Section A: Case Selection

Internet penetration varies widely across the sample. Japan and the United States both have high levels of internet access, with penetration rates above 90%, reflecting mature digital infrastructures and widespread digital literacy. In contrast, Nigeria's internet penetration remains comparatively low, at around 40%, reflecting infrastructure challenges and higher costs of access, which can skew online samples toward wealthier, more urban populations. India and the Philippines fall in the middle of this spectrum, with rapidly growing internet user bases but significant rural-urban digital divides.

The cases also span a wide range of corruption levels and institutional capacity. According to Transparency International's Corruption Perceptions Index, Brazil, Nigeria, and the Philippines rank relatively poorly, with persistent governance challenges and high levels of perceived public sector corruption. For instance, Brazil ranked 94th, Nigeria 154th, and the Philippines 117th out of 180 countries in 2021, indicating significant challenges in transparency and accountability. In contrast, Japan and the United States score much higher on institutional strength and rule of law, creating different baseline conditions for political trust and participation (Transparency International 2023).

The cases also vary significantly in terms of democratic consolidation, which allows us to look for evidence of cross-platform differences across both long-established and more fragile systems. According to Freedom House (2024), the United States scores 83/100 and Japan 96/100, placing them at the high end of democratic performance, though both have faced recent debates over institutional resilience. By contrast, the Philippines scores 55/100 and India 66/100, reflecting measurable declines in political rights and civil liberties tied to constraints on media, civil society, and minority protections. Nigeria scores 45/100, consistent with its status as a relatively young democracy marked by recurring electoral violence and institutional weakness.

Economic development levels also vary widely. The United States and Japan are advanced, high-income economies, while India and Nigeria remain lower-middle-income countries with significant income inequality and large informal sectors. Brazil and the Philippines fall in the upper-middle-income range but face high levels of economic inequality and regional disparities, which can affect survey representativeness and response rates (World Bank 2025).

Finally, the cases differ in their levels of ethnic and cultural diversity. Nigeria, India, and the Philippines have high levels of ethnic fractionalization, with Alesina et al.'s index (2003) reporting scores above 0.7 on a 0–1 scale. This diversity presents challenges for survey sampling, as subgroup representation can significantly impact the accuracy of public opinion measures. In contrast, Japan is one of the world's most ethnically homogeneous societies, reducing the risk of subgroup bias but potentially limiting the generalizability of findings.

Section B: Further Information on Survey Protocols

Further Information on Morning Consult Sampling Procedures

Morning Consult recruits survey respondents from multiple online panels. Recruitment methods and compensation vary by panel, which Morning Consult argues allows them to reach a broader range of respondents and minimizes the risk of systematically missing respondents who might not be reached by a single recruitment method or who might be more or less responsive to a single type of compensation. Morning Consult employs quotas during recruitment to match the composition of the target population. Morning Consult also employs a range of quality assurance measures before, during, and after fielding. These include digital fingerprinting to guard against duplicate respondents, various checks to ensure that opt-in respondents meet eligibility criteria, checks for speeding and straightlining, and multiple fraud detection techniques. The data are then weighted to match the target population using iterative proportional fitting (raking).

Survey Weights

Morning Consult created survey weights for each of the six countries in our sample. The demographics weighted on varied across countries. In Brazil and the Philippines, the data were weighted on gender, age, education, and region. In India, Japan, and Nigeria, the data were weighted on gender, age, and region. In the United States, the data were weighted on age, gender, gender/age, region, race, ethnicity, education, race/education, and ethnicity/education.

For our Lucid samples, we create survey weights using the same set of demographic characteristics across all six countries. Specifically, we weighted on: age (i.e. the percentage of adults between the ages of 18-24; 25-44; 45-64; and 65+); gender; race; and ethnicity. SI Table1 summarizes the sources used to obtain population estimates for each demographic factor across countries. Given the extreme disparities between the percentage of respondents with a college degree in India, the Philippines, and Nigeria, and the true population parameters, the weights reported in the text do not weight on educational attainment. Alternate analyses with weights including educational attainment yield similar results.

Morning Consult Screeners

Morning Consult employed two screener questions. The first (with varying numbers) was of the form: "A boy had two marbles and lost one. How many marbles does the boy have now?" Respondents were required to enter a numerical answer. The second asked "How often do you…" followed by a series of choices that varied somewhat across countries. Common options included "Use Instagram" and "Use YouTube". Respondents could then choose between "several times a day", "about once a day", "a few times a week", "about once a week", "at least once a month or less often" and "I do not have an account or do not use." One or two of the options, depending on country, referenced a media source that does not exist (e.g. "Use Appleton Post-Dispatch"). Respondents who did not choose the last response option ("I do not have an account or do not use") failed the screener. Survey-takers who failed either or both screeners were then exited from the survey. We included the same screeners and the same exit procedures with our Lucid sample.

Section C: Attention Check and Survey Frequency Question

Shortly after the midpoint of the survey, we included a standard attention check used in the literature (Aronow et al. 2020; Ternovksi and Orr 2022; Gerver, Banerjee, and John 2024). Respondents read the following instructions:

> People are very busy these days and many do not have time to follow what goes on in the government. We are testing whether people read questions. To show that you've read this much, answer both "extremely interested" and "very interested."

Response choices were extremely interested, very interested, moderately interested, somewhat interested, and not at all interested. Respondents who correctly followed the instruction and selected the first two responses were coded as having passed the attention check. Respondents who failed the attention check were not exited from the survey and their responses are included in all analyses.

