SUPPLEMENTARY **INFORMATION FOR** "CAUSES AND CURES OF CORRUPTION"

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Screenshots from Experiment

Below are screenshots for each version of the game illustrating the Player view, Leader view when playing, and Leader view when making decisions regarding other players. All instructions were provided through pre-recorded videos.

Institutional Punishment Public Goods Game

Figure S1. Player screen. The leader's decision (Do Nothing or Take Away Points) is displayed after "Leader Action". It is displayed after the leader has made their choice.

Done

Economics Experiment

Figure S2. Leader screen for play. After all players have made their decision, leaders can choose how to react to player choices.

Figure S3. Leader screen for decision regarding players. Leaders are shown anonymized player choices and can choose to Take Points Away or Do Nothing.

Economics Experiment

Figure S4. Example of player screen after leader decision. Here the leader has chosen to Take Away Points.

Bribery Game

Figure S5. Player screen. Leader action (Do Nothing or Take Away Points) is displayed after the leader has made their decision. The key difference in the Bribery Game is the additional player choice to Contribute to Leader.

Economics Experiment

Figure S6. Leader screen for play. Note that leaders cannot contribute to themselves. After all players have made their decision, leaders can choose how to react to player choices.

Figure S7. Leader screen for decision regarding players. Leaders are shown anonymized player choices and can choose to Take Points Away, Accept Contribution to Leader, or Do Nothing.

Bribery Game with Partial Transparency

Figure S8. Player screen after Leader decision. Note that below Leader Action (Do Nothing, Take Away Points, or Accept Contribution to Leader) is the Leader's Contribution to the Pool. All other screens are identical to Bribery Game. Here the Leader has contributed 3 points to the public pool and has chosen to take away points from this player.

Bribery Game with Full Transparency

Figure S9. Player screen after Leader decision. Note that below Leader Action (Do Nothing, Take Away Points, or Accept Contribution to Leader) is the Leader's Contribution to the Pool, as in Bribery Game with Partial Transparency. However, now all Leader and Player Actions are displayed in a table. All other screens are identical to Bribery Game.

Figure S10. Leader screen for play. Note that all leader points are automatically contributed to the pool. All other screens are identical to Bribery Game.

Measures Collected

In addition to player and leader behavior in the game, we collected the following measures. This is a complete list of all measures collected. No additional measures were collected.

- 1. Prestige and Dominance Scale [Self-report version]¹
- 2. Right Wing Authoritarianism (RWA) scale²
- 3. How old are you in age?
- 4. What is your gender?
- 5. If you are student, what degree are you studying for (e.g. B Arts, B Sc)? If you are working, what is your occupation (e.g. Pharmacist)?
- 6. Major (if degree) What is your major (e.g. Chemistry) or industry (e.g. Health)?
- 7. Have you lived your entire life in Canada?
- 8. If no, where else have you lived (please list)? [Note: these countries were used to calculate the Exposure Corruption Score]
- 9. What suburb do/did you live in for most of your time in Canada?
- 10. Please specify the ethnic (cultural) group you primarily identify with (e.g. Punjabi,Cantonese Chinese, Mandarin Chinese, Japanese, European, etc.) [Note: these identities were used to calculate the Heritage Corruption Score. Cantonese Chinese were assumed to be from Hong Kong and Mandarin Chinese were assumed to be from China. Ambiguous country of origin, such as Armenian, were not included]
- 11. What is the native language of your ethnic group?
- 12. How well do you speak the native language of your ethnic group?
- 13. Inclusion of Other in the Self Scale³ for ethnic group
- 14. Inclusion of Other in the Self Scale³ for other Canadians
- 15. What is your religious background?
- 16. How important is religion in your daily life?
- 17. Vancouver Index of Accultaration⁴

The last 39 groups (194 participants) were also asked the following questions about their preferences for the game:

One more question - after having played several different versions of this game, if you were to play one more game where you chose the rules, what would you do?

In my version of the game...

Any other rules or changes?

Figure S11. After the experiment had concluded, participants were asked for their preferred game paramters.

