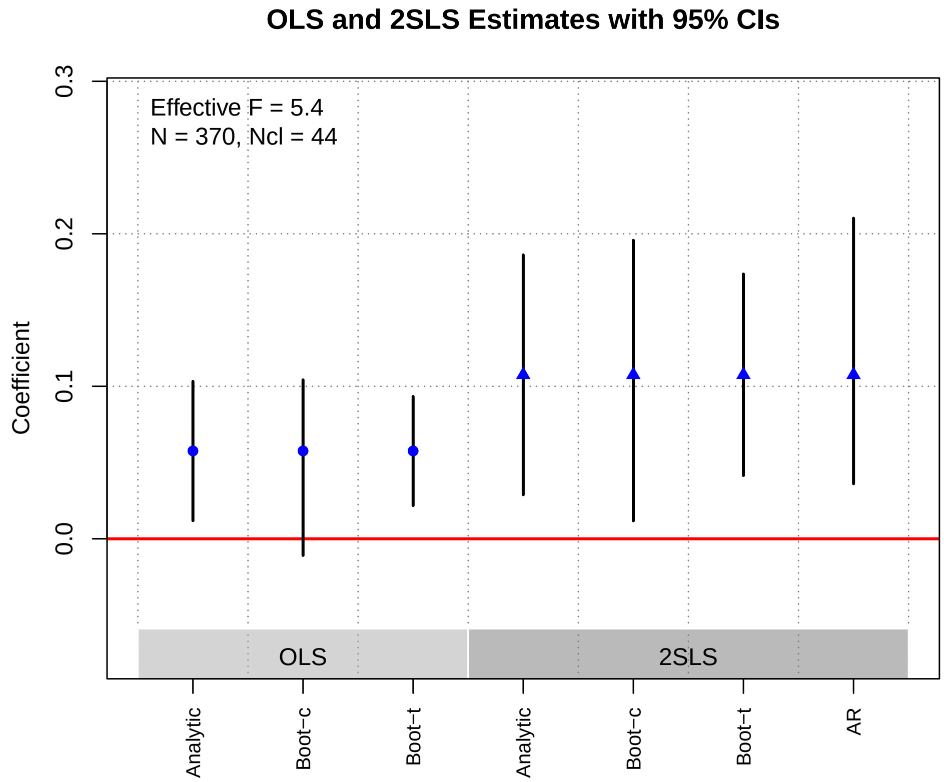
```
df <- readRDS("./data/jop_Dietrich_2015.rds")
D <- "econaid"
Y <- "mp"
Z <- c("Iinfl3","econaid_lgdp_g", "econaid_lpop_g",
       "econaid_cwar_g", "econaid_dnmp_g",
       "econaid_dnmp2_g", "econaid_dnmp3_g")
controls <- c('lgdp', 'lpop', 'cwar', 'dmp',
              'dmp2', 'dmp3', "dnmp", "dnmp2", "dnmp3")
cl<- "cowcode"
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
```

```
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0576 0.0233 2.4734  0.0119   0.1032  0.0134
## Boot.c   0.0576 0.0284 2.0287 -0.0109   0.1042  0.0760
## Boot.t   0.0576 0.0233 2.4734  0.0218   0.0933  0.0020
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.1075 0.0401 2.6795  0.0289   0.1861  0.0074
## Boot.c   0.1075 0.0463 2.3234  0.0118   0.1957  0.0300
## Boot.t   0.1075 0.0401 2.6795  0.0415   0.1736  0.0020
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   3.5039   7.0000 362.0000   0.0012
##
## $AR$ci.print
## [1] "[0.0361, 0.2102]"
##
## $AR$ci
## [1] 0.0361 0.2102
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     28.9900     47.6878     22.5931      2.1173      5.4068
##
## $rho
## [1] 0.6026
##
## $est_rf
##                    Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## Iinfl3           0.0382 0.0180  0.0341 0.0224  -0.0163    0.0748     0.184
## econaid_lgdp_g   0.0459 0.0246  0.0624 0.0483   0.0054    0.1979     0.028
## econaid_lpop_g   0.0049 0.0218  0.8229 0.0355  -0.0432    0.0956     0.696
## econaid_cwar_g  -0.0084 0.0635  0.8946 0.1003  -0.2524    0.1564     0.828
## econaid_dnmp_g  -0.0227 0.0268  0.3965 0.0308  -0.0764    0.0500     0.544
## econaid_dnmp2_g  0.0010 0.0011  0.3704 0.0014  -0.0024    0.0034     0.630
## econaid_dnmp3_g  0.0000 0.0000  0.4243 0.0000   0.0000    0.0000     0.760
##
## $est_fs
##                    Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## Iinfl3           0.1561 0.0506  0.0020 0.0601   0.0043    0.2365     0.042
## econaid_lgdp_g   0.1664 0.1524  0.2749 0.2828  -0.4874    0.6922     0.530
```

```
## econaid_lpop_g   0.1839 0.0976  0.0596 0.1589  -0.2641    0.3909     0.350
## econaid_cwar_g  -0.2848 0.3413  0.4041 0.5015  -1.5028    0.4235     0.510
## econaid_dnmp_g  -0.0235 0.0899  0.7933 0.1009  -0.2674    0.1459     0.772
## econaid_dnmp2_g -0.0009 0.0045  0.8455 0.0052  -0.0090    0.0124     0.942
## econaid_dnmp3_g  0.0000 0.0001  0.5707 0.0001  -0.0001    0.0001     0.738
##
## $p_iv
## [1] 7
##
## $N
## [1] 370
##
## $N_cl
## [1] 44
##
## $df
## [1] 362
##
## $nvalues
##      mp econaid Iinfl3 econaid_lgdp_g econaid_lpop_g econaid_cwar_g
## [1,]  2     370    370            370            370            370
##      econaid_dnmp_g econaid_dnmp2_g econaid_dnmp3_g
## [1,]            370             370             370
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



DiGiuseppe and Shea (2022)

Replication Summary	
Unit of analysis	country*year
Treatment	US support
Instrument	echelon corridor
Outcome	property rights
Model	Table1(5)

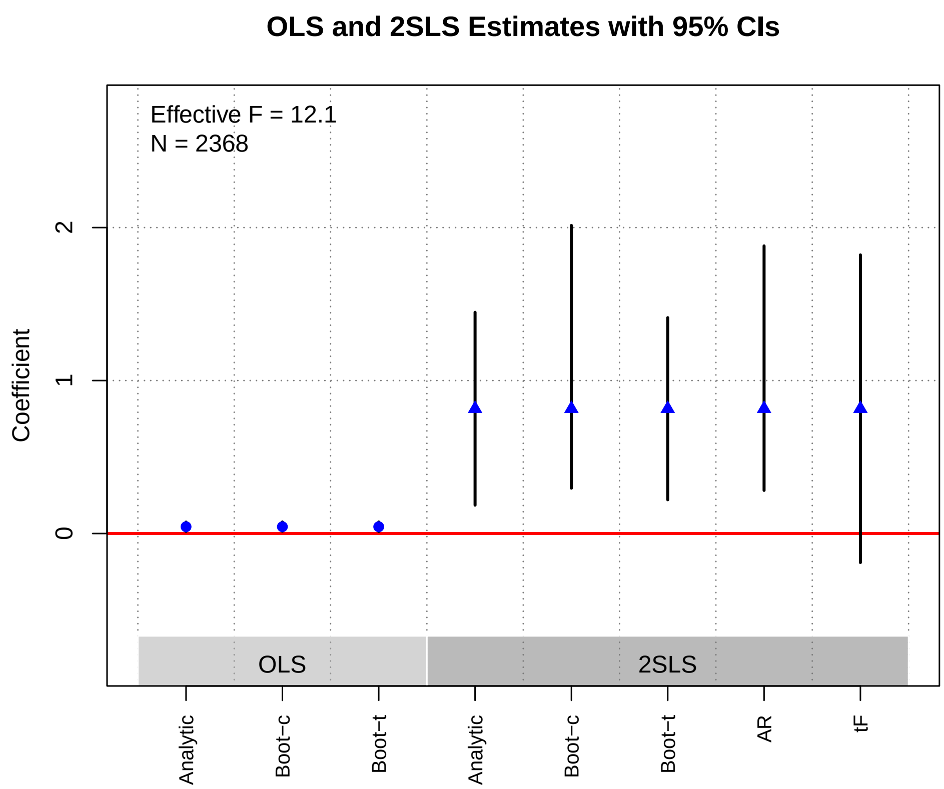
```
df <-readRDS("./data/jop_digiuseppe_2022.rds")
D <- "wi_usa_median"
Y<-"Fwi_v2stfisccap2"
Z <- "Echelon2"
controls <-c("wi_v2xcl_prpty","wi_compete", "wi_lnpop_wdi",
             "wi_lngdppc", "wi_polity2", "wi_polity2_2",  "wi_ny_gdp_totl_rt_zs",
             "wi_cwyrs", "wi_c2", "wi_c3", "coldwar")
cl<- NULL
FE<- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef      SE       t CI 2.5% CI 97.5% p.value
```

```
## Analytic 0.0443 0.0156 2.8331  0.0136   0.0749  0.0046
## Boot.c   0.0443 0.0158 2.7976  0.0148   0.0756  0.0040
## Boot.t   0.0443 0.0156 2.8331  0.0130   0.0755  0.0050
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.8158 0.3217 2.5360  0.1853   1.4463  0.0112
## Boot.c   0.8158 0.7300 1.1175  0.2964   2.0141  0.0040
## Boot.t   0.8158 0.3217 2.5360  0.2205   1.4111  0.0080
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    8.5251    1.0000 2366.0000    0.0035
##
## $AR$ci.print
## [1] "[0.2818, 1.8803]"
##
## $AR$ci
## [1] 0.2818 1.8803
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     18.8218     12.1084          NA     11.1384     12.1084
##
## $rho
## [1] 0.089
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 12.1084  3.1262  0.8158  0.3217  2.5360 -0.1899  1.8215  0.1118
##
## $est_rf
##            Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## Echelon2 0.1792 0.0615  0.0036 0.0626   0.0632    0.3006     0.002
##
## $est_fs
##            Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## Echelon2 0.2196 0.0631   5e-04 0.0658   0.0899    0.3454     0.002
##
## $p_iv
## [1] 1
##
```

```
## $N
## [1] 2368
##
## $N_cl
## NULL
##
## $df
## [1] 2355
##
## $nvalues
##      Fwi_v2stfisccap2 wi_usa_median Echelon2
## [1,]              314          2368        2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Dube and Naidu (2015)

Replication Summary	
Unit of analysis	municipality*year
Treatment	changes in US funding to Colombia
Instrument	US funding in countries outside of Latin America

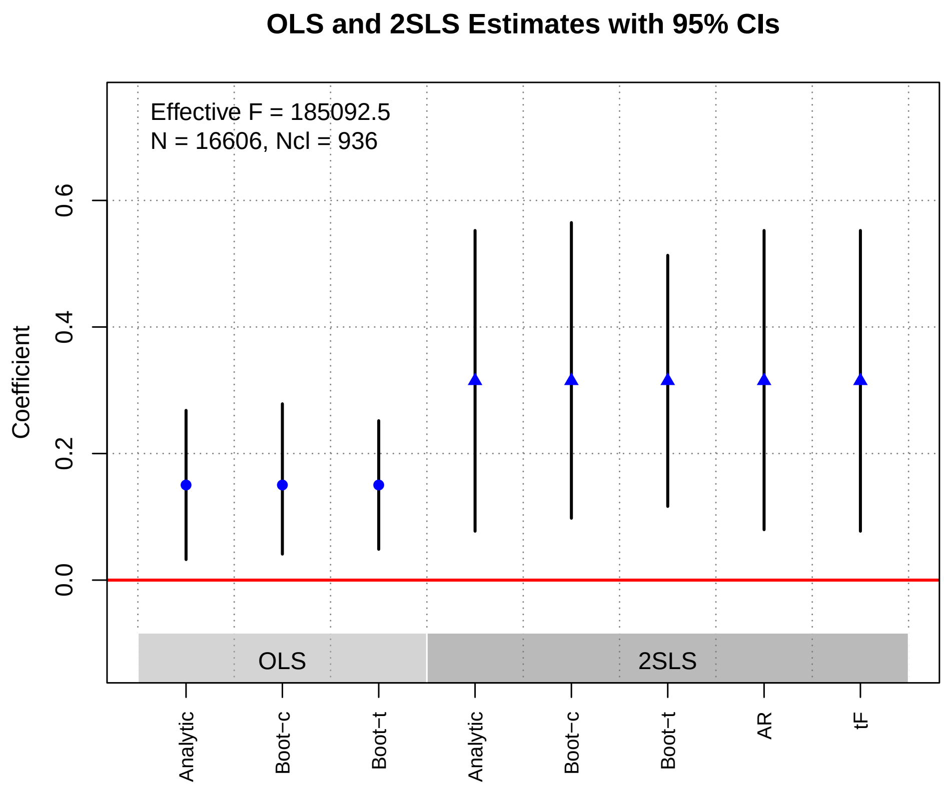
Replication Summary	
Outcome	the number of paramilitary attacks
Model	Table1(1)

```r
df<-readRDS("./data/jop_Dube_etal_2015.rds")
D <- "bases6xlrmilnar_col"
Y <- "paratt"
Z <- "bases6xlrmilwnl"
controls <-"lnnewpop"
cl <- "municipality"
FE <- c("year","municipality")
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.1503 0.0601 2.5001  0.0325   0.2682  0.0124
## Boot.c   0.1503 0.0601 2.5006  0.0411   0.2786  0.0020
## Boot.t   0.1503 0.0601 2.5001  0.0487   0.2519  0.0200
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.3149 0.1212 2.5977  0.0773   0.5525  0.0094
## Boot.c   0.3149 0.1190 2.6475  0.0978   0.5650  0.0080
## Boot.t   0.3149 0.1212 2.5977  0.1165   0.5133  0.0220
##
## $AR
## $AR$Fstat
##          F        df1        df2          p
##     6.7529     1.0000 16604.0000     0.0094
##
## $AR$ci.print
## [1] "[0.0797, 0.5525]"
##
## $AR$ci
## [1] 0.0797 0.5525
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##   7003.8727    810.8395 185092.5288 167290.8044 185092.5288
##
```

```
## $rho
## [1] 0.556
##
## $tF
##            F          cF        Coef          SE           t      CI2.5%
## 185092.5288      1.9600      0.3149      0.1212      2.5977      0.0773
##     CI97.5%     p-value
##      0.5525      0.0094
##
## $est_rf
##                   Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## bases6xlrmilwnl 1.1155 0.4293  0.0094 0.4212   0.3469    1.9988     0.008
##
## $est_fs
##                   Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## bases6xlrmilwnl 3.5422 0.0082       0 0.0087   3.5227    3.5567         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 16606
##
## $N_cl
## [1] 936
##
## $df
## [1] 935
##
## $nvalues
##      paratt bases6xlrmilnar_col bases6xlrmilwnl
## [1,]     13                  19              18
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Feigenbaum and Hall (2015)

Replication Summary	
Unit of analysis	congressional district*decade
Treatment	localized trade shocks in congressional districts
Instrument	Chinese exports to other economies*local exposure
Outcome	trade score based on congressional voting
Model	Table1(3)

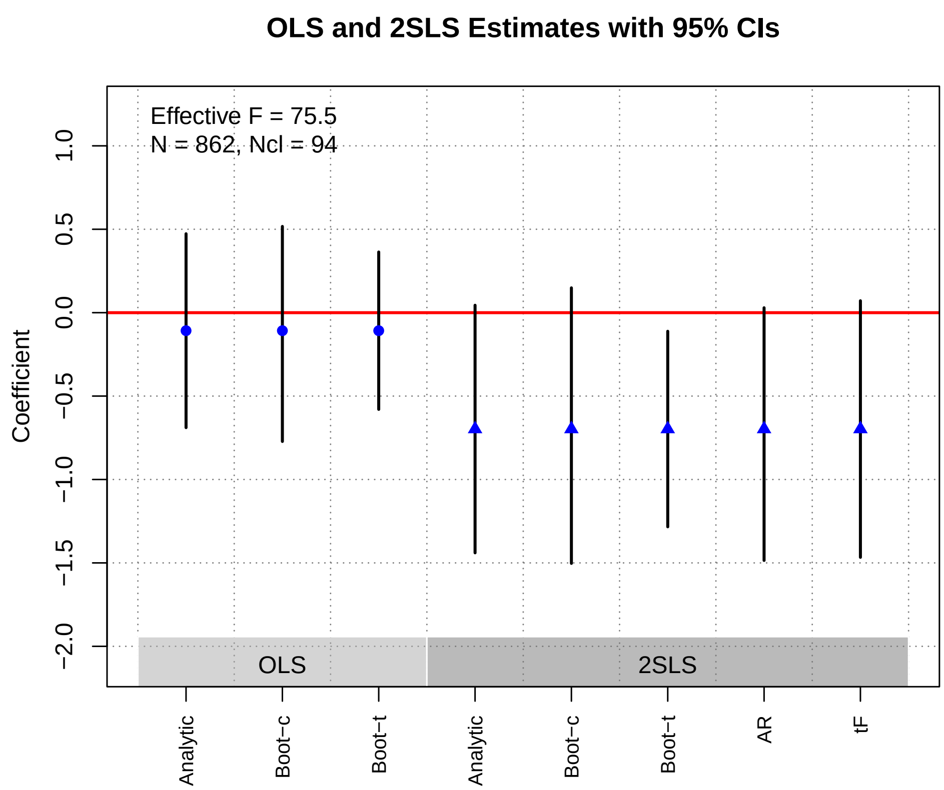
```
df<-readRDS("./data/jop_Feigenbaum_etal_2015.rds")
D <-"x"
Y <- "tradescore"
Z <- "z"
controls <- c("dem_share")
cl <- "state_cluster"
FE <- "decade"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.108 0.2965 -0.3643 -0.6891   0.4731  0.7157
## Boot.c   -0.108 0.3209 -0.3365 -0.7720   0.5169  0.7580
```