To compare the percentage of respondents who are frequent survey takers across countries and platforms we asked all respondents, "How many surveys do you answer on a typical week?" Answers were required to be numerical.

Section D: Demographic Comparisons and Benchmarks

Figure 2 in the manuscript compares sample demographics across countries on three dimensions, % female, median age, and % college degree, to population benchmarks. SI Table 1 summarizes the sources of information for our population benchmarks. Most sources report population median ages, not median ages for adults. Thus, survey sample median ages (where all respondents are 18 plus) will almost always be considerably higher than population median ages. To estimate each country's adult median age, we used population pyramid data from the World Health Organization. From the 15-19 age bracket, we estimate the population in the 18-19 year range as 40% of the bracket total. For each country we then identify the median five-year age bracket on the population pyramid and estimate the adult median age as the mid-point of that age bracket (e.g. if the median bracket was ages 25-30, we estimated the median age as 27.5).

Partisanship Comparisons

Figure 3 in the manuscript compares the percentage of respondents in each of our surveys that reported for the two top-performing parties in the last general election. As we discuss in the manuscript text, two outliers stand out. The nature of the 2022 elections in Brazil complicate benchmark comparisons as that year there was a presidential election (Lula [PT] vs. Bolsinaro [PL]); all 513 seats in the Chamber of Deputies were up for grabs; as were 27 of 81 seats in the federal Senate. The Morning Consult question, which we replicated precisely on Lucid, asked: "In the 2022 general elections, which party did you vote for?" The question listed 8 parties, an "other" option, as well as "I did not vote." Given the range of party options, the question would seem to imply it is asking about vote choice in the Chamber of Deputies elections. However, many respondents may well have responded based on how they voted in the presidential race, in which Lula [PT] received 50.9% of the vote and Bolsinaro [PL] received 49.1% of the vote in the final run-off. These are the benchmarks we included in the figure. Alternately, the PL received 16.6% of the vote in the Chamber of Deputies election and the FE Brasil coalition (dominated by PT) received 14%.

In India, both MC and Lucid significantly over-estimate support for BJP, which we note. Post-2024 election analyses note that the BJP maintained its strength in urban areas in 2024, but lost ground in rural constituencies. The survey included a question in which respondents self-reported whether they lived in an urban, suburban, or rural community. Urbanites were significantly over-represented in the MC sample (67% vs. 36% in World Bank figures) and only 14% identified as being from a rural community. This may explain the over-representation of BJP support in the MC data. Interestingly, 60% of Lucid respondents reported as being from a rural community (vs. 63% national benchmark from the World Bank). Support for the BJP is over-represented in the Lucid sample as well, though not to the extent as in the MC data.

Finally, SI Table 2 presents comparisons between our samples and actual vote totals for all parties receiving at least 5% of the vote in the last general election (and that were included in Morning Consult's list of parties in the relevant last election vote choice question).

Section E: Corruption Experiment

The corruption experiment embedded on all surveys was only slightly modified from the original version in Weitz-Shapiro and Winters (2017), which we henceforth refer to as WSW.

All respondents were shown the following text: "Imagine you live in a neighborhood like yours but in a different city in [respondent's country]. Now imagine that the current mayor of that city is running for reelection. During the mayor's first term in office, the city had various improvements, with economic growth and improved public health and public transport services.

Respondents in the treatment group were also shown the following information: "Also in that city, according to an independent organization, the mayor has accepted bribes to award public contracts." All respondents were then asked: "As a resident of the community, how likely are you to vote for the mayor?" Respondents answered on a four-point likert scale from "very likely" to "very unlikely".

Power Analyses

In every country apart from the United States (where n = 2,000), our surveys each had approximately 1,000 respondents, who were randomly assigned to the treatment and control group. This sample size is sufficient to detect a difference of about .22-.25 points in the average treatment effect across two countries on our 4-point DV.[1] For context, this means we should be able to detect a treatment that was 20% greater or smaller than the average estimated treatment effect in Weitz-Shapiro and Winters (2017). In a meta-analysis of corruption survey experiments, Incerti (2020) estimated that the average electoral effect of a corruption allegation was a 32% decrease in vote share (95% CI with fixed effects, -32.6 to -31.2; 95% CIs with random effects, -38.2 to -26.2). Thus, a 20% difference in estimated effect would be outside of even the broad confidence interval for the average effect.

[1] Based on data from WSW and a pilot, we estimated the SD in the outcome would be between .9 and 1.

For heterogeneity among subgroups, we have less power. For evenly split samples (like gender), we should be able to detect differences in treatment effect sizes across subgroups of about a third of a point on our four-point scale with 80% power at alpha = .05.

Direct Comparisons of Brazil Results to WSW

All of the analyses in the manuscript text compare estimates of experimental treatment effects and other political quantities of interest across a higher-quality, quota-based survey provider and a more economical, non-quota-based provider. However, we do have one opportunity to compare our corruption experimental results to findings from a probability-based sample: we can compare our Brazil results to those reported in Weitz-Shapiro and Winters (2017).

The Weitz-Shapiro and Winters (2017) survey was fielded by the Brazilian Institute of Public Opinion and Statistics to 2,002 individuals across 25 of Brazil's 27 states. The study employed a multistage sample with probability proportional to size sampling of cities across the states and then quota sampling at the level of the individual. Additional details on their sample are available via their online appendix. As shown in Figure 7 in the text, our results are broadly comparable.