Corruption Perception Scores

Below are histograms for distributions of heritage corruption score (the mean of the Corruption Perception Index⁵ values of players' countries of ethnic heritage) and a exposure corruption score (the mean of the Corruption Perception Index values of the countries in which they had lived). As discussed in the main text, the heritage corruption score represents the potential influence of vertically transmitted corruption norms (parent to child), whereas the exposure corruption score represents corruption norms to which the participant was directly exposed (i.e., potentially personal experience as well as vertical, horizontal, and oblique transmission).

Figure S12. Histogram of Heritage Corruption Scores.

Figure S13. Histogram of Exposure Corruption Score.

Figure S14. Histogram of Exposure Corruption Score subtracted from Heritage Corruption Score. This plot illustrates that these scores are not identical and in some cases, have very different values.

Theoretical Predictions

Here we perform an evolutionary analysis of the Bribery Game to predict player behavior under different treatments. We perform the following analyses:

- 1. We begin by analyzing the institutional punishment PGG with a fixed tax rate. We fixed the tax rate to more realistically model real world institutions, where taxes and punishment are not directly correlated and where leaders can use the punitive powers of the state without a large personal cost (since there own taxes are a small part of the taxes contributing to the pool punishment or institution).
- 2. We then introduce the Bribery Game (BG) modification, whereby players have the option to offer bribes to the leader and players have the option to accept these bribes.

We analyze these effects using an adaptive dynamics approach, testing if a homogenous (monomorphic) population can be invaded by a player or leader who systematically deviates. In working through this logic, we are able to derive a set of predictions.

Parameters and Variables

Parameters are capitalized. Evolving variables are lower case.

Standard Institutional Punishment Public Goods Game (IPGG)

We can easily show that in the standard institutional punishment PGG (IPGG):

- (a) contributions (c) will tend toward zero without punishment
- (b) levels of contributions are contingent on the strength of leaders (punishment multiplier; S) and tendency for leaders to punish contributions (dependent on α and t), and
- (c) leaders will use taxes to punish, since these are not personally costly and since punishing increases the leader's payoff by increasing the size of the public good, which they share in.

We assume fitness and payoff are synonymous. Fitness (F_i) is given by endowment (E) minus taxes (T), contribution (c_i) , and punishment (p_i) , plus the sum of all other contributions multiplied by the MPCR $\binom{M}{N}$:

$$
F_i = E - T - c_i - S \cdot p_i + M / N \cdot \sum c_j
$$

 E and T are fixed, so:

$$
F_i = 1 - c_i - S \cdot p_i + \frac{M}{N} \cdot \sum c_j
$$

Next, we define the punishment assigned to player i as a function of the leader L 's propensity to punish (α_L) and player *i*'s contribution. We use a logistic curve to describe this relationship, such that:

$$
p_i = \frac{1}{1 + e^{-\alpha_L(c_i - t_L)}}
$$

We illustrate this function in the figure below for different values of α and t , where t is the threshold contribution for punishment. Negative α indicates higher punishment for lower contributions (i.e. prosocial punishment), where more negative α indicates a steeper (more punitive) slope. Positive α indicates higher punishment for higher contributions (i.e. antisocial punishment), where more positive α indicates a steeper (more punitive) slope.

The threshold t determines the rate at which 50% of the punishment taxes are assigned. Lower t indicates a lower cutoff (e.g. if $\alpha < 0$, less tolerance for smaller contributions). Higher t indicates a higher cutoff. In the case when α is negative, this indicates more tolerance for smaller contributions.

Figure S15. (a) Different negative values of α with a threshold of $t = 0$. 5. i.e. larger punishments for smaller contributions. (b) Different positive values of α with a threshold of $t = 0.5$, i.e. larger punishments for larger contributions. (c) Negative values of α with extreme thresholds **t**. When $t = 0.1$ and α is large and negative (-100), there is a very large **punishment for contributions less than 0.1 and almost no punishment for contributions**

more than 0.1 (almost a step function). In contrast, when $t = 0.9$ and α is large and **negative (-100), there is a very large punishment for contributions less than 0.9 and almost no punishment for contributions more than 0.9 (again, almost a step function). Thus, by** adjusting α and t , we can capture a great range of Leader punitive preferences.