```
## Boot.t   -0.108 0.2965 -0.3643 -0.5797   0.3637  0.6240
##
## $est_2sls
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.6976 0.3786 -1.8424 -1.4397   0.0445  0.0654
## Boot.c   -0.6976 0.4149 -1.6814 -1.5029   0.1488  0.1080
## Boot.t   -0.6976 0.3786 -1.8424 -1.2837  -0.1115  0.0260
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   3.4825   1.0000 860.0000   0.0624
##
## $AR$ci.print
## [1] "[-1.4852, 0.0294]"
##
## $AR$ci
## [1] -1.4852  0.0294
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##   1189.3393    204.4798     75.5233     71.3779     75.5233
##
## $rho
## [1] 0.7622
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 75.5233  2.0310 -0.6976  0.3786 -1.8424 -1.4666  0.0714  0.0754
##
## $est_rf
##      Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## z -0.5863 0.3145  0.0623 0.3581  -1.2933    0.1381     0.108
##
## $est_fs
##     Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## z 0.8405 0.0967       0 0.0995   0.6847    1.0665         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 862
```

```
##
## $N_cl
## [1] 94
##
## $df
## [1] 858
##
## $nvalues
##      tradescore   x   z
## [1,]        709 698 697
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Flores-Macias and Kreps (2013)

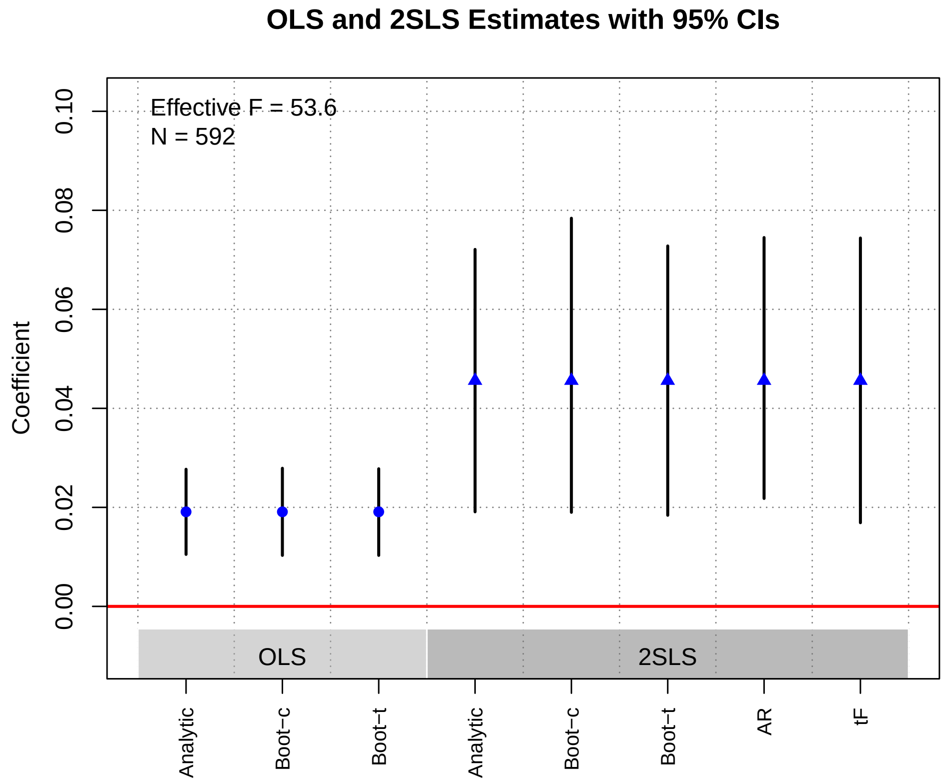
Replication Summary	
Unit of analysis	country*year
Treatment	trade volume
Instrument	lagged energy production
Outcome	foreign policy convergence
Model	Table2(1)

```r
df<- readRDS("./data/jop_Flores_etal_2013.rds")
D <- "log_tot_trade"
Y <- "log_HRVOTE"
Z <- "lag_log_energ_prod"
controls <- c("log_cinc", "us_aid100", "log_tot_ustrade",
              "Joint_Dem_Dum", "pts_score", "dummy2004")
cl <- NULL
FE <- 'statea'
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0191 0.0044 4.3531  0.0105   0.0277       0
## Boot.c   0.0191 0.0045 4.2043  0.0103   0.0279       0
## Boot.t   0.0191 0.0044 4.3531  0.0103   0.0278       0
##
## $est_2sls
##              Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0456 0.0135 3.3747  0.0191   0.0721   7e-04
## Boot.c   0.0456 0.0149 3.0575  0.0190   0.0784   0e+00
## Boot.t   0.0456 0.0135 3.3747  0.0184   0.0728   2e-03
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##  14.1713   1.0000 590.0000   0.0002
##
## $AR$ci.print
## [1] "[0.0218, 0.0745]"
##
## $AR$ci
## [1] 0.0218 0.0745
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##   F.standard    F.robust   F.cluster F.bootstrap F.effective
##      66.1143     53.6345          NA     46.7306     53.6345
##
## $rho
## [1] 0.3295
##
## $tF
```

```
##        F       cF     Coef       SE        t  CI2.5% CI97.5% p-value
## 53.6345  2.1276  0.0456  0.0135  3.3747  0.0169  0.0744  0.0019
##
## $est_rf
##                      Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## lag_log_energ_prod 0.1086 0.0301   3e-04 0.0324   0.0442    0.1717         0
##
## $est_fs
##                      Coef    SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## lag_log_energ_prod 2.3803 0.325       0 0.3482   1.7085    3.0661         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 592
##
## $N_cl
## NULL
##
## $df
## [1] 543
##
## $nvalues
##      log_HRVOTE log_tot_trade lag_log_energ_prod
## [1,]         32           590                581
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Gehlbach and Keefer (2012)

Replication Summary	
Unit of analysis	nondemocratic episode
Treatment	age of ruling party less leader years in office
Instrument	whether the first ruler in a nondemocratic episode is a military leader
Outcome	private invest
Model	Table1(4)

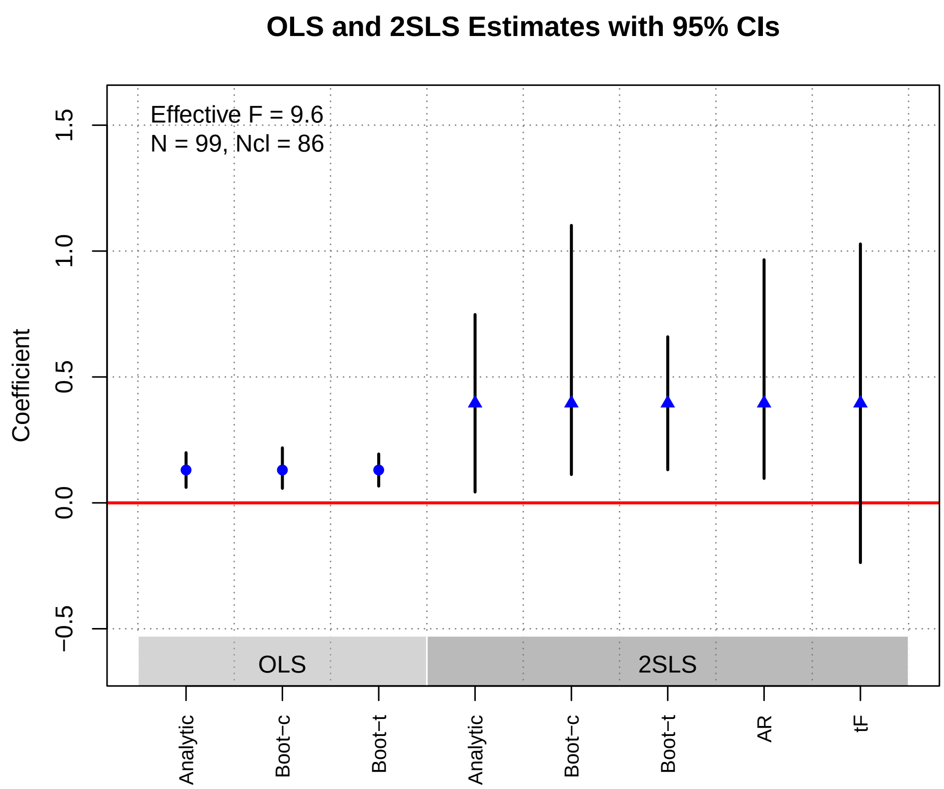
```
df<- readRDS("./data/jop_Gelbach_etal_2012.rds")
D <- "gov1_yrs"
Y <- "gfcf_priv_gdp"
Z <- "military_first_alt"
controls <- c("tenure", "stabs", "fuelex_gdp", "oresex_gdp",
              "frac_ethn", "frac_relig", "frac_ling", "pop_yng_pct",
              "pop_tot", "pop_ru_pct", "land_km", "gdppc_ppp_2005_us")
cl <- "ifs_code"
FE <-NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef      SE       t CI 2.5% CI 97.5% p.value
```

```
## Analytic 0.1304 0.0351 3.7118  0.0615   0.1992   2e-04
## Boot.c   0.1304 0.0415 3.1420  0.0577   0.2185   4e-03
## Boot.t   0.1304 0.0351 3.7118  0.0666   0.1941   0e+00
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.3956 0.1798 2.2001  0.0432   0.7479  0.0278
## Boot.c   0.3956 1.0008 0.3952  0.1126   1.1019  0.0120
## Boot.t   0.3956 0.1798 2.2001  0.1316   0.6595  0.0130
##
## $AR
## $AR$Fstat
##       F     df1     df2       p
##  6.3658  1.0000 97.0000  0.0133
##
## $AR$ci.print
## [1] "[0.0971, 0.9654]"
##
## $AR$ci
## [1] 0.0971 0.9654
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##      6.3713      9.2042      9.5714      8.9279      9.5714
##
## $rho
## [1] 0.2641
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
##  9.5714  3.5187  0.3956  0.1798  2.2001 -0.2371  1.0282  0.2204
##
## $est_rf
##                      Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## military_first_alt -3.3385 1.4135  0.0182 1.5017  -6.8607   -0.9219     0.008
##
## $est_fs
##                      Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## military_first_alt -8.4401 2.7281   0.002 2.8247 -13.8425   -2.9101     0.004
##
## $p_iv
## [1] 1
##
```

```
## $N
## [1] 99
##
## $N_cl
## [1] 86
##
## $df
## [1] 85
##
## $nvalues
##      gfcf_priv_gdp gov1_yrs military_first_alt
## [1,]            99       63                  2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Grossman et al. (2017)

Replication Summary	
Unit of analysis	region * year
Treatment	government fragmentation
Instrument	the number of distinct landmasses;

Replication Summary	
	length of medium and small streams; over-time variation in the number of regional governments
Outcome	public goods provision
Model	Table1(8)