Sensitivity Analyses

A major potential threat to generalizability from convenience samples to the general population is the potential for distributional differences in treatment effect moderators (i.e. variables that influence both selection into the sample and that moderate the effect of the treatment) across the survey samples and the general population. In the manuscript text, we explore two potential moderators – gender and educational attainment – that are correlated with selection into our sample and that past work suggests may moderate the electoral effects of corruption. However, there are other potential moderators that we are not able to examine. A sensitivity analysis allows us to estimate how strong an omitted moderator would have to be to overwhelm our estimated average treatment effect.

SI Table 3 reports Robustness Values (Huang 2024, Cinelli and Hazlett 2020) for the unweighted estimated treatment effects in the MC and Lucid samples across all six countries. In most cases, the value of RVq is approximately .40, which suggests that an omitted moderator would have to explain 40% of the residual variance of both the treatment and the outcome to bring our estimated treatment effect to 0. (The RVα values present the percentage of the residual variance of both treatment and outcome that an omitted moderator would have to explain to make our estimated treatment effect no longer statistically significant, $p < .05$, two-tailed test). To construct bias contour plots that help visualize this sensitivity to an omitted moderator relative to observed benchmarks for gender and college educational attainment we estimated a series of regressions in which assignment to the corruption treatment group is the independent variable of interest, and indicator variables for female respondents and respondents with at least a four-year college degree are included as control variables. SI Tables 4-5 present the results of these regressions. In all countries except the United States, Morning Consult's gender question, which we mirrored on the Lucid surveys, asked "What is your gender?" The response choices were male or female. In the United States, the question wording was the same, but a third response choice of "Not listed" was given. Two respondents (out of 2,108) in the Morning Consult survey chose the "Not listed" option, as did five respondents (out of 2,000) in the Lucid survey. The female variable used in the regressions in SI Tables 4-5 and for the moderation analyses reported in the text treats these respondents as missing. SI Figures 1-6 present the bias control plots. While these sensitivity analyses do not tell us whether such a confounder exists, they do tell us the scale of confounding that would be needed to overwhelm our estimated treatment effect.

Alternative Operationalizations of the Dependent Variable

In the manuscript text, all analyses use the four-point dependent variable employed by Weitz-Shapiro and Winters (2017) and as prescribed in our pre-analysis plan. SI Figures 7-9 replicate the corresponding figures in the manuscript text, but using a dichotomized version of the dependent variable, which parallels the operationalization of treatment effects reported in Incerti's (2020) meta-analysis.

Section F: Trust Measures

The analysis in the paper concludes by comparing estimates of trust in government, social trust, and confidence in financial institutions across platforms in each country. We measured trust in government with the following question:

How much can you trust the Government in XXX to do the right thing? Please place yourself on a 0 to 10 scale where 0 indicates strong distrust that the government will do the right thing; 10 indicates strong trust that the government will do the right thing; and 5 indicates neither trust nor distrust that the government will do the right thing.

We measured social trust using the following question taken from the World Values Survey:

To what extent does the following statement describe you (0 to 10 scale): "I assume that people have only the best intentions." (0 does not describe me at all; 10 describes me perfectly)

Finally, we measured confidence in financial institutions with the following question:

How much confidence do you have in banks and financial institutions? (A great deal of confidence; quite a lot of confidence; not very much confidence; none at all).

References

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., & Wacziarg, R. 2003. Fractionalization. *Journal of Economic growth*, *8*, 155-194.

Aronow, Peter, et al. 2020. "Evidence of rising rates of inattentiveness on Lucid in 2020." *SocArXiv* 49: 59-63.

Cinelli, C. & Hazlett, C. 2020. "Making Sense of Sensitivity: Extending Omitted Variable Bias." *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 82: 39-67.

Freedom House. 2024. *Freedom in the World 2024: The Mounting Damage of Disinformation*. Washington, DC: Freedom House. Available at: https://freedomhouse.org/report/freedom-world/2024/mounting-damage-disinformation.

Gerver, Mollie, Sanchayan Banerjee, and Peter John. 2024. "Nudging against consent is effective but lowers welfare." *Scientific Reports* 14(1): 14864.

Huang, M. 2024. "Sensitivity Analysis for the Generalization of Experimental Results." *Journal of the Royal Statistical Society Series A: Statistics in Society* 187: 900-918.

Incerti, Trevor. 2020. "Corruption Information and Vote Share: A Meta-analysis and Lessons for Experimental Design." *American Political Science Review* 114: 761-774.

Ternovski, J. and Orr, L., 2022. "A Note on Increases in Inattentive Online Survey-takers Since 2020." *Journal of Quantitative Description: Digital Media 2*.

Transparency International. (2023). Corruption Perceptions Index. https://www.transparency.org ;

Weitz-Shapiro, R., & Winters, M. S. 2017. "Can Citizens Discern? Information Credibility, Political Sophistication, and the Punishment of Corruption in Brazil." *The Journal of Politics*, *79*(1), 60-74.