Substituting p_i into F_i , payoff then becomes:

$$
F_i = 1 - c_i - S \cdot \frac{1}{1 + e^{-\alpha_L(c_i - t_L)}} + \frac{M}{N} \cdot \sum_{i} c_i
$$

Where the variables with subscript L capture the punishment preferences of the player designated as the Leader.

We solve this analytically by performing an invasion analysis of a monomorphic resident population (denoted with subscript r). In this homogenous population, everyone has the same contribution and everyone has the same preferences for punishment. Thus:

$$
F_r = 1 - c_r - S \cdot \frac{1}{1 + e^{-\alpha_r(c_r - t_r)}} + \frac{M}{N} \cdot \sum c_r
$$

Since everyone makes the same contribution, we can simplify our function:

$$
F_r = 1 - c_r - S \cdot \frac{1}{1 + e^{-\alpha_r(c_r - t_r)}} + \frac{M}{N} \cdot N \cdot c_r
$$

= 1 - c_r - S \cdot \frac{1}{1 + e^{-\alpha_r(c_r - t_r)}} + M \cdot c_r

Invader with a different contribution

Let us now consider an invader (mutant) with a different contribution. That is, a player who deviates from the other players in how much they contribute to the public good. We denote this player with a subscript m . Without loss of generality, we will assume that the population is large enough so that the individual player's contribution doesn't significantly affect the size of the public good. That is:

$$
Nc_r \approx (N-1)c_r + c_m
$$

The growth rate $f_r(m)$ of the "mutant" (who offers a different contribution) player m in the resident *population of is given by:*

$$
f_r(m) = F_m - F_r
$$

= $1 - c_m - S \cdot \frac{1}{1 + e^{-\alpha_r(c_m - t_r)}} + M \cdot c_r - \left(1 - c_r - S \cdot \frac{1}{1 + e^{-\alpha_r(c_r - t_r)}} + M \cdot c_r\right)$
= $-c_m - S \cdot \frac{1}{1 + e^{-\alpha_r(c_m - t_r)}} + c_r + S \cdot \frac{1}{1 + e^{-\alpha_r(c_r - t_r)}}$
= $c_r - c_m - S \left(\frac{1}{1 + e^{-\alpha_r(c_m - t_r)}} + \frac{1}{1 + e^{-\alpha_r(c_r - t_r)}}\right)$

Next, we find the selection gradient, by differentiating with respect to the mutant contribution and evaluating at the resident trait value $m = r$:

$$
\frac{\delta f}{\delta c_m}\Big|_{c_m=c_r} = -1 - \frac{\alpha_r S e^{-\alpha_r (c_m - t_r)}}{(e^{-\alpha_r (c_m - t_r)} + 1)^2}
$$

$$
= -1 - \frac{\alpha_r S e^{\alpha_r (c_m + t_r)}}{(e^{\alpha_r c_m} + e^{\alpha_r t_r})^2}
$$

We see here that the resident contribution is irrelevant (it disappears). We can also see that if there were no punishment, the second part of this equation (the part after -1) would disappear and this derivative would always be negative. That is, a lower contribution would always be favored if leaders did not punish. Thus, any equilibrium value is contingent upon punishment. We can look to see if higher contributions are ever favored (or if there is an equilibrium value) by looking at when this derivative is >0:

$$
0 < -1 - \frac{\alpha_r \, S \, e^{\alpha_r \, (c_m + t_r)}}{(e^{\alpha_r \, c_m} + e^{\alpha_r \, t_r})^2}
$$
\n
$$
1 < -\frac{\alpha_r \, S \, e^{\alpha_r \, (c_m + t_r)}}{(e^{\alpha_r \, c_m} + e^{\alpha_r \, t_r})^2}
$$
\n
$$
(e^{\alpha_r \, c_m} + e^{\alpha_r \, t_r})^2 < -\alpha_r \, S \, e^{\alpha_r \, (c_m + t_r)}
$$
\n
$$
(e^{\alpha_r \, c_m} + e^{\alpha_r \, t_r})^2 < -\alpha_r \, S \, (e^{\alpha_r \, c_m} + e^{\alpha_r \, t_r})
$$
\n
$$
e^{\alpha_r \, c_m} + e^{\alpha_r \, t_r} < -\alpha_r \, S
$$