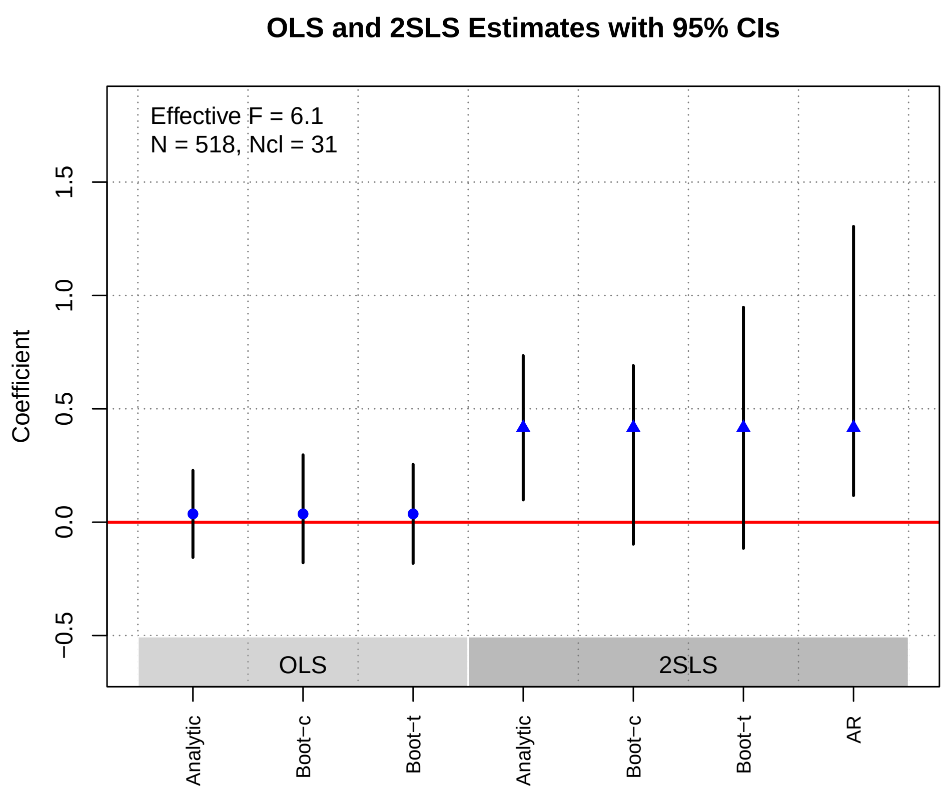
```
df<-readRDS("./data/jop_Grossman_2017.rds")
Y <- "ServicesCA"
D <- "ladminpc_l5"
Z <- c("lmeanMINUSi_adminpc_l6", "lmeanMINUSi_adminpc2_l6",
       "herf", "herf2", "llength", "llength2")
controls <- c("lpop_l", "wdi_urban_l", "lgdppc_l", "conflict_l",
              "dpi_state_l", "p_polity2_l",
              "loilpc_l", "aid_pc_l","al_ethnic")
cl <- "ccodecow"
FE <- "year"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0364 0.0978 0.3721 -0.1554   0.2282  0.7098
## Boot.c   0.0364 0.1258 0.2895 -0.1790   0.2970  0.8229
## Boot.t   0.0364 0.0978 0.3721 -0.1818   0.2547  0.7271
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.4164 0.1623 2.5650  0.0982   0.7345  0.0103
## Boot.c   0.4164 0.2090 1.9921 -0.0970   0.6905  0.1687
## Boot.t   0.4164 0.1623 2.5650 -0.1152   0.9479  0.1198
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   3.8390   6.0000 511.0000   0.0009
##
## $AR$ci.print
## [1] "[0.1177, 1.3043]"
##
## $AR$ci
## [1] 0.1177 1.3043
##
## $AR$bounded
## [1] TRUE
##
```

```
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     39.9978     40.9874     11.9593      1.3650      6.1390
##
## $rho
## [1] 0.581
##
## $est_rf
##                            Coef     SE p.value     SE.b  CI.b2.5% CI.b97.5%
## lmeanMINUSi_adminpc_l6   6.0801 7.3987  0.4112  11.4854  -20.6116   26.8729
## lmeanMINUSi_adminpc2_l6 -3.9097 2.3810  0.1006   3.2048  -10.4348    2.9268
## herf                    -0.0170 2.4059  0.9943 513.5579  -52.6863 1666.2240
## herf2                   -0.0545 1.7185  0.9747 264.9752 -858.7571   27.1893
## llength                  0.0669 0.0507  0.1867   0.9606   -0.8039    3.2769
## llength2                -0.0029 0.0037  0.4309   0.0356   -0.1211    0.0301
##                         p.value.b
## lmeanMINUSi_adminpc_l6     0.5083
## lmeanMINUSi_adminpc2_l6    0.2396
## herf                       0.7542
## herf2                      0.7104
## llength                    0.3979
## llength2                   0.4729
##
## $est_fs
##                             Coef      SE p.value     SE.b   CI.b2.5% CI.b97.5%
## lmeanMINUSi_adminpc_l6   27.1296 12.2417  0.0267  19.5077   -11.1236   63.2320
## lmeanMINUSi_adminpc2_l6 -13.3452  4.9245  0.0067   6.4294   -27.6467   -2.0240
## herf                      3.5973  4.6318  0.4374 393.6449 -1446.3184   49.5651
## herf2                    -2.4844  3.1500  0.4303 203.8267   -33.1074  746.7476
## llength                   0.0536  0.0526  0.3084   0.9708    -0.7520    2.6548
## llength2                  0.0002  0.0039  0.9671   0.0359    -0.0929    0.0329
##                         p.value.b
## lmeanMINUSi_adminpc_l6     0.1500
## lmeanMINUSi_adminpc2_l6    0.0167
## herf                       0.9667
## herf2                      0.9688
## llength                    0.4583
## llength2                   0.8375
##
## $p_iv
## [1] 6
##
## $N
## [1] 518
##
## $N_cl
```

```
## [1] 31
##
## $df
## [1] 476
##
## $nvalues
##      ServicesCA ladminpc_l5 lmeanMINUSi_adminpc_l6 lmeanMINUSi_adminpc2_l6 herf
## [1,]        518         518                     518                      518   15
##      herf2 llength llength2
## [1,]    15      29       29
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Healy and Malhotra (2013)

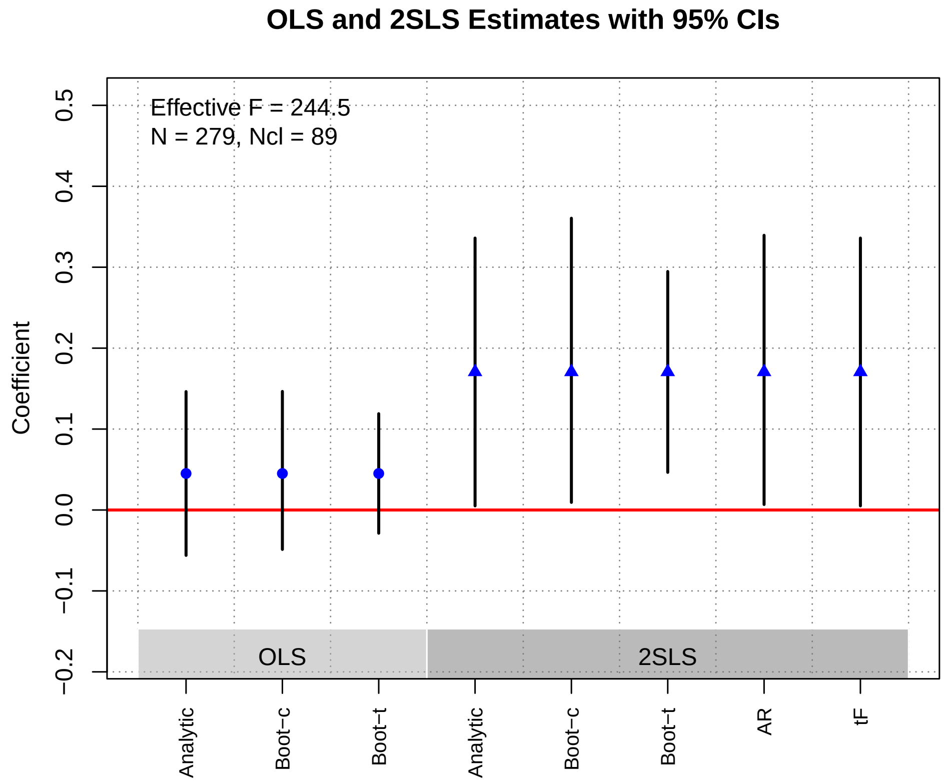
Replication Summary	
Unit of analysis	individual
Treatment	the share of a respondent's siblings who are female
Instrument	whether the younger sibling is a sister
Outcome	gender-role attitude in 1973
Model	Table1(1)

```r
df <- readRDS("./data/jop_Healy_etal_2013.rds")
D <-"share_sis"
Y <- "womens_rights73"
Z <- "closest"
controls <- "num_sib"
cl <- "PSU"
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0451 0.0516 0.8743 -0.0561   0.1463  0.3819
## Boot.c   0.0451 0.0508 0.8894 -0.0487   0.1465  0.3500
## Boot.t   0.0451 0.0516 0.8743 -0.0287   0.1190  0.2320
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.1706 0.0844 2.0203  0.0051   0.3360  0.0434
## Boot.c   0.1706 0.0868 1.9644  0.0094   0.3605  0.0380
## Boot.t   0.1706 0.0844 2.0203  0.0465   0.2947  0.0040
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   4.1446   1.0000 277.0000   0.0427
##
## $AR$ci.print
## [1] "[0.0068, 0.3394]"
##
## $AR$ci
## [1] 0.0068 0.3394
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##    255.3329    252.1198    244.4704    247.1398    244.4704
##
## $rho
## [1] 0.6932
##
## $tF
##        F        cF      Coef        SE         t    CI2.5%   CI97.5%   p-value
```

```
## 244.4704   1.9600   0.1706   0.0844   2.0203   0.0051   0.3360   0.0434
##
## $est_rf
##           Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## closest 0.0832 0.0409  0.0421 0.0414    0.005    0.1719     0.038
##
## $est_fs
##           Coef     SE p.value  SE.b CI.b2.5% CI.b97.5% p.value.b
## closest 0.4876 0.0312       0 0.031   0.4274    0.5498         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 279
##
## $N_cl
## [1] 89
##
## $df
## [1] 276
##
## $nvalues
##      womens_rights73 share_sis closest
## [1,]               7        17       2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Henderson and Brooks (2016) (a)

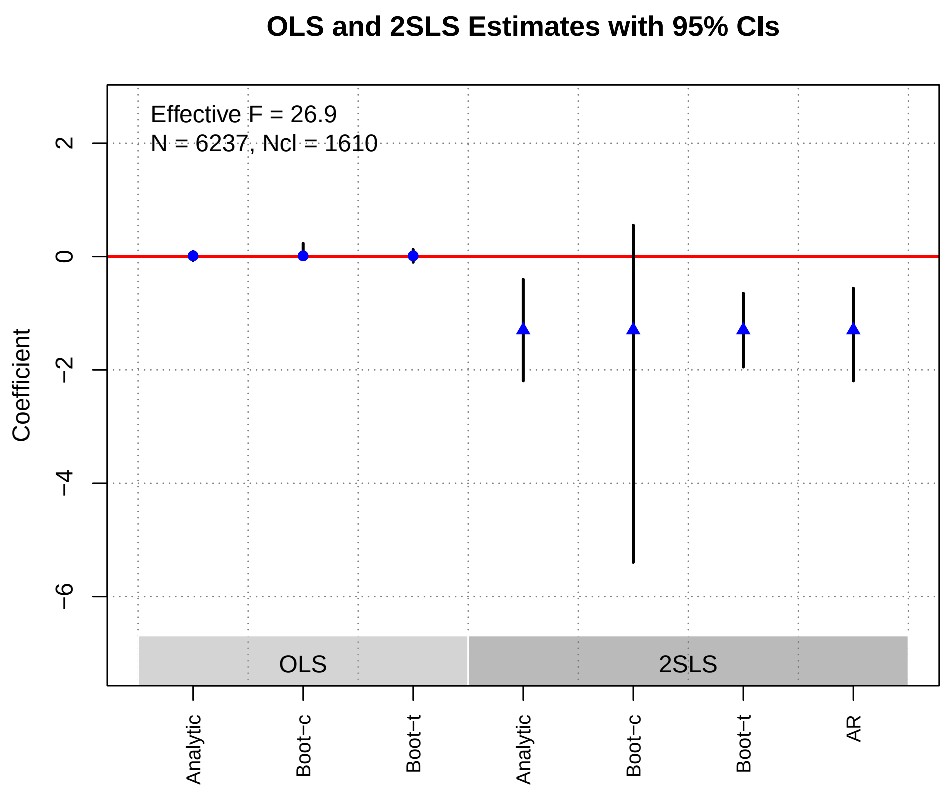
Replication Summary	
Unit of analysis	district*year
Treatment	Democratic vote margins
Instrument	rain around election day
Outcome	incumbent roll call positioning
Model	Table3(1)

```
df<- readRDS("./data/jop_Henderson_etal_2016.rds")
df$fe_id_num<-df$`as.factor(fe_id_num)`
D <- "dose"
Y <- "vote"
Z <- c("rain_day", "rain_day_prev")
controls <- c("d_inc", "dist_prev", "midterm", "pres_party", "black",
              "construction", "educ", "minc", "farmer", "forborn",
              "gvtwkr", "manuf", "pop", "unempld", "urban", "retail",
              "sos", "gov", "comp_cq", "redistricted", "dose_prv", "vote_prv")
cl <- "fe_id_num" # incumbent
FE <- "fe_id_num"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0124 0.0415 0.2996 -0.0689   0.0937  0.7645
## Boot.c   0.0124 0.0538 0.2312  0.0184   0.2348  0.0100
## Boot.t   0.0124 0.0415 0.2996 -0.1000   0.1248  0.9570
##
## $est_2sls
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -1.2984 0.4571 -2.8403 -2.1943  -0.4024  0.0045
## Boot.c   -1.2984 1.7590 -0.7381 -5.3953   0.5541  0.1460
## Boot.t   -1.2984 0.4571 -2.8403 -1.9498  -0.6469  0.0000
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    6.2335    2.0000 6234.0000    0.0020
##
## $AR$ci.print
## [1] "[-2.1943, -0.5578]"
##
## $AR$ci
## [1] -2.1943 -0.5578
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     26.4294     21.5068     22.8295     11.0267     26.9117
##
## $rho
## [1] 0.1066
##
## $est_rf
##                 Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## rain_day      0.0326 0.0100  0.0011 0.0110   0.0162    0.0591     0.000
## rain_day_prev 0.0153 0.0081  0.0585 0.0122  -0.0248    0.0239     0.938
##
## $est_fs
##                  Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## rain_day      -0.0144 0.0031       0 0.0043  -0.0194   -0.0024     0.008
## rain_day_prev -0.0187 0.0031       0 0.0045  -0.0196   -0.0019     0.020
##
## $p_iv
## [1] 2
##
```

```
## $N
## [1] 6237
##
## $N_cl
## [1] 1610
##
## $df
## [1] 1609
##
## $nvalues
##      vote dose rain_day rain_day_prev
## [1,] 6230 5138     5321          5326
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Henderson and Brooks (2016) (b)

Replication Summary	
Unit of analysis	district*year
Treatment	Democratic vote margins
Instrument	rain around election weekend

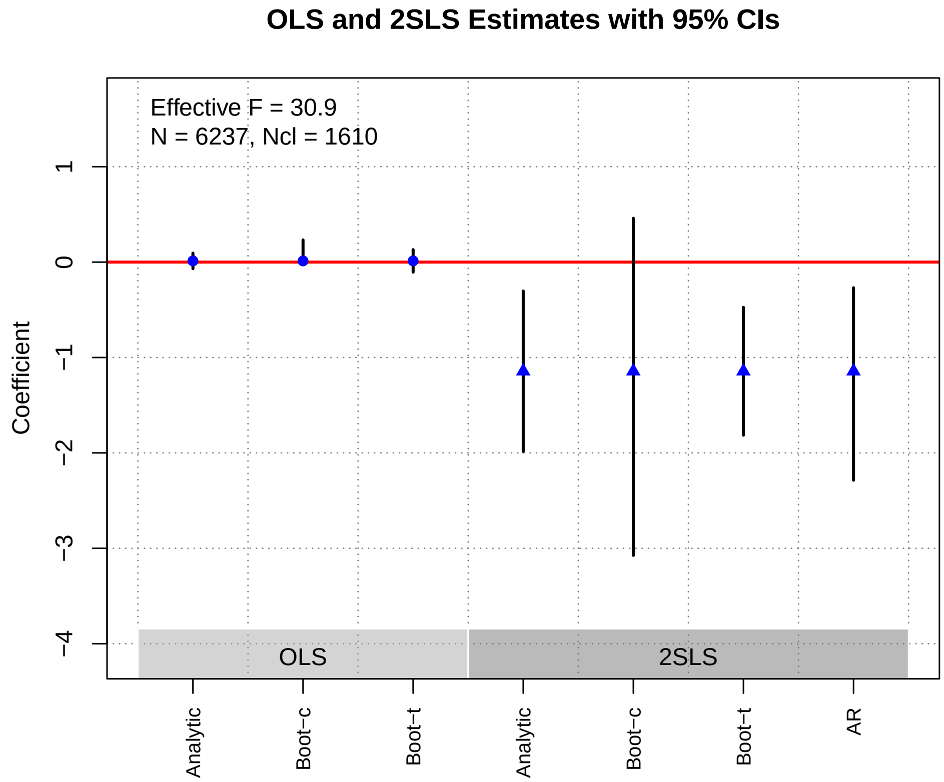
Replication Summary	
Outcome	incumbent roll call positioning
Model	Table3(2)