World Bank, *World Development Indicators* (Washington, DC: World Bank, 2025), available at https://data.worldbank.org

SI Table 1. Sources for Demographic Information across Countries

Country	Gender	Age	Race/Ethnicity	College Education
Brazil	CIA World Factbook	World Health Organization	2022 Census	2022 Census
India	CIA World Factbook	World Health Organization	CIA World Factbook	World Bank
Japan	CIA World Factbook	World Health Organization	CIA World Factbook	World Bank
Nigeria	CIA World Factbook	World Health Organization	CIA World Factbook	World Bank
Philippines	CIA World Factbook	World Health Organization	CIA World Factbook	Philippines Statistical Authority
United States	U.S. Census	U.S. Census	U.S. Census	U.S. Census

SI Table 2: Self-Reported Vote Chocie vs. Actual Totals in Last General Election

	Actual	*MC*	*MC (Wt)*	*Lucid*	*Lucid (Wt)*
*Brazil**					
PL	16.6	30.6	31	29.5	30.2
FE Brasil	14	43.2	42.9	40.2	41.4
UNIAO	9.3	2	2.2	4.2	3.6
PP	8	1.6	1.6	1.7	1.4
PSD	7.6	7.9	7.4	10	8.3
MDB	7.2	2.7	2.9	4.4	5.0
India					
BJP	38.4	64.2	68.2	51	53.6
INC	22.3	22.3	20	20	22.3
Japan					
LDP	26.7	32.9	32.7	30.3	29.8
CDP	21.2	20.9	21.5	18.5	22.7
DPP	11.3	15.7	15.2	20.3	17.4
Komeito	10.9	4	4.2	3.2	2.5
Japan Innovation Party	9.4	13.4	13.6	14.2	15.1
Japanese Communist Party	6.2	6	6.1	6.2	6
Nigeria					
APC	36.6	37.6	36.9	40.3	38.1
PDP	29.1	28.8	29.8	23.6	30.2
Philippines					
PDP	22.8	18	19.4	24.5	24.7
Nationalist Party	13.8	11.5	11.3	8.4	9.4
NUP	12.7	14.2	13.9	13.7	13.2
NPC	11.7	3.7	3.7	5.4	5.5
Lakas	9.2	3.3	3.3	4	2.6
USA					
Trump	49.7	48.4	50.3	45.9	48.1
Harris	48.2	48.6	47.2	54.1	48.4

Note: See manuscript text and SI for a discussion of complications in the case of Brazil.

SI Table 3: Robustness Values for Mayoral Corruption Experiments

		Morning Consult		Lucid	
		RVq	RVα	RVq	RVα
Brazil		.39	.36	.32	.28
India		.22	.17	.31	.27
Japan		.43	.39	.34	.30
Nigeria		.41	.37	.41	.38
Philippines		.37	.33	.41	.37
USA		.35	.32	.41	.38

Note: RVq and RVα estimate the minimum amount of variation in the treatment effect heterogeneity that an omitted moderator must explain to reduce the estimated treatment effect to 0 or to render it statistically insignificant, respectively.

SI Table 4: Corruption Experiment Results, Morning Consult Surveys

	Brazil	Brazil	India	India	Japan	Japan	Nigeria	Nigeria	Philip.	Philip.	USA	USA
Mayoral corruption treatment	-1.09	-1.09	-0.45	-0.46	-0.97	-0.97	-1.08	-1.08	-0.87	-0.88	-0.88	-0.87
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female		0.04		0.03		0.00		0.12		0.08		-0.12
		(0.58)		(0.66)		(0.98)		(0.06)		(0.19)		(0.01)
College		0.08		0.15		0.05		0.02		-0.12		0.25
		(0.27)		(0.04)		(0.38)		(0.78)		(0.05)		(0.00)
Constant	3.34	3.29	3.32	3.19	2.81	2.77	3.47	3.39	3.33	3.34	3.04	3.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1,027	1,027	1,011	1,011	1,007	1,007	1,012	1,012	1,016	1,016	2,108	2,106
R-squared	0.20	0.20	0.06	0.06	0.24	0.24	0.22	0.22	0.18	0.18	0.16	0.18

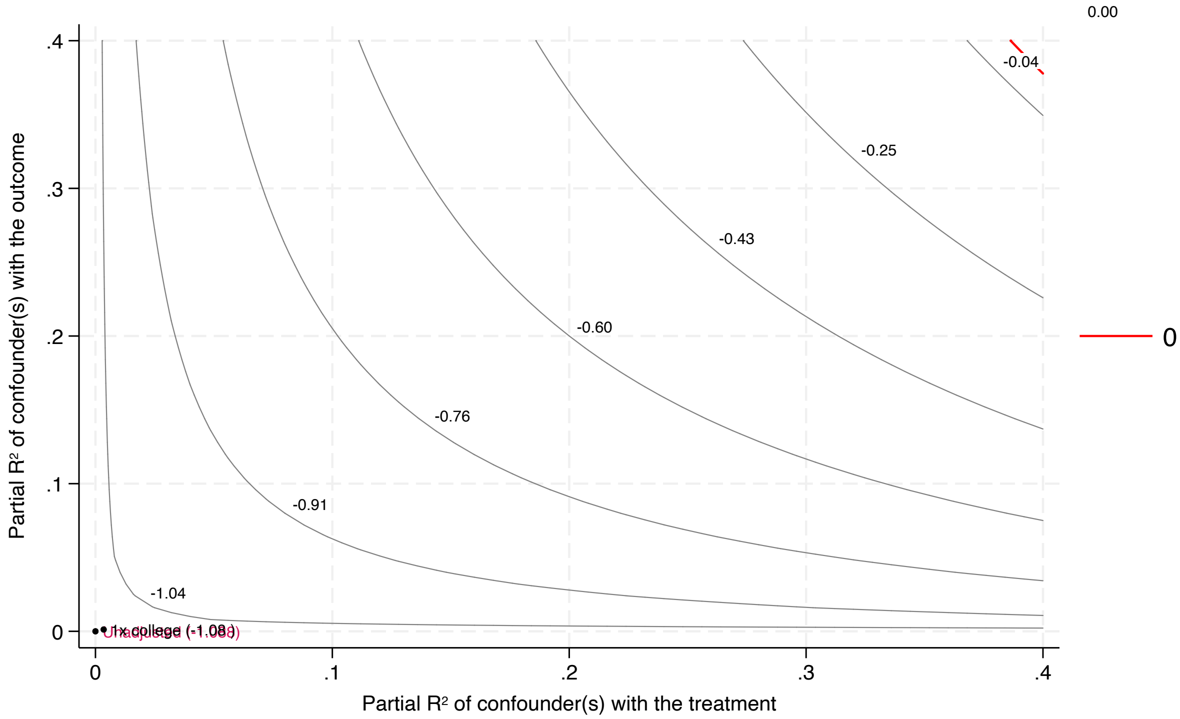
Note: P-values in parentheses; all significance tests are two-tailed.