For this to be true, α_r must be large and negative (i.e. leaders must be more punitive toward lower values). Since the threshold, t_r and contributions c_m are both restricted to [0,1], we can simplify this function at look at it at the different values of t_r and evaluate c_m at the two extreme resident contributions of 0 & 1:

Assume: $c_m = 0$; $t_r = 0$

$$
1 + 1 < -\alpha_r \, S
$$
\n
$$
2 < -\alpha_r \, S
$$

Assume: $c_m = 0$; $t_r = 1$

$$
1+e^{\alpha_r} < -\alpha_r \, S
$$

Looking first at when contributions are zero, we see that a higher contribution can invade only when leaders have a stronger propensity to punish low contributors. For the same increase in contribution, we see that the punitive propensity can be less if their strength (i.e. punishment multiplier) is greater. Also, since more negative a_r values (i.e. $a_r \ll 0$) will cause e^{α_r} to tend toward zero, as you might imagine, a higher threshold for punishment (t) allows for less of a punitive slope (α) ; differential treatment of high vs low contributions) for this condition to be met.

Assume: $c_m = 1$; $t_r = 0$

$$
e^{\alpha_r}+1<-\alpha_r\,S
$$

Assume: $c_m = 1$; $t_r = 1$

$$
2e^{\alpha_r} < -\alpha_r S
$$

When resident contributions are maximal $(c_r = 1)$, we see a similar pattern as before. The case when contributions are maximal and punishment thresholds are high is the case where a_r can be lowest and contributions sustained. Of course, since contributions are maximum, we should really look at when this condition is not met (i.e. look at when lower contributions can invade).

These analyses reveal that non-zero contributions can be sustained in the standard institutional PGG—even maximum contributions—as long as leaders punish lower values ($\alpha \ll 0$) and they are powerful enough to do so $S \gg 0$. As punitive preferences rise and leaders become more powerful, higher contributions can be sustained. Therefore, the stability of these contributions are contingent on a preference for punishment. Since leaders do not punish themselves and taxes are always extracted, we can assume that leaders are willing to punish, but we analyze the evolution of punitive preferences in the next section.

Invading Leader with different punitive preferences

Let us check the intuitive answer that leaders will punish low contributions (since there is no cost to themselves and they benefit from public good provisioning).

As before, the payoff of a player i is given by:

$$
F_i = 1 - c_i - S \cdot \frac{1}{1 + e^{-\alpha_L(c_i - t_L)}} + \frac{M}{N} \cdot \sum_{i} c_i
$$

But since a Leader does not punish themselves, the fitness payoff for leaders (F_L) simplifies to:

$$
F_L = 1 - c_L + \frac{M}{N} \cdot \sum c_j
$$

It is trivial to show that a Leader is not incentivized to contribute (remember from before that the derivative is negative without punishment. Leaders experience no punishment), but their payoff is affected by the size of the public good, so their payoff is effectively:

$$
F_L = 1 + \frac{M}{N} \cdot \sum c_j
$$

We can re-arrange the player fitness in terms of this public good:

$$
M_{N} \cdot \sum c_{j} = F_{i} - 1 + c_{i} + S \cdot \frac{1}{1 + e^{-\alpha_{L}(c_{i} - t_{L})}}
$$

and substitute it in the Leader fitness:

$$
F_L = 1 + F_i - 1 + c_i + S \cdot \frac{1}{1 + e^{-\alpha_L(c_i - t_L)}}
$$

$$
= F_i + c_i + S \cdot \frac{1}{1 + e^{-\alpha_L(c_i - t_L)}}
$$

As before, let's assume a monomorphic population with respect to contributions and Leader punishment preferences, with a migrant Leader (denoted with a subscript m) with different punishment preferences:

$$
f_{Lr}(m) = F_{Lm} - F_{Lr}
$$

= $F_r + c_r + S \cdot \frac{1}{1 + e^{-\alpha_m(c_r - t_m)}} - \left(F_r + c_r + S \cdot \frac{1}{1 + e^{-\alpha_r(c_r - t_r)}}\right)$
= $S \cdot \left(\frac{1}{1 + e^{-\alpha_m(c_r - t_m)}} - \frac{1}{1 + e^{-\alpha_r(c_r - t_r)}}\right)$