```
df<- readRDS("./data/jop_Henderson_etal_2016.rds")
df$fe_id_num<-df$`as.factor(fe_id_num)`
D <- "dose"
Y <- "vote"
Z <- c("rain_weekend", "rain_weekend_prev")
controls <- c("d_inc", "dist_prev", "midterm", "pres_party", "black",
              "construction", "educ", "minc", "farmer", "forborn",
              "gvtwkr", "manuf", "pop", "unempld", "urban", "retail",
              "sos", "gov", "comp_cq", "redistricted", "dose_prv", "vote_prv")
cl <- "fe_id_num" # incumbent
FE <- "fe_id_num"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0124 0.0415 0.2996 -0.0689   0.0937  0.7645
## Boot.c   0.0124 0.0529 0.2348  0.0249   0.2328  0.0180
## Boot.t   0.0124 0.0415 0.2996 -0.1058   0.1307  0.9620
##
## $est_2sls
##              Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -1.1444 0.4293 -2.6654 -1.9859  -0.3029  0.0077
## Boot.c   -1.1444 0.9093 -1.2585 -3.0745   0.4598  0.2080
## Boot.t   -1.1444 0.4293 -2.6654 -1.8147  -0.4740  0.0000
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    4.7151    2.0000 6234.0000    0.0090
##
## $AR$ci.print
## [1] "[-2.2864, -0.2685]"
##
## $AR$ci
## [1] -2.2864 -0.2685
##
## $AR$bounded
## [1] TRUE
##
##
```

```
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     30.3614     24.5741     26.3171     13.5977     30.9359
##
## $rho
## [1] 0.1141
##
## $est_rf
##                     Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## rain_weekend      0.0306 0.0109  0.0050 0.0114   0.0073    0.0530     0.004
## rain_weekend_prev 0.0175 0.0095  0.0665 0.0144  -0.0308    0.0241     0.876
##
## $est_fs
##                     Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## rain_weekend      -0.0192 0.0034       0 0.0048  -0.0256   -0.0068         0
## rain_weekend_prev -0.0213 0.0035       0 0.0049  -0.0235   -0.0043         0
##
## $p_iv
## [1] 2
##
## $N
## [1] 6237
##
## $N_cl
## [1] 1610
##
## $df
## [1] 1609
##
## $nvalues
##      vote dose rain_weekend rain_weekend_prev
## [1,] 6230 5138         5401              5407
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Johns and Pelc (2016)

Replication Summary	
Unit of analysis	WTO dispute
Treatment	the number third parties
Instrument	trade stake of the rest of the world
Outcome	becoming a third party
Model	Table2(2)

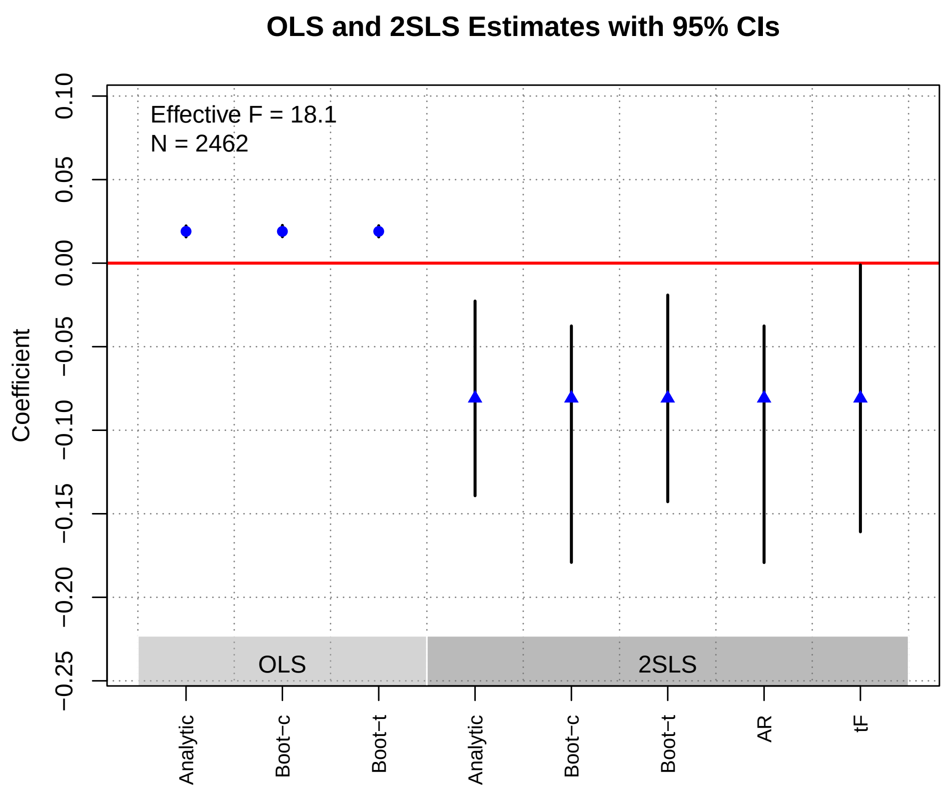
```
df<-readRDS("./data/jop_Johns_etal_2016.rds")
D='third_num_excl'
Y='thirdparty'
Z='ln_ROW_before_disp'
controls=c("ln_gdpk_partner", "ln_history_third", "ln_history_C",
    "Multilateral", "trade_before_dispute",  "ARTICLEXXII")
cl <- NULL
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE        t CI 2.5% CI 97.5% p.value
## Analytic 0.019 0.0017 11.3469  0.0157   0.0223       0
```

```
## Boot.c   0.019 0.0017 11.1617  0.0158   0.0226       0
## Boot.t   0.019 0.0017 11.3469  0.0157   0.0224       0
##
## $est_2sls
##             Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.0809 0.0297 -2.7247 -0.1392  -0.0227  0.0064
## Boot.c   -0.0809 0.0385 -2.1019 -0.1791  -0.0376  0.0000
## Boot.t   -0.0809 0.0297 -2.7247 -0.1428  -0.0191  0.0200
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##   19.7186    1.0000 2460.0000    0.0000
##
## $AR$ci.print
## [1] "[-0.1792, -0.0376]"
##
## $AR$ci
## [1] -0.1792 -0.0376
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     16.9224     18.1200          NA     19.3946     18.1200
##
## $rho
## [1] 0.0828
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 18.1200  2.6873 -0.0809  0.0297 -2.7247 -0.1608 -0.0011  0.0469
##
## $est_rf
##                       Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## ln_ROW_before_disp -0.0137 0.0031       0 0.0032  -0.0198   -0.0077         0
##
## $est_fs
##                      Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## ln_ROW_before_disp 0.1692 0.0397       0 0.0384   0.0925    0.2403         0
##
## $p_iv
## [1] 1
##
## $N
```

```
## [1] 2462
##
## $N_cl
## NULL
##
## $df
## [1] 2454
##
## $nvalues
##      thirdparty third_num_excl ln_ROW_before_disp
## [1,]          2             17               2281
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Kriner and Schickler (2014)

Replication Summary	
Unit of analysis	month
Treatment	committee investigations
Instrument	number of days that Congress was in session in a given month
Outcome	presidential approval

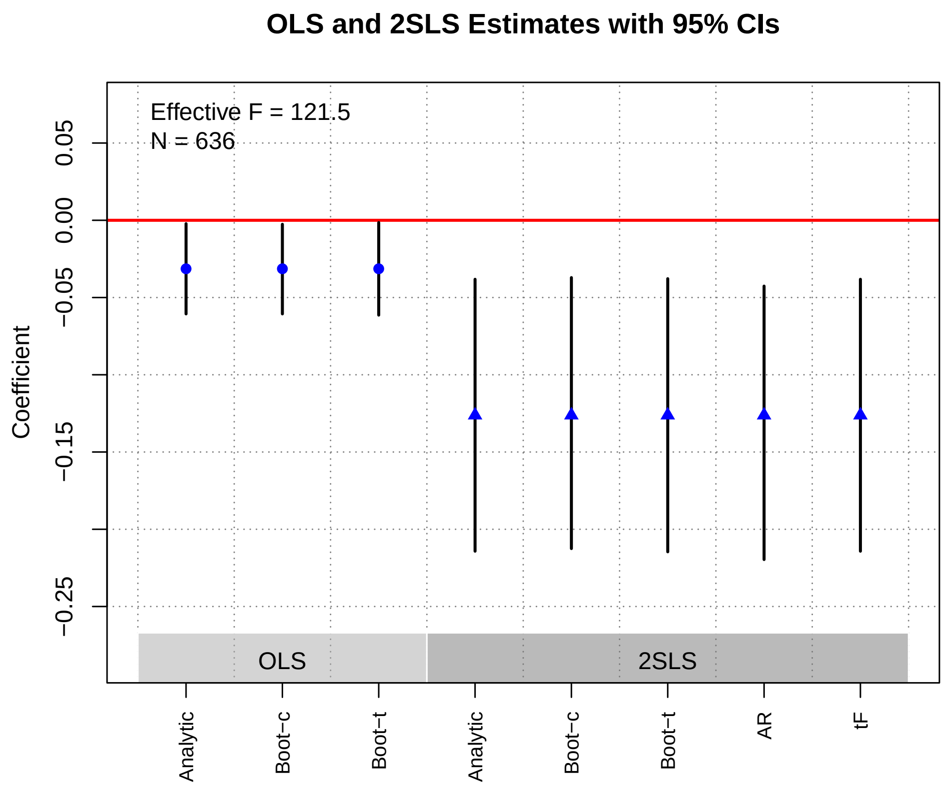
Replication Summary	
Model	Table1(1)

```
df<-readRDS("./data/jop_Kriner_etal_2014.rds")
D <- "misconductdays"
Y <- "approval"
Z <- "alldaysinsession"
controls <- c("icst1", "positive", "negative", "vcaslast6mos",
              "iraqcaslast6mos", "honeymoon", "approvalt1", "ike","jfk",
              "lbj","rmn","ford","carter","reagan","bush","clinton","wbush")
cl <- NULL
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.0314 0.0149 -2.1103 -0.0606  -0.0022  0.0348
## Boot.c   -0.0314 0.0150 -2.0909 -0.0606  -0.0026  0.0280
## Boot.t   -0.0314 0.0149 -2.1103 -0.0614  -0.0015  0.0440
##
## $est_2sls
##              Coef     SE       t CI 2.5% CI 97.5% p.value
## Analytic -0.1262 0.0449 -2.8096 -0.2142  -0.0382   0.005
## Boot.c   -0.1262 0.0450 -2.8028 -0.2125  -0.0371   0.006
## Boot.t   -0.1262 0.0449 -2.8096 -0.2146  -0.0378   0.009
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   8.9171   1.0000 634.0000   0.0029
##
## $AR$ci.print
## [1] "[-0.2196, -0.0426]"
##
## $AR$ci
## [1] -0.2196 -0.0426
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##   F.standard    F.robust   F.cluster F.bootstrap F.effective
##     105.5872    121.5394          NA    126.1856    121.5394
```

```
##
## $rho
## [1] 0.382
##
## $tF
##        F       cF     Coef       SE        t   CI2.5%  CI97.5%  p-value
## 121.5394   1.9600  -0.1262   0.0449  -2.8096  -0.2142  -0.0382   0.0050
##
## $est_rf
##                     Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## alldaysinsession -0.035 0.0119  0.0032 0.0119  -0.0575   -0.0106     0.006
##
## $est_fs
##                     Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## alldaysinsession 0.2777 0.0252       0 0.0247   0.2309    0.3273         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 636
##
## $N_cl
## NULL
##
## $df
## [1] 618
##
## $nvalues
##      approval misconductdays alldaysinsession
## [1,]      185             52               49
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Lei and Zhou (2022)

Replication Summary	
Unit of analysis	city*year
Treatment	subway approval
Instrument	whether the city has more than 3 million residents* population size
Outcome	mayor promotion
Model	Table3(A)