SI Table 5: Corruption Experiment Results, Lucid Surveys

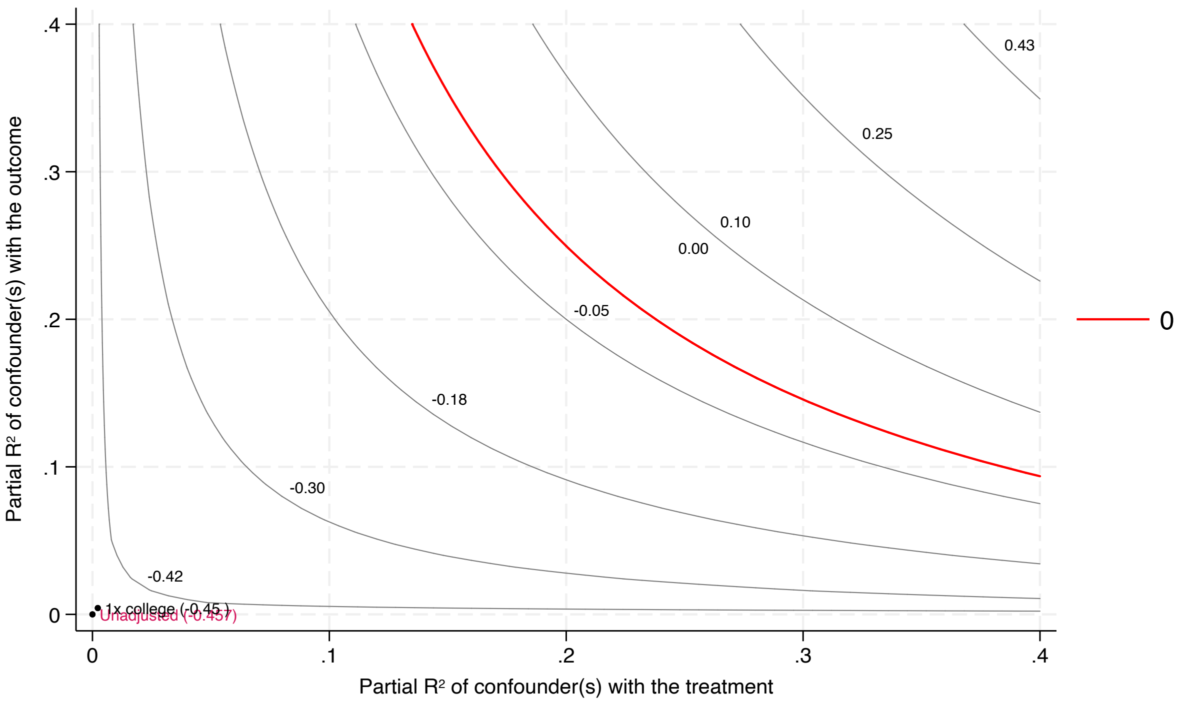
	Brazil	Brazil	India	India	Japan	Japan	Nigeria	Nigeria	Philip.	Philip.	USA	USA
Mayoral corruption treatment	-0.75	-0.75	-0.67	-0.67	-0.77	-0.77	-1.03	-1.03	-0.97	-0.98	-1.06	-1.06
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female		0.08		-0.02		-0.18		0.01		-0.01		0.03
		(0.20)		(0.77)		(0.00)		(0.91)		(0.80)		(0.59)
College		-0.02		0.25		0.12		0.05		0.04		0.09
		(0.80)		(0.00)		(0.03)		(0.53)		(0.54)		(0.07)
Constant	3.55	3.50	3.44	3.24	2.87	2.87	3.52	3.47	3.47	3.45	3.05	3.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	1,000	1,000	1,055	1,055	1,000	1,000	1,001	1,001	1,126	1,052	2,000	1,995
R-squared	0.13	0.14	0.12	0.14	0.15	0.16	0.22	0.23	0.22	0.23	0.22	0.22

Note: P-values in parentheses; all significance tests are two-tailed.