We can then take the partial derivative with respect to α_m and t_m :

$$
\frac{\delta f}{\delta \alpha_m}|_{\alpha_m = \alpha_r} = -\frac{S(c_r - t_m)e^{a_m(c_r + t_m)}}{(e^{\alpha_m c_r} + e^{\alpha_m t_m})^2}
$$

This is an implicit solution, however, since the punitive slope α_m is always on the exponent, regardless of other values, the derivative will always be negative, approaching 0 when $\alpha_m = -\infty$ (leaders become more punitive toward smaller contributions). A stronger leader (larger S) will make this a larger negative slope. The only other way for this derivative to be 0 (or positive) is if the resident contribution is equal the threshold t_m or below it (i.e. $c_r - t_m \le 0$). So let's look at the partial derivative with respect to the threshold:

$$
\frac{\delta f}{\delta t_m}\big|_{t_m=t_r} = \frac{\alpha_m S e^{a_m (c_r + t_m)}}{(e^{\alpha_m c_r} + e^{\alpha_m t_m})^2}
$$

Again, we have an implicit solution. However, here the sign of the derivative is entirely dependent on the sign of α_m . If $\alpha_m < 0$, the threshold will tend toward the lowest value $(t_m = 0)$ and thus Leaders will steeply punish non-contributors and be less punitive toward higher contributions. If $\alpha_m > 0$, the threshold will tend toward the highest value $(t_m = 1)$ and thus leaders will punish maximum contributors, but will be less punitive toward lower contributions. So, t_m will either equal 0 or 1. But from the partial derivative with respect to α_m (i.e. $\frac{\delta f}{\delta \alpha_m}$), we know that α_m will always be negative, except when $c_r - t_m \le 0$. If the threshold were 0, then $c_r \le 0$, or really $c_r = 0$, since there can't be negative contributions. If the threshold were 1, then $c_r - 1 \le 0$, which can only be true when $c_r = 1$. We are therefore left with the following situations:

- 1. Leaders are more punitive toward lower values, leading to higher contributions.
- 2. Contributions are maximum, contributions and threshold are equal, and Leader punitive values are irrelevant.
- 3. Contributions are zero, contributions and threshold are equal, and and Leader punitive values are irrelevant.

To know which (if any) of these situations are Evolutionarily Stable Strategies (ESS), we need to take the second derivative and look when it is less than 0 at these values:

$$
\frac{\delta^2 f}{\delta a_m^2} = \frac{S(c_r - t_m)^2 e^{a_L(c_r - t_L)} \left(e^{a_L(c_r - t_L)} - 1\right)}{(e^{a_L(c_r - t_L)} + 1)^3}
$$

$$
\frac{S(c_r - t_m)^2 e^{a_L(c_r - t_L)} \left(e^{a_L(c_r - t_L)} - 1\right)}{(e^{a_L(c_r - t_L)} + 1)^3} < 0
$$

This can only be negative when $e^{a_L(c_r-t_L)} < 1$.

$$
\frac{\delta^2 f}{\delta t_m^2} = \frac{\alpha^2 S e^{a_m (c_r - t_m)} \left(e^{a_m (c_r - t_m)} - 1\right)}{(e^{a_m (c_r - t_m)} + 1)^3}
$$

$$
\frac{\alpha^2 S e^{a_m (c_r - t_m)} \left(e^{a_m (c_r - t_m)} - 1\right)}{(e^{a_m (c_r - t_m)} + 1)^3} < 0
$$

This has the same requirement and can only be negative when $e^{a_m(c_r-t_m)} < 1$, which is true when $a_m(c_r - t_m) < 0$, which is met when $a_m < 0$ or $c_r - t_m < 0$.