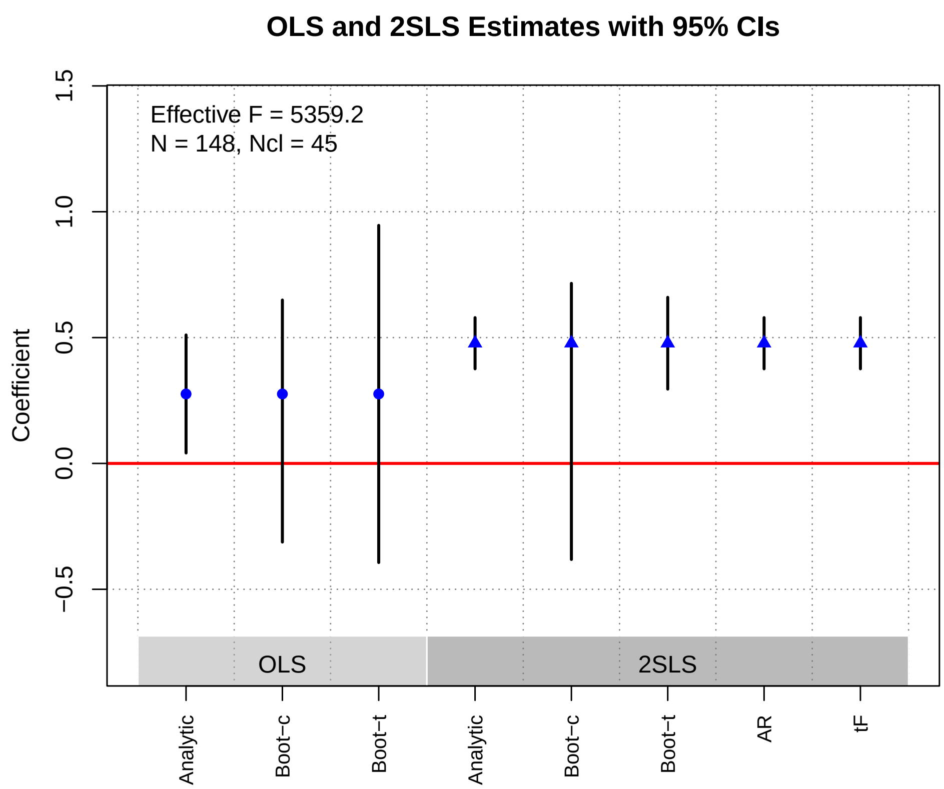
```
df<-readRDS("./data/jop_Lei_2022.rds")
Y <-'Mayor_promotion3y'
D <-'Mayor_plan'
Z <-'iv1'
controls<-c( 'Per_pop_2', 'iv1_int')
cl<-"City_Code"
FE<-c("provinceyear","City_Code")
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##           Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.276 0.1196 2.3077  0.0416   0.5104  0.0210
```

```
## Boot.c   0.276 0.2428 1.1369 -0.3124   0.6492  0.2111
## Boot.t   0.276 0.1196 2.3077 -0.3938   0.9458  0.2940
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.4776 0.0519 9.2026  0.3759   0.5793  0.0000
## Boot.c   0.4776 0.2865 1.6670 -0.3816   0.7154  0.2312
## Boot.t   0.4776 0.0519 9.2026  0.2953   0.6599  0.0050
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##  83.1817   1.0000 146.0000   0.0000
##
## $AR$ci.print
## [1] "[0.3759, 0.5793]"
##
## $AR$ci
## [1] 0.3759 0.5793
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     53.4747   2276.8055   5359.1714    135.3685   5359.1714
##
## $rho
## [1] 0.7604
##
## $tF
##         F        cF      Coef        SE         t    CI2.5%   CI97.5%   p-value
## 5359.1714    1.9600    0.4776    0.0519    9.2026    0.3759    0.5793    0.0000
##
## $est_rf
##       Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## iv1 0.4833 0.0534       0 0.2991  -0.3889    0.7384    0.2312
##
## $est_fs
##       Coef     SE p.value  SE.b CI.b2.5% CI.b97.5% p.value.b
## iv1 1.0119 0.0138       0 0.087   0.9963    1.3413         0
##
## $p_iv
## [1] 1
##
## $N
```

```
## [1] 148
##
## $N_cl
## [1] 45
##
## $df
## [1] 39
##
## $nvalues
##      Mayor_promotion3y Mayor_plan iv1
## [1,]                 2          2   2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Lerman et al. (2017)

Replication Summary	
Unit of analysis	individual
Treatment	public versus only private health insurance
Instrument	born 1946 or 1947
Outcome	support ACA

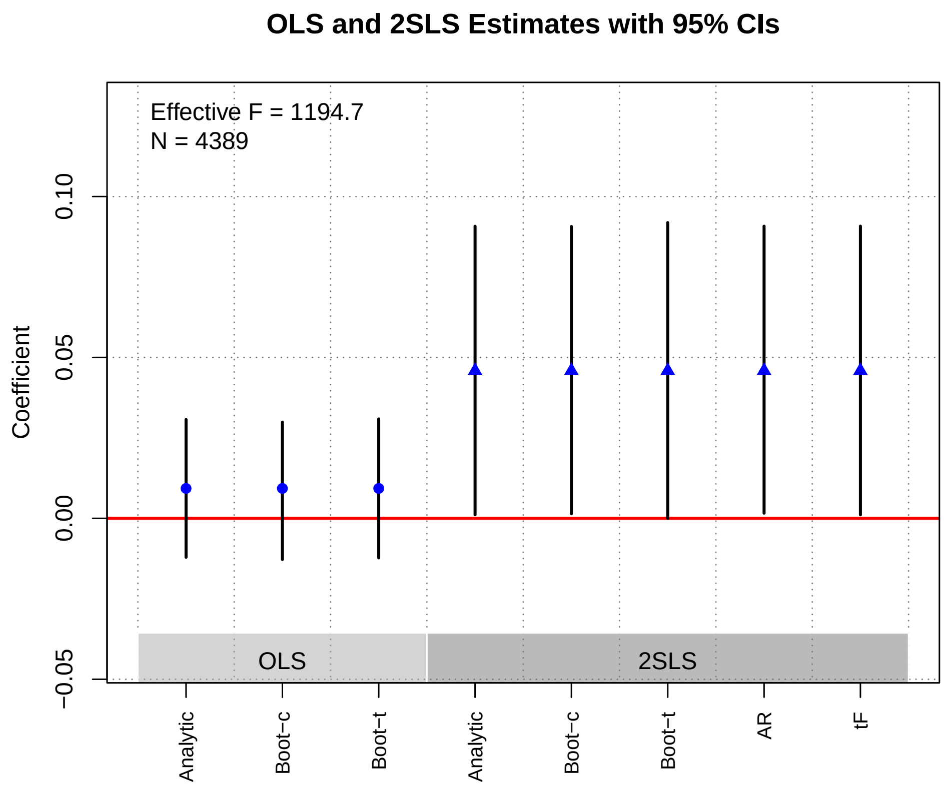
Replication Summary	
Model	Table1(1)

```r
df<-readRDS("./data/jop_Lerman_2017.rds")
Y <-'suppafford'
D <-'privpubins3r'
Z <-'byr4647'
controls<-c( 'rep', 'ind', 'con', 'mod',
              'ideostrength', 'hcsocial', 'fininsur',
             'healthcaresupport', 'child18', 'male',
             'married', 'labor', 'mobility', 'homeowner',
             'religimp','employed', 'votereg', 'vote08',
             'black', 'hispanic2', 'military', 'educ',
              'fincome', 'newsint', 'publicemp', 'bornagain')
cl<-NULL
FE<-NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0093 0.0109 0.8542 -0.0121   0.0307   0.393
## Boot.c   0.0093 0.0110 0.8499 -0.0128   0.0299   0.428
## Boot.t   0.0093 0.0109 0.8542 -0.0123   0.0309   0.404
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0459 0.0229 2.0095  0.0011   0.0908  0.0445
## Boot.c   0.0459 0.0228 2.0136  0.0014   0.0907  0.0460
## Boot.t   0.0459 0.0229 2.0095  0.0000   0.0919  0.0490
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    4.0770    1.0000 4387.0000    0.0435
##
## $AR$ci.print
## [1] "[0.0016, 0.0908]"
##
## $AR$ci
## [1] 0.0016 0.0908
##
## $AR$bounded
## [1] TRUE
##
```

```
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##    1272.162    1194.659          NA    1219.037    1194.659
##
## $rho
## [1] 0.4752
##
## $tF
##         F        cF      Coef        SE         t    CI2.5%   CI97.5%   p-value
## 1194.6594    1.9600    0.0459    0.0229    2.0095    0.0011    0.0908    0.0445
##
## $est_rf
##           Coef   SE p.value SE.b CI.b2.5% CI.b97.5% p.value.b
## byr4647 0.0202 0.01  0.0441 0.01    6e-04      0.04     0.046
##
## $est_fs
##           Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## byr4647 0.4401 0.0127       0 0.0126   0.4144    0.4637         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 4389
##
## $N_cl
## NULL
##
## $df
## [1] 4361
##
## $nvalues
##      suppafford privpubins3r byr4647
## [1,]          2            2       2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Lorentzen et al. (2014)

Replication Summary	
Unit of analysis	city
Treatment	large firm dominance in 2007
Instrument	same variable measured in 1999
Outcome	pollution information transparency index
Model	Table1(2)

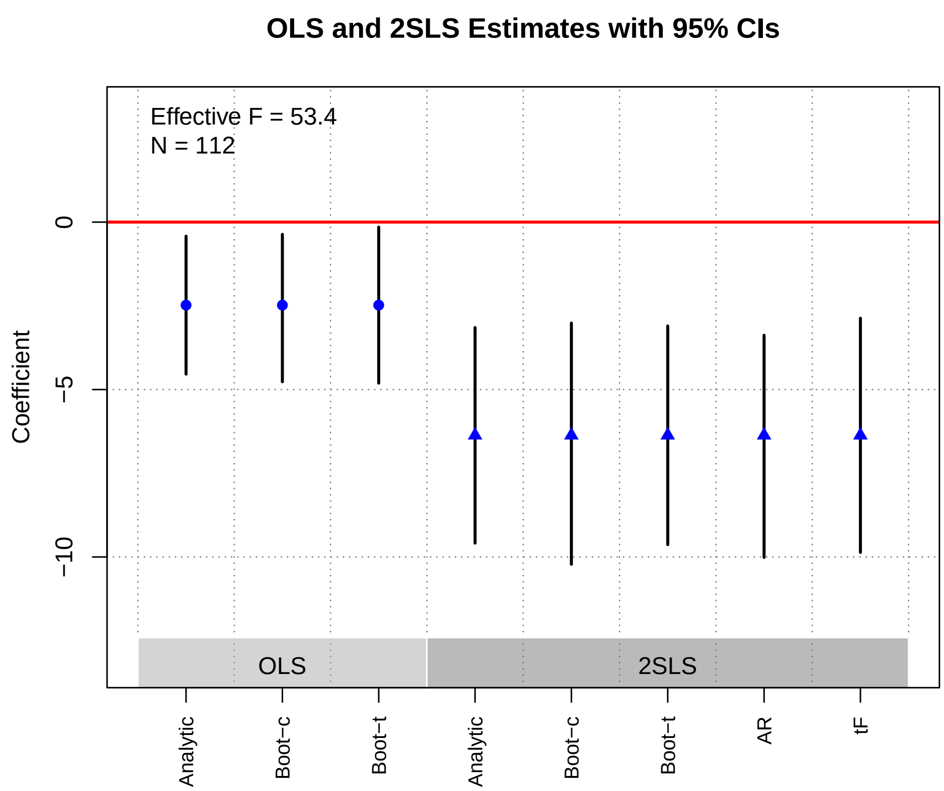
```
df<-readRDS("./data/jop_Lorentzen_2014.rds")
D <- "lfd2007"
Y <- "pitiave3"
Z <- "lfd99"
controls <- c("lbudgetrev", "lexpratio", "tertratio", "sat_air_pca")
cl <- NULL
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##              Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic -2.4789 1.0508 -2.359 -4.5385  -0.4193  0.0183
## Boot.c   -2.4789 1.0839 -2.287 -4.7685  -0.3650  0.0260
```

```
## Boot.t   -2.4789 1.0508 -2.359 -4.8087  -0.1490  0.0380
##
## $est_2sls
##             Coef     SE       t  CI 2.5% CI 97.5% p.value
## Analytic -6.3664 1.6421 -3.8769  -9.5850  -3.1478   1e-04
## Boot.c   -6.3664 1.8039 -3.5293 -10.2173  -3.0137   0e+00
## Boot.t   -6.3664 1.6421 -3.8769  -9.6326  -3.1002   0e+00
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##  17.3155   1.0000 110.0000   0.0001
##
## $AR$ci.print
## [1] "[-10.0120, -3.3777]"
##
## $AR$ci
## [1] -10.0120  -3.3777
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     53.6182     53.4100          NA     54.0367     53.4100
##
## $rho
## [1] 0.5796
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 53.4100  2.1292 -6.3664  1.6421 -3.8769 -9.8628 -2.8700  0.0004
##
## $est_rf
##          Coef     SE p.value  SE.b CI.b2.5% CI.b97.5% p.value.b
## lfd99 -3.4227 0.8379       0 0.869  -4.9598   -1.6119         0
##
## $est_fs
##         Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## lfd99 0.5376 0.0736       0 0.0731   0.3853    0.6695         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 112
```

```
##
## $N_cl
## NULL
##
## $df
## [1] 106
##
## $nvalues
##      pitiave3 lfd2007 lfd99
## [1,]      108     112   112
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Pianzola et al. (2019)

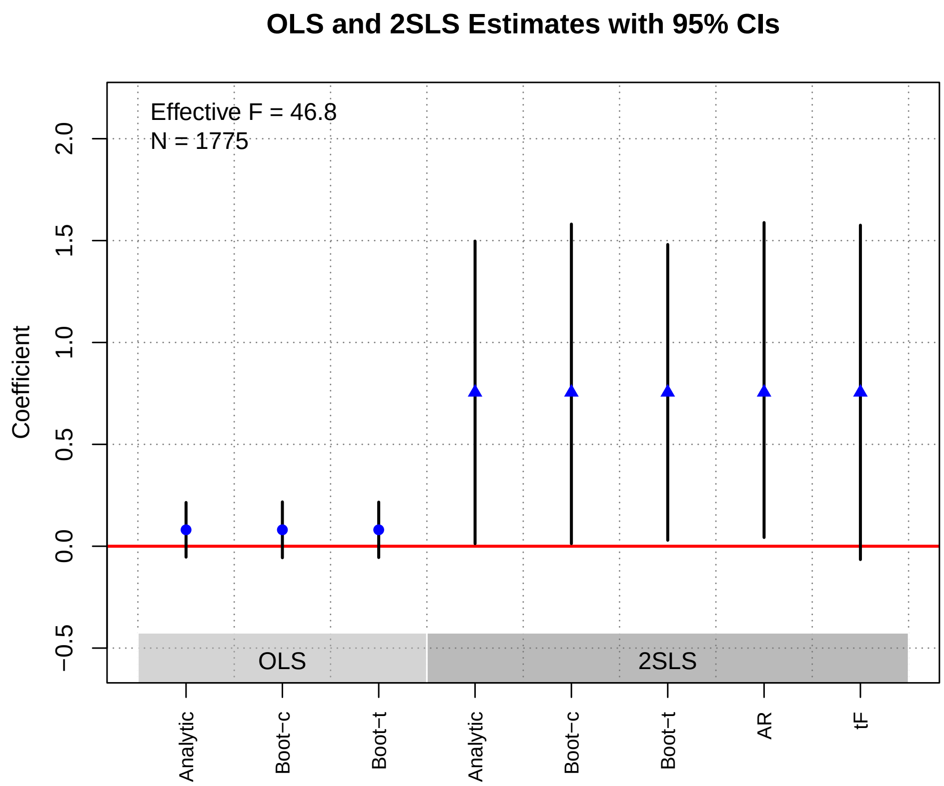
Replication Summary	
Unit of analysis	individual
Treatment	smartvote use
Instrument	random assignment of the e-mail treatment
Outcome	vote intentions
Model	Table4(3)

```r
df <- readRDS("./data/jop_Pianzola_etal_2019.rds")
D <- "smartvote"
Y <- "diff_top_ptv"
Z <- "email"
controls <- NULL
cl <- NULL
FE <- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0805 0.0684 1.1767 -0.0536   0.2146  0.2393
## Boot.c   0.0805 0.0693 1.1608 -0.0566   0.2175  0.2600
## Boot.t   0.0805 0.0684 1.1767 -0.0554   0.2164  0.2520
##
## $est_2sls
##           Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.755 0.3788 1.9934  0.0126   1.4974  0.0462
## Boot.c   0.755 0.4035 1.8710  0.0128   1.5809  0.0440
## Boot.t   0.755 0.3788 1.9934  0.0293   1.4808  0.0430
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    4.2767    1.0000 1773.0000    0.0388
##
## $AR$ci.print
## [1] "[0.0429, 1.5883]"
##
## $AR$ci
## [1] 0.0429 1.5883
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     46.7293     46.7612          NA     44.7324     46.7612
##
## $rho
## [1] 0.1602
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
```

```
## 46.7612  2.1662  0.7550  0.3788  1.9934 -0.0654  1.5755  0.0713
##
## $est_rf
##         Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## email 0.1032 0.0499  0.0386 0.0516   0.0016    0.2042     0.044
##
## $est_fs
##         Coef   SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## email 0.1367 0.02       0 0.0204   0.0956    0.1736         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 1775
##
## $N_cl
## NULL
##
## $df
## [1] 1773
##
## $nvalues
##      diff_top_ptv smartvote email
## [1,]           18         2     2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Schleiter and Tavits (2016)

Replication Summary	
Unit of analysis	election
Treatment	opportunistic election calling
Instrument	prime Minister dissolution power
Outcome	vote share of Prime Minister's party
Model	Table3(b4)