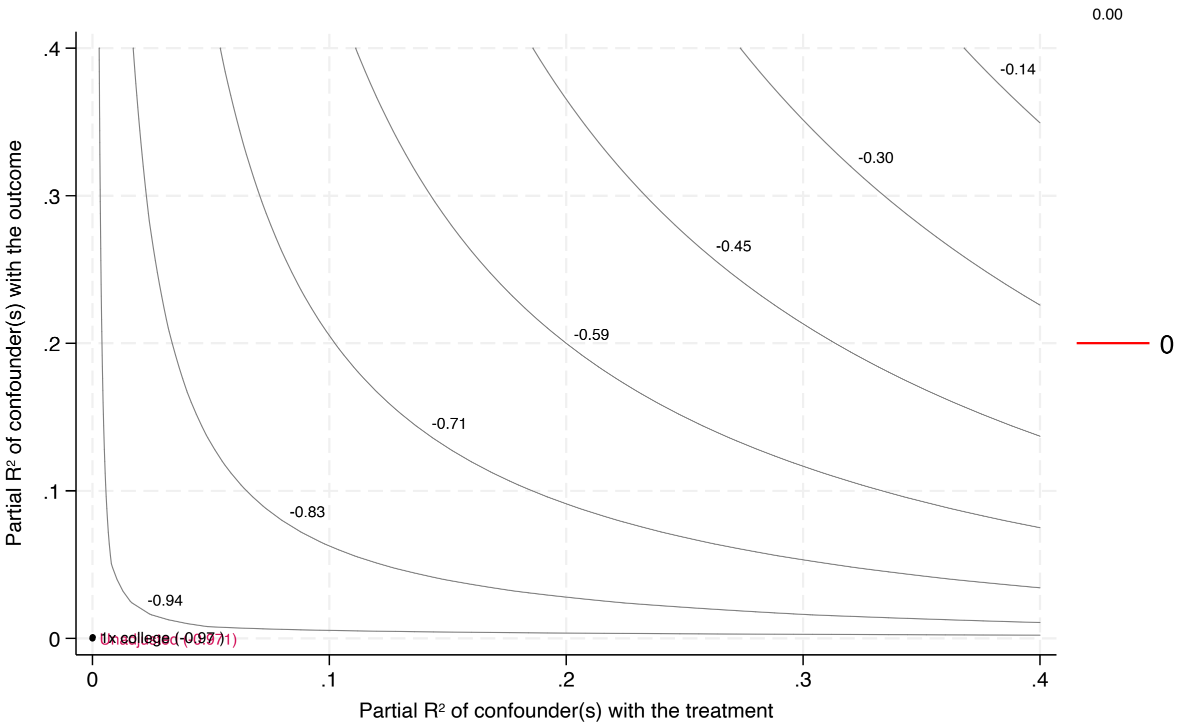
SI Figure 1: Bias Contour Plot with College Benchmark: Brazil (MC)



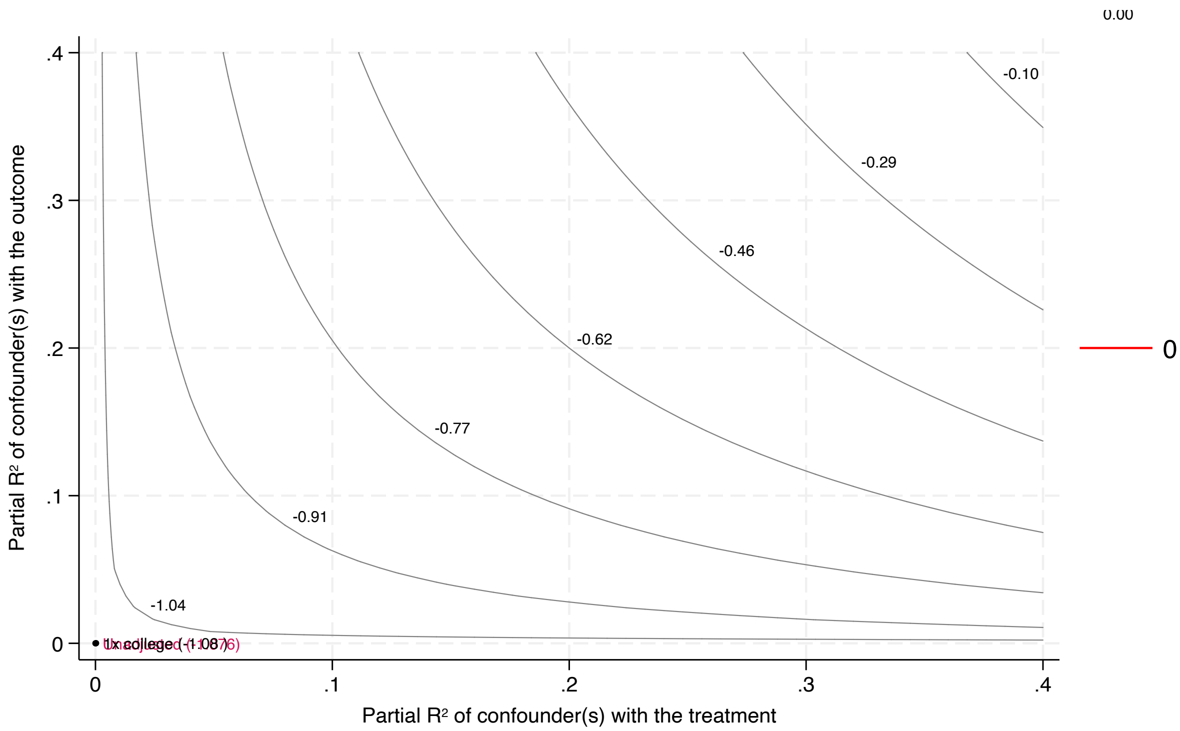
SI Figure 2: Bias Contour Plot with College Benchmark: India (MC)