Thus, cases 2 and 3 are not ESS strategies and only case (1) above applies. We can therefore conclude that leaders who are more punitive toward lower contributions will invade. Based on our invasion analysis of contributions, this means that contributions will increase. Moreover, from these analyses we can see that contributions will be higher when leaders are stronger $(S \text{ is higher}).$

Do we find the same conclusion when leaders can accept bribes offered by players?

Bribery Game

The fitness functions in the BG are similar to the IPGG, but players have one additional choice and leaders can make money through a second channel. We can show the following:

- 1. Players have no incentive to offer bribes, except if they will be punished for not doing so.
- 2. Leaders have a greater incentive to punish for lack of bribes than for lack of contributions
- 3. As in the IPGG, Leaders have a greater ability to impose their will when S is higher.
- 4. If players have a non-zero tendency to contribute (beyond punishment, for reasons not explicitly captured by this model, such as internalized norms), a Leader's incentive to punish for bribes will be slightly dampened when economic potential is higher (multiplier on public good, M , is higher).

A player's fitness in the BG is given by:

$$
F_i = 1 - c_i - \mathbf{b}_i - S \cdot p_i + \frac{M}{N} \cdot \sum c_j
$$

And the Leader's fitness is:

$$
F_L = 1 + \frac{M}{N} \cdot \sum c_j + \sum b_j
$$

Note the bolded \boldsymbol{b} for the bribe. Note also that as in the IPGG, Leaders have no incentive to contribute, since they do not punish themselves.

The punishment can now be conditioned not only on the contribution, but also the bribe:

$$
p_i = \frac{1}{1 + e^{-\alpha_L(c_i - t_L)}} + \frac{1}{1 + e^{-\beta_L(b_i - h_L)}}
$$

There are two additional constraints that we are ignoring for now: (1) the percent punishment cannot exceed 100% (i.e. 1) and $b_i + c_i \le 1$. The player payoff or fitness functions then becomes:

$$
F_i = 1 - c_i - b_i - S \cdot \left(\frac{1}{1 + e^{-\alpha_L (c_i - t_L)}} + \frac{1}{1 + e^{-\beta_L (b_i - h_L)}} \right) + \frac{M}{N} \cdot \sum_{i} c_i
$$

From the function above, we can see that from the player's perspective, bribes and contributions are symmetric in terms of loss to endowment and potential loss via punishment. If anything players have even less of an incentive to offer a bribe than contribute, since there is no return on bribes, but there is at least the potential return from the public good for contributions. Thus, player behavior

for bribes, as with contributions, are dependent on leader punishment behavior. Thus, we need to analyze the invasion of leaders with different punitive preferences:

Invading Leaders with different punitive preferences Leaders should be optimizing their fitness:

$$
F_L = 1 + \frac{M}{N} \cdot \sum c_j + \sum b_j
$$

Assuming a monomorphic population, this becomes:

$$
F_{Lr} = 1 + Mc_r + Nb_r
$$

And players fitness become:

$$
F_r = 1 - c_r - b_r - S \cdot \left(\frac{1}{1 + e^{-\alpha_r(c_r - t_r)}} + \frac{1}{1 + e^{-\beta_r(b_r - h_r)}}\right) + Mc_r
$$

Since a Leader's punitive ability are symmetric with respect to contributions are bribes, the key is which punishment enhances their fitness (recall that there is a tradeoff between these punishment allocations). We can see that punishing for bribes is always more fitness enhancing since $Nb > Mc$. At least, it is always more fitness enhancing if we're in a public goods dilemma (i.e. $M_{/N}$ < 1). Thus, as in our analysis of the IPGG, Leaders are incentivized to punish, but this time, to punish low bribes, instead of low contributions. And again, this ability is greater when $\mathcal S$ is greater. Therefore, this logic makes opposite predictions for strong leaders/institutions in the BG versus the IPGG: stronger leaders will encourage more bribes when bribery is an option (BG), but more contributions to the public good when bribery is not an option (IPGG).