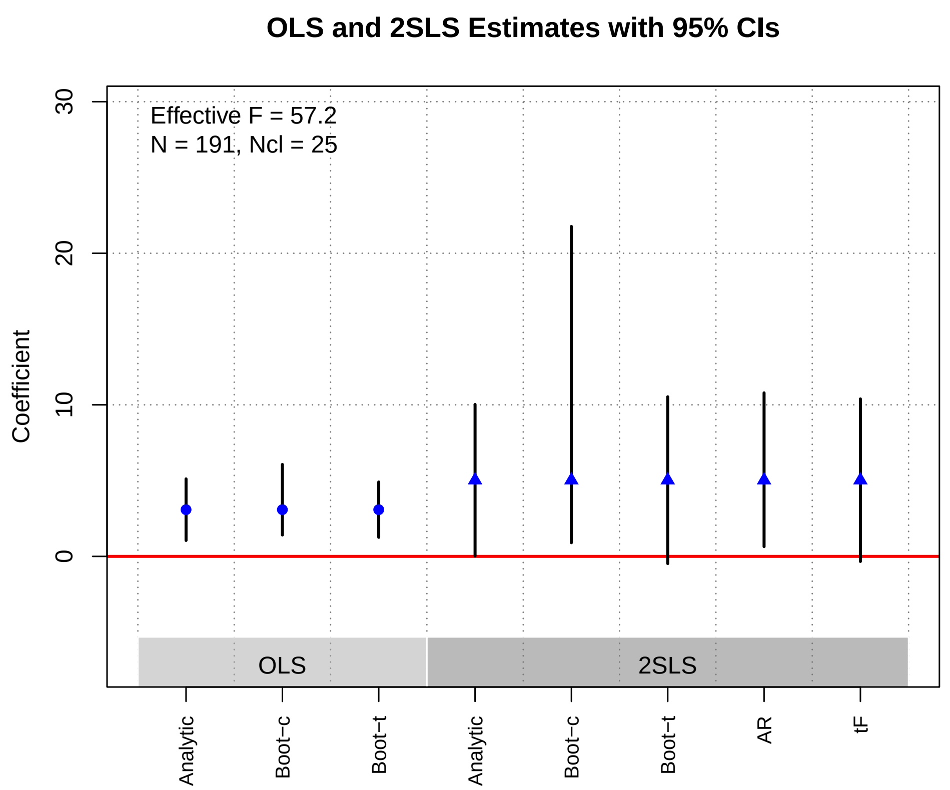
```
df<- readRDS("./data/jop_Schleiter_etal_2016.rds")
D <- "term2"
Y <- "pm_voteshare_next"
Z <- "disspm"
controls <- c("pm_voteshare", "gdp_chg1yr", "cpi1yr",  "dumcpi1yr")
cl <- "countryn"
FE <- "decade"
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 3.0828 1.0369 2.9730  1.0504   5.1152  0.0029
## Boot.c   3.0828 1.1687 2.6378  1.4097   6.0648  0.0000
```

```
## Boot.t   3.0828 1.0369 2.9730  1.2556   4.9100  0.0050
##
## $est_2sls
##            Coef      SE      t CI 2.5% CI 97.5% p.value
## Analytic 5.0282  2.5494 1.9723  0.0314  10.0250  0.0486
## Boot.c   5.0282 28.4027 0.1770  0.9022  21.7689  0.0220
## Boot.t   5.0282  2.5494 1.9723 -0.4756  10.5320  0.0670
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   5.1692   1.0000 189.0000   0.0241
##
## $AR$ci.print
## [1] "[0.6433, 10.7899]"
##
## $AR$ci
## [1]  0.6433 10.7899
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##    107.0322     75.6881     57.1949     23.2205     57.1949
##
## $rho
## [1] 0.6117
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 57.1949  2.1037  5.0282  2.5494  1.9723 -0.3350 10.3914  0.0661
##
## $est_rf
##          Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## disspm 0.3124 0.1412  0.0269 0.1953   0.0726    0.7915     0.004
##
## $est_fs
##          Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## disspm 0.0621 0.0082       0 0.0129   0.0242    0.0748     0.018
##
## $p_iv
## [1] 1
##
## $N
## [1] 191
```

```
##
## $N_cl
## [1] 25
##
## $df
## [1] 179
##
## $nvalues
##      pm_voteshare_next term2 disspm
## [1,]               157     2      6
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Schubiger (2021)

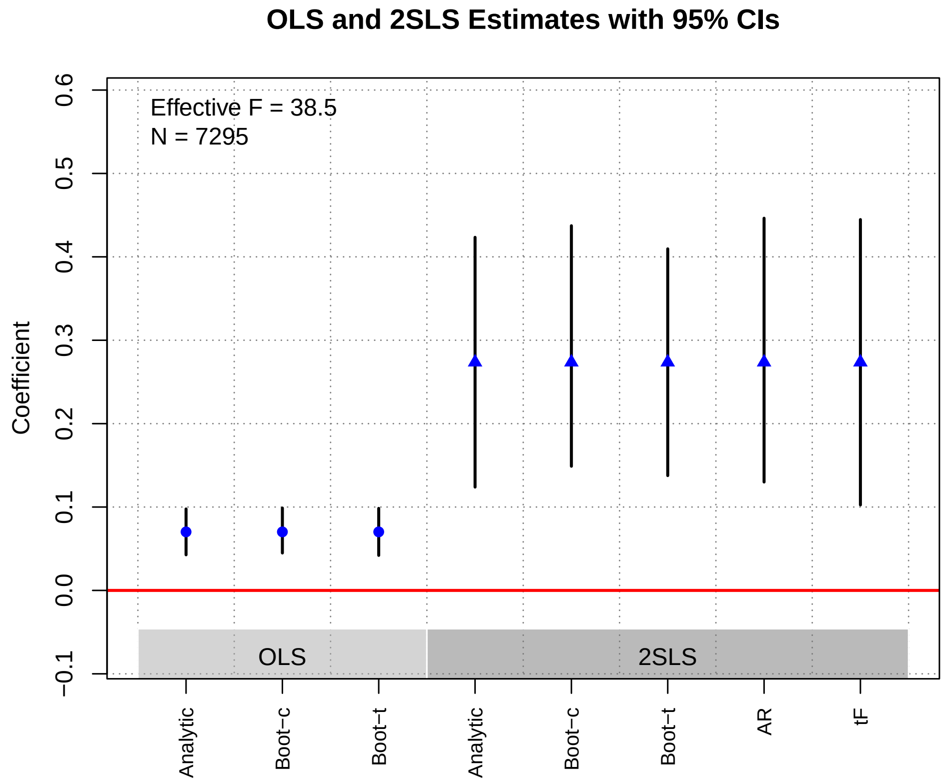
Replication Summary	
Unit of analysis	community
Treatment	exposure to state violence
Instrument	location of a community inside or outside the emergency zone
Outcome	counterinsurgent mobilization

```r
df <-readRDS("./data/jop_Schubiger_2021.rds")
D <- "violence_est_period2"
Y<-"autodefensa"
Z <- "emzone"
controls <-"distance"
cl<- NULL
FE<- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0702 0.0140 5.0069  0.0427   0.0977       0
## Boot.c   0.0702 0.0139 5.0376  0.0449   0.0988       0
## Boot.t   0.0702 0.0140 5.0069  0.0420   0.0984       0
##
## $est_2sls
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.2736 0.0764 3.5814  0.1239   0.4234   3e-04
## Boot.c   0.2736 0.0763 3.5854  0.1489   0.4373   0e+00
## Boot.t   0.2736 0.0764 3.5814  0.1377   0.4096   1e-03
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##   12.7351    1.0000 7293.0000    0.0004
##
## $AR$ci.print
## [1] "[0.1300, 0.4463]"
##
## $AR$ci
## [1] 0.1300 0.4463
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     39.9899     38.5348          NA     40.7383     38.5348
##
## $rho
## [1] 0.0739
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
```

```
## 38.5348  2.2392  0.2736  0.0764  3.5814  0.1025  0.4447  0.0017
##
## $est_rf
##          Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## emzone 0.0172 0.0048   4e-04 0.0046   0.0088    0.0265         0
##
## $est_fs
##          Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## emzone 0.0629 0.0101       0 0.0099   0.0443    0.0812         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 7295
##
## $N_cl
## NULL
##
## $df
## [1] 7292
##
## $nvalues
##      autodefensa violence_est_period2 emzone
## [1,]           2                    2      2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Stewart and Liou (2017)

Replication Summary	
Unit of analysis	insurgency*year
Treatment	foreign territory
Instrument	log total border length and the total number of that state's neighbors
Outcome	civilian casualties
Model	Table3(1)

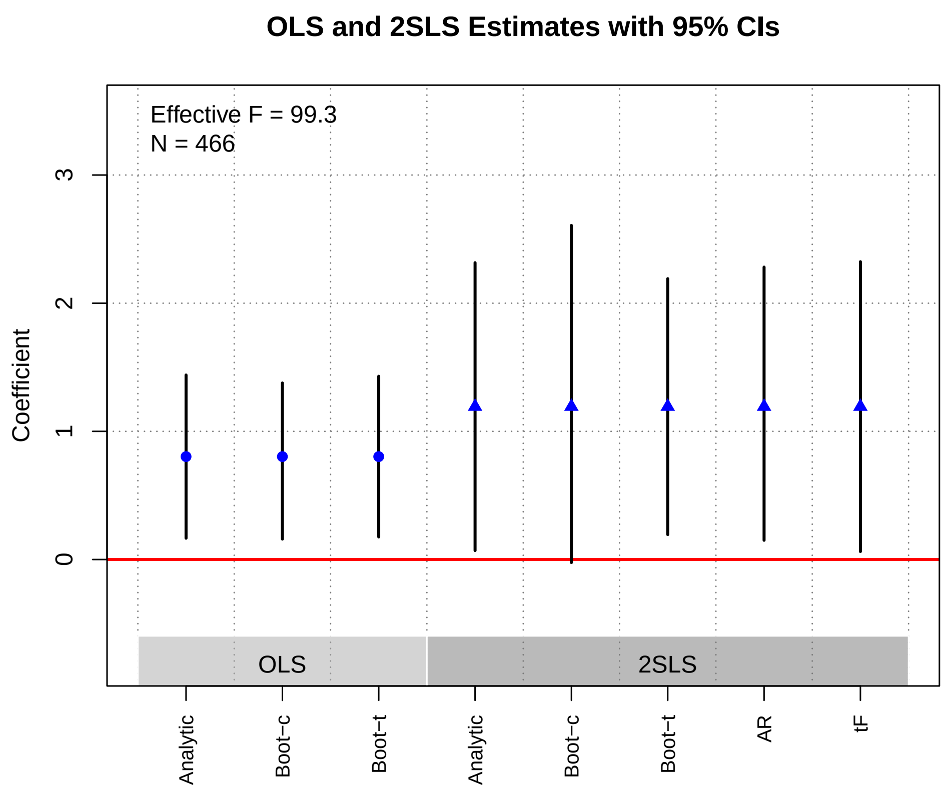
```
df <- readRDS("./data/jop_Stewart_2017.rds")
D <- "exterrdum_low"
Y <- "oneside_best_log"
Z <- "total_border_ln"
controls <- c("bd_log", "terrdum", "strengthcent_ord", "rebstrength_ord",
              'nonmilsupport', 'rebestsize', 'l1popdensity',
              'l1gdppc_log','l1gdppc_change')
cl <- NULL
FE <- c("year","countrynum")
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef      SE       t CI 2.5% CI 97.5% p.value
```

```
## Analytic 0.803 0.3249 2.4716  0.1662   1.4398  0.0135
## Boot.c   0.803 0.3197 2.5115  0.1593   1.3776  0.0160
## Boot.t   0.803 0.3249 2.4716  0.1759   1.4301  0.0120
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 1.1929 0.5730 2.0817  0.0698   2.3161  0.0374
## Boot.c   1.1929 1.3352 0.8935 -0.0238   2.6069  0.0560
## Boot.t   1.1929 0.5730 2.0817  0.1944   2.1914  0.0160
##
## $AR
## $AR$Fstat
##        F      df1      df2        p
##   5.0089   1.0000 464.0000   0.0257
##
## $AR$ci.print
## [1] "[0.1500, 2.2817]"
##
## $AR$ci
## [1] 0.1500 2.2817
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     33.9859     99.3150          NA     61.9897     99.3150
##
## $rho
## [1] 0.2786
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 99.3150  1.9734  1.1929  0.5730  2.0817  0.0621  2.3238  0.0387
##
## $est_rf
##                    Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## total_border_ln -7.0905 3.3952  0.0368 4.5209 -15.0266     0.144     0.056
##
## $est_fs
##                    Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## total_border_ln -5.9438 0.5964       0 0.7549  -7.2741    -4.616         0
##
## $p_iv
## [1] 1
##
```

```
## $N
## [1] 466
##
## $N_cl
## NULL
##
## $df
## [1] 404
##
## $nvalues
##      oneside_best_log exterrdum_low total_border_ln
## [1,]              113             2              45
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



Urpelainen and Zhang (2022)

Replication Summary	
Unit of analysis	district*year
Treatment	wind turbine capacity

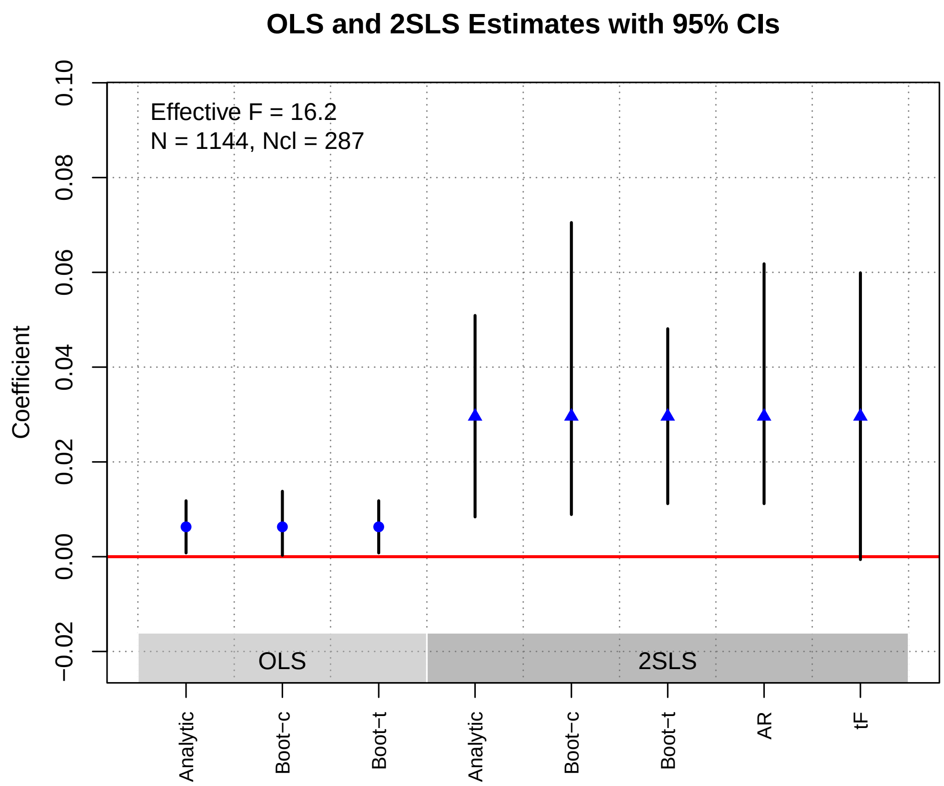
Replication Summary	
Instrument	time trend multiplied by the wind resource of the electoral district
Outcome	Democratic vote
Model	Table3(B1)