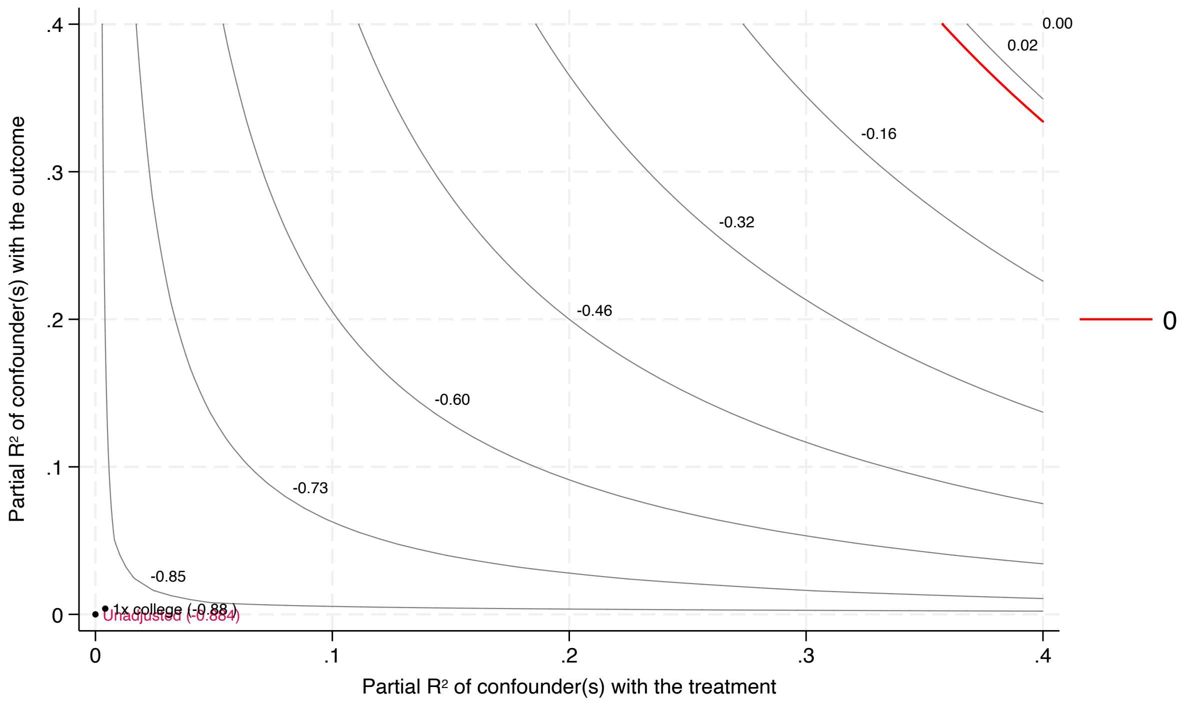
SI Figure 3: Bias Contour Plot with College Benchmark: Japan (MC)



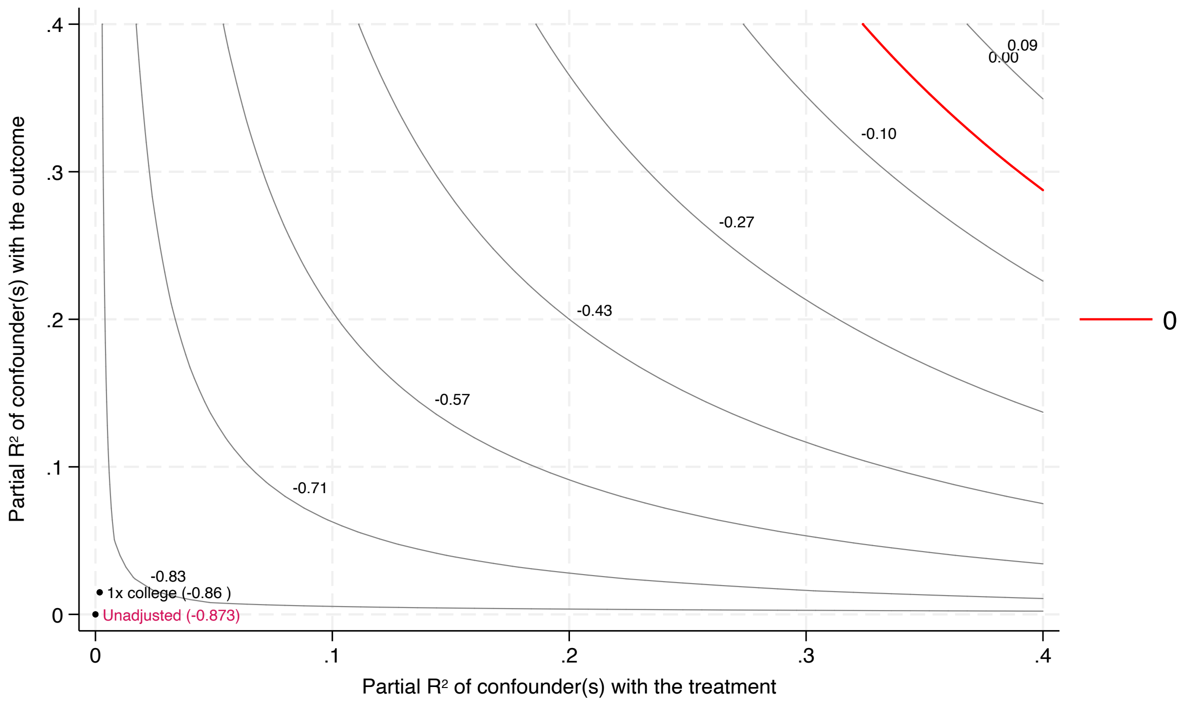
SI Figure 4: Bias Contour Plot with College Benchmark: Nigeria (MC)