A Leader's payoff through bribes increases with the size of the population. For a Leader to be incentivized to punish contributions, at least one of the following must be true:

- (a) The world needs to no longer be in a public goods dilemma (i.e. $M_{N} \ge 1$) and it's individually advantageous to contribute to the public good—this may well be true in some real world cases (such as theoretically during times of massive growth where real world \dot{M} is very high), but is not captured in our game.
- (b) Players must be more reluctant to offer bribes rather than contribute or have a non-zero tendency to contribute. This is possible since players do have a potential personal return on contributions (via the public good provisioning), but not on bribes, but could also be true if there is an existing norm for prosocial contributions or an anti-corruption norm against offering bribes (when we experimentally model these dynamics, we measure proxies for corruption/anticorruption norms through exposure to these norms). Such normative

preferences are more likely to overcome the leader's payoff associated with bribes when economic potential is higher.

Predictions Summary

The logic laid out thus far leads to the following predictions:

- 1. For the regression on contribution: $c = \beta_1 S + \beta_2 M + \epsilon$:
	- a. $\beta_1 > 0$ in IPGG, i.e. stronger leaders result in higher contributions
	- b. β_1 < 0 if BG, i.e. stronger leaders results in lower contributions
	- c. $\beta_2 > 0$ in IPGG
	- d. $\beta_2 \ge 0$ in BG (depending on prior contribution preferences not captured by our formal theory)
- 2. For the regression on bribes: $b = \beta_1 S + \beta_2 M + \epsilon$:
	- a. $\beta_1 > 0$, i.e. more bribes offered when leaders more powerful
	- b. $\beta_2 \leq 0$, i.e. no change in bribes or less bribes offered when economic potential is higher
- 3. In the BG, for the regression on punishment: $p = \beta_1 c + \beta_2 b + \beta_3 b \times S + \beta_4 b \times M + \epsilon$:
	- a. $\beta_3 < 0$, i.e. more punishment will be allocated for bribes when leaders are more powerful.
	- b. $\beta_4 \leq 0$, i.e. no change in punishment based on economic potential, but if there is a change, it will be less when economic potential is higher.
- 4. By corollary, for the regression on Leader decisions: Accept Bribe = $\beta_1 S + \beta_2 M + \epsilon$:
	- a. $\beta_1 > 0$, i.e. more acceptance of bribes (compared to doing nothing or punishing) when leaders are more powerful.

Data Analyses

We analyzed our data using generalized linear mixed models (GLMM), calculating coefficients using a Monte Carlo-Markov Chain (MCMC) implemented by the R package *MCMCglmm*⁶ . All Bayesian models pass the Gelman and Rubin⁷ convergence diagnostic, implemented in the *gelman.diag* function of the *coda*⁸ package. Categorical models are rescaled to log odds as per Hadfield⁹ course notes for *MCMCglmm*. Confidence intervals (95%) were calculated as Highest Posterior Density (HPD) using the *HPDinterval* function in the *coda* package⁸.

We provide a frequentist equivalent to each analysis (with no substantive difference in interpretation).

All data and analytic code is available at DataDryad: ADD LINK.

Variables

Cost of Corruption

Here we compare behavior in the standard institutional punishment Public Goods Game to behavior in the Bribery Game – identical in all ways, except the additional option of the bribe. Here and in all cases, we show the R code for the model, with the output in a clean table format. The data and R code are available on DataDryad.

Contributions

Bayesian

Model

```
mcmcmodel <- MCMCglmm(cContribution ~ factor(MPCR)+factor(LeaderPower) 
+ factor(Cond) + Period + factor(Version) + Subjects + 
as.numeric(Order) + scale(age) + male, random=~PID:GroupNum, 
data=levi[levi$Cond=="BG" | levi$Cond=="Control",])
For the standardized version, zContribution was regressed instead.
```
Results

Table S1. MCMC GLMM regression on raw, unstandardized contribution.

coefficients.