```
df <-readRDS("./data/jop_urpelainen_2022.rds")
D <- "cum_capacity_turbine"
Y<-"demvotesmajorpercent"
Z <- "inter"
controls <-NULL
cl<- "district_fixed"
FE<- c("stateyear_fixed","district_fixed")
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0063 0.0028 2.2395   8e-04   0.0118  0.0251
## Boot.c   0.0063 0.0034 1.8493   3e-04   0.0138  0.0360
## Boot.t   0.0063 0.0028 2.2395   8e-04   0.0118  0.0370
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0296 0.0109 2.7312  0.0084   0.0509  0.0063
## Boot.c   0.0296 0.0162 1.8305  0.0089   0.0705  0.0040
## Boot.t   0.0296 0.0109 2.7312  0.0112   0.0481  0.0040
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    9.5546    1.0000 1142.0000    0.0020
##
## $AR$ci.print
## [1] "[0.0112, 0.0618]"
##
## $AR$ci
## [1] 0.0112 0.0618
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
```

```
##     93.4366     27.8543     16.1654     15.4507     16.1654
##
## $rho
## [1] 0.3269
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 16.1654  2.7897  0.0296  0.0109  2.7312 -0.0006  0.0599  0.0550
##
## $est_rf
##         Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## inter 0.9095 0.2942   0.002 0.3085   0.2104    1.4265     0.004
##
## $est_fs
##          Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## inter 30.6883 7.6327   1e-04 7.8073  12.7978   42.9032         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 1144
##
## $N_cl
## [1] 287
##
## $df
## [1] 286
##
## $nvalues
##      demvotesmajorpercent cum_capacity_turbine inter
## [1,]                  965                  141   777
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Webster et al. (2022)

Replication Summary	
Unit of analysis	individual
Treatment	percentage of angry words that a respondent wrote in his or her emotional recall prompt
Instrument	treatment assignment indicator
Outcome	social polarization: do favors
Model	Table2(1)

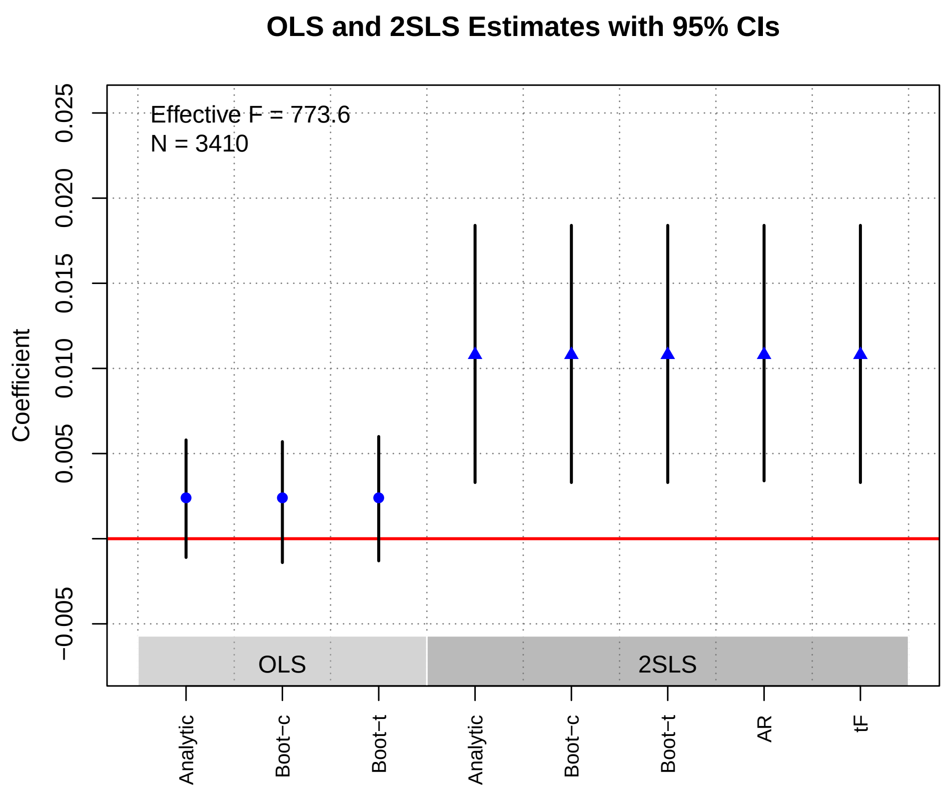
```
df <-readRDS("./data/jop_Webster_2022.rds")
D <- "anger"
Y<-"fourpack_1_01"
Z <- "treated"
controls <-"democrat"
cl<- NULL
FE<- NULL
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##             Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0024 0.0018 1.3413 -0.0011   0.0058  0.1798
```

```
## Boot.c   0.0024 0.0018 1.2898 -0.0014   0.0057  0.2060
## Boot.t   0.0024 0.0018 1.3413 -0.0013   0.0060  0.1910
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0108 0.0039 2.8123  0.0033   0.0184  0.0049
## Boot.c   0.0108 0.0039 2.7734  0.0033   0.0184  0.0100
## Boot.t   0.0108 0.0039 2.8123  0.0033   0.0184  0.0040
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    7.9872    1.0000 3408.0000    0.0047
##
## $AR$ci.print
## [1] "[0.0034, 0.0184]"
##
## $AR$ci
## [1] 0.0034 0.0184
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##    801.9232    773.5894          NA    779.5140    773.5894
##
## $rho
## [1] 0.4365
##
## $tF
##        F       cF     Coef       SE        t   CI2.5%  CI97.5%  p-value
## 773.5894   1.9600   0.0108   0.0039   2.8123   0.0033   0.0184   0.0049
##
## $est_rf
##          Coef    SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## treated 0.031 0.011  0.0047 0.0111   0.0094    0.0523      0.01
##
## $est_fs
##           Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## treated 2.8585 0.1028       0 0.1024   2.6694    3.0661         0
##
## $p_iv
## [1] 1
##
## $N
```

```
## [1] 3410
##
## $N_cl
## NULL
##
## $df
## [1] 3407
##
## $nvalues
##      fourpack_1_01 anger treated
## [1,]             5   252       2
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



West (2017)

Replication Summary	
Unit of analysis	individual
Treatment	Obama win
Instrument	IEM (prediction market) price
Outcome	political efficacy

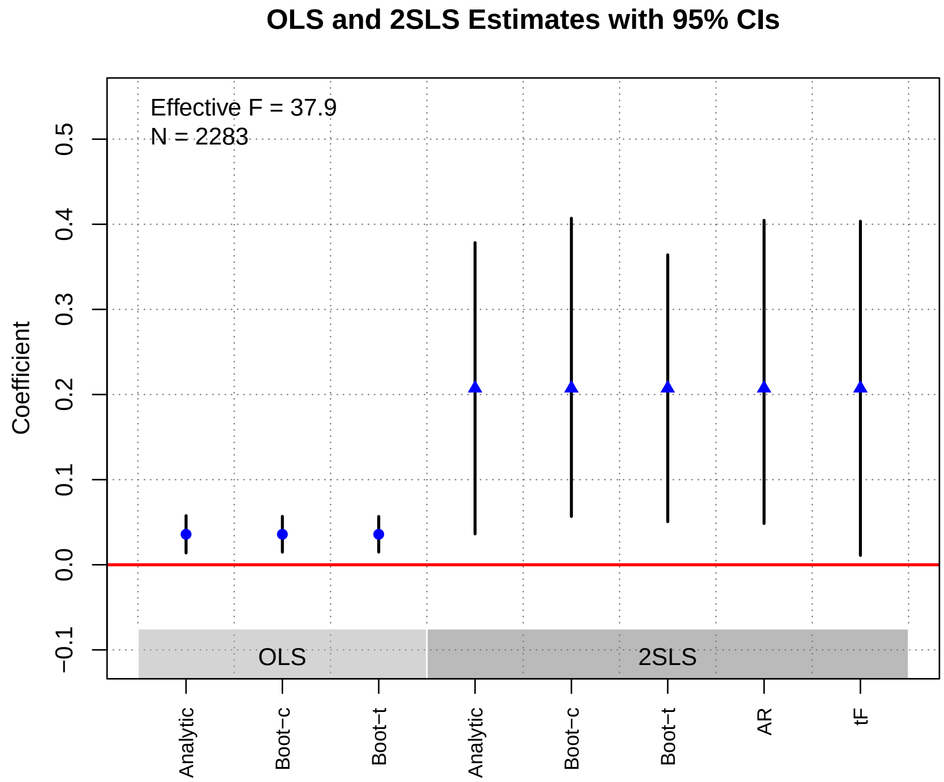
Replication Summary	
Model	Table1(4)

```
df<- readRDS("./data/jop_West_2017.rds")
D <- "obama"
Y <- "newindex"
Z <- "avgprice"
controls <- c("partyd1", "partyd2", "partyd3",
              "partyd4", "partyd5", "wa01_a", "wa02_a",
              "wa03_a", "wa04_a", "wa05_a",   "wfc02_a",
              "ra01_b",  "rd01", "wd02_b", "rkey",
              "wave_1", "dt_w12", "dt_w12_2")
cl <- NULL
FE <- c("state","religion")
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.0358 0.0112 3.2084  0.0139   0.0577  0.0013
## Boot.c   0.0358 0.0113 3.1796  0.0148   0.0568  0.0000
## Boot.t   0.0358 0.0112 3.2084  0.0149   0.0567  0.0000
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.2073 0.0873 2.3758  0.0363   0.3784  0.0175
## Boot.c   0.2073 0.0912 2.2726  0.0568   0.4071  0.0080
## Boot.t   0.2073 0.0873 2.3758  0.0506   0.3641  0.0060
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    6.5244    1.0000 2281.0000    0.0107
##
## $AR$ci.print
## [1] "[0.0485, 0.4046]"
##
## $AR$ci
## [1] 0.0485 0.4046
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
```

```
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##     41.7917     37.8652          NA     38.8778     37.8652
##
## $rho
## [1] 0.1362
##
## $tF
##       F      cF    Coef      SE       t  CI2.5% CI97.5% p-value
## 37.8652  2.2493  0.2073  0.0873  2.3758  0.0110  0.4036  0.0384
##
## $est_rf
##            Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## avgprice 0.1407 0.0559  0.0119 0.0547   0.0361    0.2459     0.008
##
## $est_fs
##            Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## avgprice 0.6784 0.1103       0 0.1088   0.4526    0.8865         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 2283
##
## $N_cl
## NULL
##
## $df
## [1] 2211
##
## $nvalues
##      newindex obama avgprice
## [1,]      122     2      141
##
## attr(,"class")
## [1] "ivDiag"
```

```r
plot_coef(g)
```



Ziaja (2020)

Replication Summary	
Unit of analysis	country*year
Treatment	number of democracy donors
Instrument	constructed instrument
Outcome	democracy scores
Model	Table1(B2)

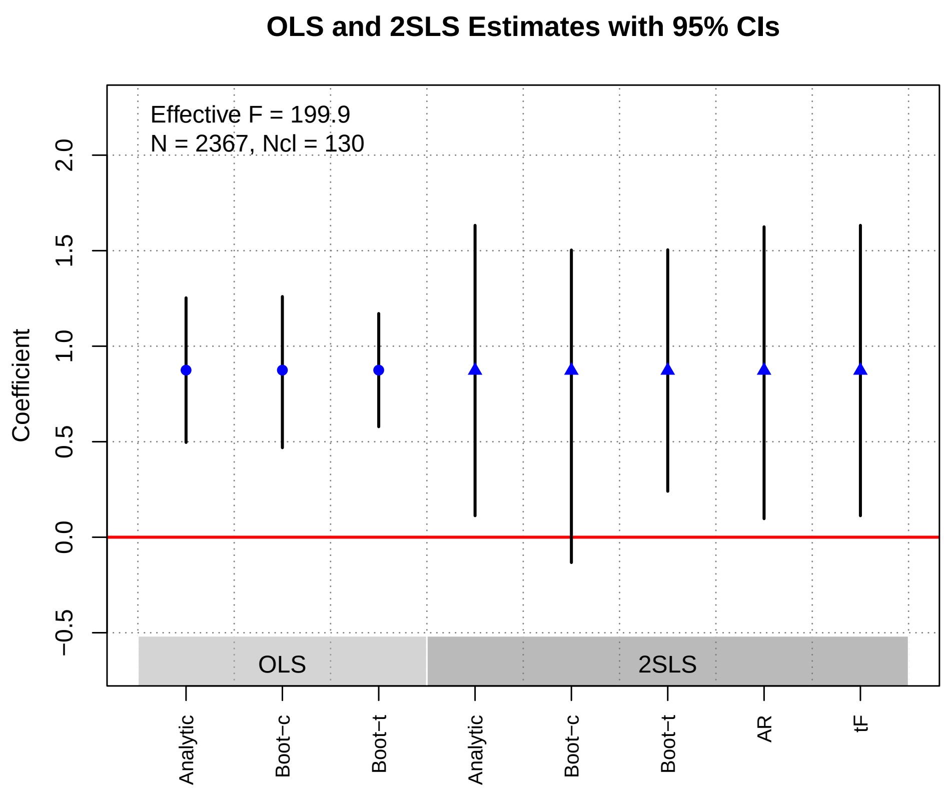
```
df <-readRDS("./data/jop_Ziaja_2020.rds")
D <- "l.CMgnh"
Y <- "v2x.polyarchy.n"
Z <- "l.ZwvCMgwh94"
controls <-c("l.pop.log.r", "l.gdpcap.log.r", "l.war25")
cl<- "cnamef"
FE<- c("cnamef", "periodf")
weights<-NULL
(g<-ivDiag(data=df, Y=Y, D=D, Z=Z, controls=controls, FE =FE,
  cl =cl,weights=weights, cores = cores))
```

```
## $est_ols
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.8746 0.1931 4.5298  0.4962    1.2531       0
## Boot.c   0.8746 0.2013 4.3455  0.4686    1.2597       0
```

```
## Boot.t   0.8746 0.1931 4.5298  0.5784   1.1709       0
##
## $est_2sls
##            Coef     SE      t CI 2.5% CI 97.5% p.value
## Analytic 0.8726 0.3877 2.2505  0.1126   1.6325  0.0244
## Boot.c   0.8726 0.4150 2.1026 -0.1325   1.5034  0.0940
## Boot.t   0.8726 0.3877 2.2505  0.2406   1.5046  0.0040
##
## $AR
## $AR$Fstat
##         F       df1       df2         p
##    4.8018    1.0000 2365.0000    0.0285
##
## $AR$ci.print
## [1] "[0.0971, 1.6248]"
##
## $AR$ci
## [1] 0.0971 1.6248
##
## $AR$bounded
## [1] TRUE
##
##
## $F_stat
##  F.standard    F.robust   F.cluster F.bootstrap F.effective
##   1158.1467    775.0850    199.9166    215.1208    199.9166
##
## $rho
## [1] 0.586
##
## $tF
##        F       cF     Coef       SE        t   CI2.5%  CI97.5%  p-value
## 199.9166   1.9600   0.8726   0.3877   2.2505   0.1126   1.6325   0.0244
##
## $est_rf
##                 Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## l.ZwvCMgwh94 0.0599 0.0273  0.0285 0.0299  -0.0086    0.1088     0.094
##
## $est_fs
##                 Coef     SE p.value   SE.b CI.b2.5% CI.b97.5% p.value.b
## l.ZwvCMgwh94 0.0686 0.0049       0 0.0047   0.0616    0.0799         0
##
## $p_iv
## [1] 1
##
## $N
## [1] 2367
```