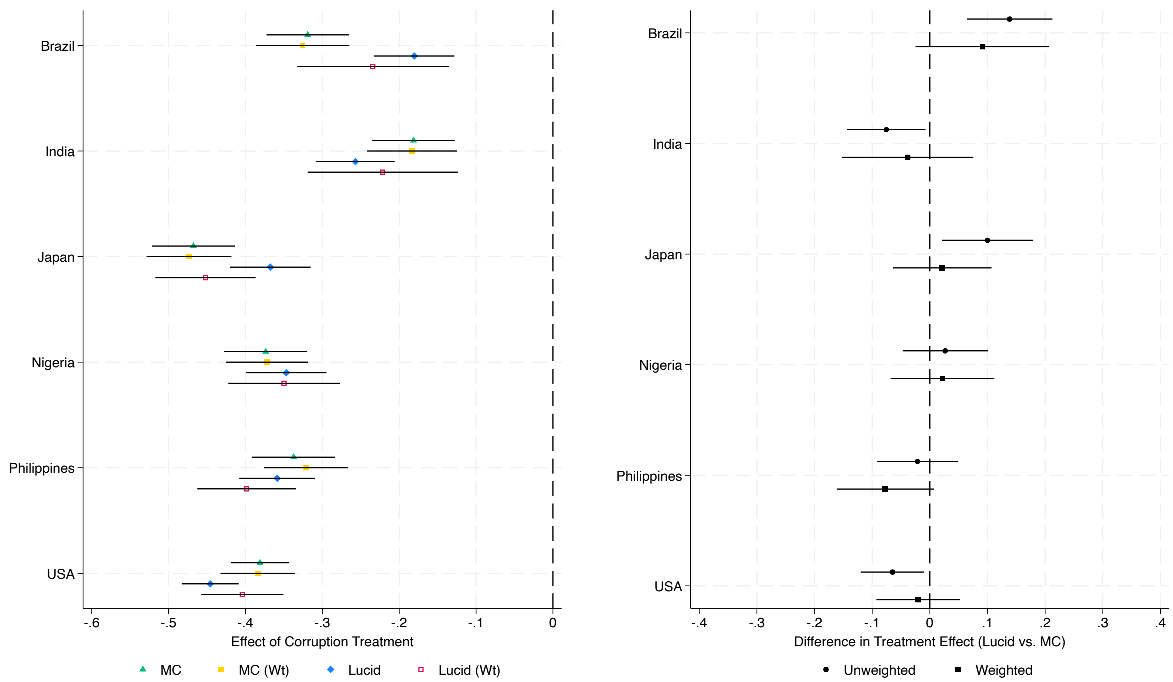
SI Figure 5: Bias Contour Plot with College Benchmark: Philippines (MC)



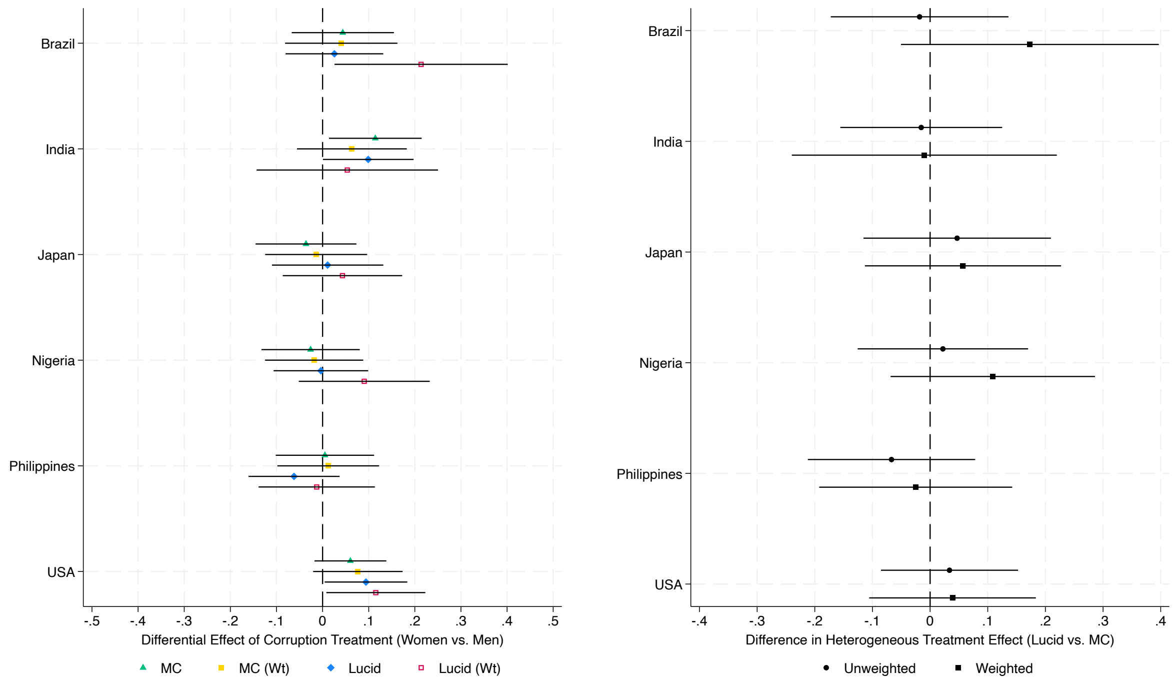
SI Figure 6: Bias Contour Plot with College Benchmark: USA (MC)



SI Figure 7: Corruption Treatment Effects, Binary Dependent Variable



SI Figure 8: Heterogeneous Treatment Effects by Gender, Binary DV



SI Figure 9: Heterogeneous Treatment Effects by College, Binary DV