```
##
## $N_cl
## [1] 130
##
## $df
## [1] 129
##
## $nvalues
##      v2x.polyarchy.n l.CMgnh l.ZwvCMgwh94
## [1,]            2038      24         2283
##
## attr(,"class")
## [1] "ivDiag"
```

```
plot_coef(g)
```



References

Acharya, A., Blackwell, M., and Sen, M. (2016). The political legacy of american slavery. *The Journal of Politics*, 78(3):621–641. Publisher: University of Chicago Press Chicago, IL. Cited on pages 2 and 105.

Alt, J., Marshall, J., and Lassen, D. (2016). Credible sources and sophisticated voters: when does new information induce economic voting? *The Journal of Politics*, 78(2):327–342. Publisher: University of Chicago Press Chicago, IL. Cited on pages 2 and 108.

Arias, E. and Stasavage, D. (2019). How large are the political costs of fiscal austerity? *The Journal of Politics*, 81(4):1517–1522. Cited on pages 2 and 110.

Baccini, L. and Weymouth, S. (2021). Gone for good: Deindustrialization, white voter backlash, and us presidential voting. *American Political Science Review*, 115(2):550–567. Cited on pages 1 and 5.

Barth, E., Finseraas, H., and Moene, K. (2015). Political reinforcement: how rising inequality curbs manifested welfare generosity. *American Journal of Political Science*, 59(3):565–577. Publisher: Wiley Online Library. Cited on pages 1 and 42.

Bhavnani, R. and Lee, A. (2018). Local embeddedness and bureaucratic performance: evidence from india. *The Journal of Politics*, 80(1):71–87. Publisher: University of Chicago Press Chicago, IL. Cited on pages 2 and 113.

Blair, R. A., Di Salvatore, J., and Smidt, H. M. (2022). When do un peacekeeping operations implement their mandates? *American Journal of Political Science*, 66(3):664–680. Cited on pages 1 and 45.

Blattman, C., Hartman, A., and Blair, R. (2014). How to promote order and property rights under weak rule of law? an experiment in changing dispute resolution behavior through community education. *American Political Science Review*, page 100–120. Publisher: JSTOR. Cited on pages 1 and 7.

Carnegie, A. and Marinov, N. (2017). Foreign aid, human rights, and democracy promotion: Evidence from a natural experiment. *American Journal of Political Science*, 61(3):671–683. Publisher: Wiley Online Library. Cited on pages 1 and 47.

Charron, N., Dahlström, C., Fazekas, M., and Lapuente, V. (2017). Careers, connections, and corruption risks: Investigating the impact of bureaucratic meritocracy on public procurement processes. *The Journal of Politics*, 79(1):89–104. Publisher: University of Chicago Press Chicago, IL. Cited on pages 2 and 118.

Charron, N. and Lapuente, V. (2013). Why do some regions in europe have a higher quality of government? *The Journal of Politics*, 75(3):567–582. Publisher: Cambridge University Press New York, USA. Cited on pages 2 and 115.

Chong, A., León-Ciliotta, G., Roza, V., Valdivia, M., and Vega, G. (2019). Urbanization patterns, information diffusion, and female voting in rural paraguay. *American Journal of Political Science*, 63(2):323–341. Publisher: Wiley Online Library. Cited on pages 1 and 50.

Cirone, A. and Van Coppenolle, B. (2018). Cabinets, committees, and careers: the causal effect of committee service. *The Journal of Politics*, 80(3):948–963. Publisher: University of Chicago Press Chicago, IL. Cited on pages 2 and 120.

Colantone, I. and Stanig, P. (2018). Global competition and brexit. *American political science review*, 112(2):201–218. Cited on pages 1 and 10.

Colantone, I. and Stanig, P. (2018). The trade origins of economic nationalism: Import competition and voting behavior in western europe. *American Journal of Political Science*, 62(4):936–953. Publisher: Wiley Online Library. Cited on pages 1 and 53.

Coppock, A. and Green, D. (2016). Is voting habit forming? new evidence from experiments and regression discontinuities. *American Journal of Political Science*, 60(4):1044–1062. Publisher: Wiley Online Library. Cited on pages 1 and 55.

Croke, K., Grossman, G., Larreguy, H., and Marshall, J. (2016). Deliberate disengagement: How education can decrease political participation in electoral authoritarian regimes. *American Political Science Review*, 110(3):579–600. Publisher: Cambridge University Press. Cited on pages 1 and 12.

De La O, A. (2013). Do conditional cash transfers affect electoral behavior? evidence from a randomized experiment in mexico. *American Journal of Political Science*, 57(1):1–14. Publisher: Wiley Online Library. Cited on pages 1 and 58.

Dietrich, S. and Wright, J. (2015). Foreign aid allocation tactics and democratic change in africa. *The Journal of Politics*, 77(1):216–234. Publisher: University of Chicago Press Chicago, IL. Cited on pages 2 and 123.

DiGiuseppe, M. and Shea, P. E. (2022). Us patronage, state capacity, and civil conflict. *The Journal of Politics*, 84(2):767–782. Cited on pages 2 and 126.

Dower, P., Finkel, E., Gehlbach, S., and Nafziger, S. (2018). Collective action and representation in autocracies: Evidence from russia's great reforms. *American Political Science Review*, 112(1):125–147. Publisher: Cambridge University Press. Cited on pages 1, 15 and 17.

Dube, O. and Naidu, S. (2015). Bases, bullets, and ballots: The effect of us military aid on political conflict in colombia. *The Journal of Politics*, 77(1):249–267. Publisher: University of Chicago Press Chicago, IL. Cited on pages 2 and 128.

Feigenbaum, J. and Hall, A. (2015). How legislators respond to localized economic shocks: Evidence from chinese import competition. *The Journal of Politics*, 77(4):1012–1030. Publisher: University of Chicago Press Chicago, IL. Cited on pages 2 and 131.

Flores-Macias, G. and Kreps, S. (2013). The foreign policy consequences of trade: China's commercial relations with africa and latin america, 1992–2006. *The Journal of Politics*, 75(2):357–371. Publisher: Cambridge University Press New York, USA. Cited on pages 2 and 133.

Gehlbach, S. and Keefer, P. (2012). Private investment and the institutionalization of collective action in autocracies: ruling parties and legislatures. *The Journal of Politics*, 74(2):621–635. Publisher: Cambridge University Press New York, USA. Cited on pages 2 and 136.

Gerber, A., Huber, G., and Washington, E. (2010). Party affiliation, partisanship, and political beliefs: A field experiment. *American Political Science Review*, 104(4):720–744. Publisher: Cambridge University Press. Cited on pages 1 and 20.

Goldstein, R. and You, H. (2017). Cities as lobbyists. *American Journal of Political Science*, 61(4):864–876. Publisher: Wiley Online Library. Cited on pages 2 and 60.

Grossman, G., Pierskalla, J., and Boswell Dean, E. (2017). Government fragmentation and public goods provision. *The Journal of Politics*, 79(3):823–840. Publisher: University of Chicago Press Chicago, IL. Cited on pages 2 and 138.

Hager, A. and Hilbig, H. (2019). Do inheritance customs affect political and social inequality? *American Journal of Political Science*, 63(4):758–773. Publisher: Wiley Online Library. Cited on pages 2, 63 and 65.

Hager, A. and Krakowski, K. (2022). Does state repression spark protests? evidence from secret police surveillance in communist poland. *American Political Science Review*, 116(2):564–579. Cited on pages 1 and 25.

Hager, A., Krakowski, K., and Schaub, M. (2019). Ethnic riots and prosocial behavior: Evidence from kyrgyzstan. *American Political Science Review*, 113(4):1029–1044. Cited on pages 1 and 22.

Healy, A. and Malhotra, N. (2013). Childhood socialization and political attitudes: Evidence from a natural experiment. *The Journal of Politics*, 75(4):1023–1037. Publisher: Cambridge University Press New York, USA. Cited on pages 2 and 141.

Henderson, J. and Brooks, J. (2016). Mediating the electoral connection: The information effects of voter signals on legislative behavior. *The Journal of Politics*, 78(3):653–669. Cited on pages 2, 144 and 146.

Hong, J. Y., Park, S., and Yang, H. (2022). In strongman we trust: The political legacy of the new village movement in south korea. *American Journal of Political Science*. Cited on pages 2 and 68.

Johns, L. and Pelc, K. (2016). Fear of crowds in world trade organization disputes: Why don't more countries participate? *The Journal of Politics*, 78(1):88–104. Publisher: University of Chicago Press Chicago, IL. Cited on pages 2 and 149.

Kapoor, S. and Magesan, A. (2018). Independent candidates and political representation in india. *American Political Science Review*, 112(3):678–697. Publisher: Cambridge University Press. Cited on pages 1 and 27.

Kim, J. (2019). Direct democracy and women's political engagement. *American Journal of Political Science*, 63(3):594–610. Publisher: Wiley Online Library. Cited on pages 2 and 70.

Kocher, M., Pepinsky, T., and Kalyvas, S. (2011). Aerial bombing and counterinsurgency in the vietnam war. *American Journal of Political Science*, 55(2):201–218. Publisher: Wiley Online Library. Cited on pages 2 and 73.

Kriner, D. and Schickler, E. (2014). Investigating the president: Committee probes and presidential approval, 1953–2006. *The Journal of Politics*, 76(2):521–534. Publisher: Cambridge University Press New York, USA. Cited on pages 2 and 151.

Kuipers, N. and Sahn, A. (2022). The representational consequences of municipal civil service reform. *American Political Science Review*, pages 1–17. Cited on pages 1 and 30.

Laitin, D. and Ramachandran, R. (2016). Language policy and human development. *American Political Science Review*, 110(3):457–480. Publisher: Cambridge University Press. Cited on pages 1 and 32.

Lei, Z. and Zhou, J. A. (2022). Private returns to public investment: Political career incentives and infrastructure investment in china. *The Journal of Politics*, 84(1):455–469. Cited on pages 2 and 154.

Lelkes, Y., Sood, G., and Iyengar, S. (2017). The hostile audience: The effect of access to broadband internet on partisan affect. *American Journal of Political Science*, 61(1):5–20. Publisher: Wiley Online Library. Cited on pages 2 and 75.

Lerman, A., Sadin, M., and Trachtman, S. (2017). Policy uptake as political behavior: evidence from the affordable care act. *The American Political Science Review*, 111(4):755. Publisher: Cambridge University Press. Cited on pages 2 and 156.

López-Moctezuma, G., Wantchekon, L., Rubenson, D., Fujiwara, T., and Pe Lero, C. (2020). Policy deliberation and voter persuasion: Experimental evidence from an election in the philippines. *American Journal of Political Science*. Cited on pages 2 and 78.

Lorentzen, P., Landry, P., and Yasuda, J. (2014). Undermining authoritarian innovation: the power of china's industrial giants. *The Journal of Politics*, 76(1):182–194. Publisher: Cambridge University Press New York, USA. Cited on pages 2 and 159.

McClendon, G. (2014). Social esteem and participation in contentious politics: A field experiment at an lgbt pride rally. *American Journal of Political Science*, 58(2):279–290. Publisher: Wiley Online Library. Cited on pages 2 and 80.

Meredith, M. (2013). Exploiting friends-and-neighbors to estimate coattail effects. *American Political Science Review*, page 742–765. Publisher: JSTOR. Cited on pages 1 and 35.

Nellis, G. and Siddiqui, N. (2018). Secular party rule and religious violence in pakistan. *The American Political Science Review*, 112(1):49. Publisher: Cambridge University Press. Cited on pages 1 and 37.

Pianzola, J., Trechsel, A., Vassil, K., Schwerdt, G., and Alvarez, R. (2019). The impact of personalized information on vote intention: Evidence from a randomized field experiment. *The Journal of Politics*, 81(3):833–847. Publisher: The University of Chicago Press Chicago, IL. Cited on pages 2 and 161.

Ritter, E. and Conrad, C. (2016). Preventing and responding to dissent: The observational challenges of explaining strategic repression. *American Political Science Review*, 110(1):85–99. Publisher: Cambridge University Press. Cited on pages 1 and 40.

Rueda, M. (2017). Small aggregates, big manipulation: Vote buying enforcement and collective monitoring. *American Journal of Political Science*, 61(1):163–177. Publisher: Wiley Online Library. Cited on pages 2 and 83.

Schleiter, P. and Tavits, M. (2016). The electoral benefits of opportunistic election timing. *The Journal of Politics*, 78(3):836–850. Publisher: University of Chicago Press Chicago, IL. Cited on pages 2 and 164.

Schubiger, L. I. (2021). State violence and wartime civilian agency: Evidence from peru. *The Journal of Politics*, 83(4):1383–1398. Cited on pages 2 and 166.

Sexton, R., Wellhausen, R., and Findley, M. (2019). How government reactions to violence worsen social welfare: evidence from peru. *American Journal of Political Science*, 63(2):353–367. Publisher: Wiley Online Library. Cited on pages 2 and 85.

Spenkuch, J. and Tillmann, P. (2018). Elite influence? religion and the electoral success of the nazis. *American Journal of Political Science*, 62(1):19–36. Publisher: Wiley Online Library. Cited on pages 2 and 88.

Stewart, M. and Liou, Y. (2017). Do good borders make good rebels? territorial control and civilian casualties. *The Journal of Politics*, 79(1):284–301. Publisher: University of Chicago Press Chicago, IL. Cited on pages 2 and 169.

Stokes, L. (2016). Electoral backlash against climate policy: A natural experiment on retrospective voting and local resistance to public policy. *American Journal of Political Science*, 60(4):958–974. Publisher: Wiley Online Library. Cited on pages 2 and 90.

Tajima, Y. (2013). The institutional basis of intercommunal order: Evidence from indonesia's democratic transition. *American Journal of Political Science*, 57(1):104–119. Publisher: Wiley Online Library. Cited on pages 2 and 93.

Trounstine, J. (2016). Segregation and inequality in public goods. *American Journal of Political Science*, 60(3):709–725. Publisher: Wiley Online Library. Cited on pages 2 and 95.

Urpelainen, J. and Zhang, A. T. (2022). Electoral backlash or positive reinforcement? wind power and congressional elections in the united states. *The Journal of Politics*, 84(3):1306–1321. Cited on pages 2 and 171.

Vernby, K. (2013). Inclusion and public policy: Evidence from sweden's introduction of noncitizen suffrage. *American Journal of Political Science*, 57(1):15–29. Publisher: Wiley Online Library. Cited on pages 2 and 98.

Webster, S. W., Connors, E. C., and Sinclair, B. (2022). The social consequences of political anger. *The Journal of Politics*, 84(3):1292–1305. Cited on pages 3 and 174.

West, E. (2017). Descriptive representation and political efficacy: Evidence from obama and clinton. *The Journal of Politics*, 79(1):351–355. Publisher: University of Chicago Press Chicago, IL. Cited on pages 3 and 176.

Wood, A. K. and Grose, C. R. (2022). Campaign finance transparency affects legislators' election outcomes and behavior. *American Journal of Political Science*, 66(2):516–534. Cited on pages 2 and 100.

Zhu, B. (2017). Mncs, rents, and corruption: Evidence from china. *American Journal of Political Science*, 61(1):84–99. Publisher: Wiley Online Library. Cited on pages 2 and 103.

Ziaja, S. (2020). More donors, more democracy. *The Journal of Politics*, 82(2):433–447. Publisher: The University of Chicago Press Chicago, IL. Cited on pages 3 and 179.