Frequentist

Model

```
model <- lmer(cContribution ~ 
factor(MPCR)+factor(LeaderPower)+factor(Cond) + Period + 
factor(Version) + Subjects + Order +age+male+ (1| PID)+ (1 | 
GroupNum), data= data=levi[levi$Cond=="BG" | levi$Cond=="Control",])
```


Table S3. Multilevel model regressing raw, unstandardized contribution with random effects for participants within groups. The variance explained by both fixed and random factors10,11

 $i s \, R^2 = 0.76.$

Coefficient 95% CI p-value Economic Potential 0.62 $0.27.$ 0.96 .001 **Strong Leader** -0.10 -0.45 . 0.25 .602 **Bribery Game** $0.39.$ -0.44 0.49 $< .001$ 0.00 Period -0.01 -0.01 . $.144$ **Version** 0.42 $0.09,$ 0.73 .013 0.20 Subjects $-0.15,$.777 0.03 Order 0.17 0.21 $< .001$ $0.14.$ Age 0.00 $-0.02.$ 0.01 .852 0.23 $0.09.$ Male 0.37 .002 -0.85 $-2.23, -0.24$ $(Intercept)$.109 2716 Obs. N 248 Group Num. 56 R^2 0.76

Standardized Score

Table S4. Multilevel model regressing z-score of contribution to calculate standardized coefficients, with random effects for participants within groups. The variance explained by both fixed and random factors^{10,11} is $R^2 = 0.76$ **.**

Causes of Corruption

Here we test the predictors of player contributions, bribes, and leader behavior based on our theoretical predictions:

Contributions

Our theory predicts a negative interaction between game (IPGG vs BG) and leader power (S) and between game and economic potential (M) . That is, stronger leaders will increase contributions in the IPGG, but decrease contributions in BG. And higher economic potential will increase contributions in the IPGG, but will have no effect or a smaller effect in the BG.

Bayesian

Model

```
zContribution \sim factor(MPCR) \star factor(Cond) + factor(LeaderPower) \starfactor(Cond) + factor(Cond) + Period + factor(Version) + Subjects + 
as.numeric(Order) + scale(age) + male
```
Results

Table S5. MCMC GLMM regression on raw, unstandardized contribution.

Table S6. MCMC GLMM regression on z-score of contribution to calculate standardized coefficients.

We can graph these effects:

Figure S16. Comparison of contributions in the IPGG (Control) and BG for weak vs strong leaders by poor vs rich economic potential. Overall contributions are lower in BG in all

contexts. Overall contributions are higher in richer economic potential contexts. As predicted, when leaders are stronger, we see a slight increase in contributions in the IPGG, but a decrease in the BG. Also, as predicted, the effect of economic potential on increasing contributions is weaker in the BG compared to the IPGG.

Summary

These results partially support our hypothesis. Stronger leaders barely increase contributions in the IPGG, but clearly decrease contributions in the BG (as predicted). Moreover, the effect of richer economic potential is lower in the BG compared to the IPGG (as predicted).

Next, we test our prediction that stronger leaders increase bribes (rather than contributions) in the BG.

Frequentist

Model

Results

```
cContribution \sim factor(MPCR) \star factor(Cond) + factor(LeaderPower) \starfactor(Cond) + factor(Cond) + Period + factor(Version) + 
     Subjects + as.numeric(Order) + scale(age) + male + (1 | PID) + 
(1 | GroupNum)
   Data: dat[dat$Cond == "BG" | dat$Cond == "Control", ]
```


Table S7. Multilevel model regressing raw, unstandardized contribution with random effects for participants within groups. The variance explained by both fixed and random factors10,11

 $i s \, R^2 = 0.76.$

Table S8. Multilevel model regressing z-score of contribution to calculate standardized coefficients, with random effects for participants within groups. The variance explained by both fixed and random factors^{10,11} is $R^2 = 0.76$ **.**

Bribes

Our theory predicts a positive effect of leader power (S) on bribes, but no effect or a negative effect of economic potential (M) . That is, stronger leaders will increase bribes.

Bayesian

Model

```
mcmcmodel <- MCMCglmm(zBribe ~ factor(MPCR) + factor(LeaderPower) + 
                          Period + factor(Version) + Subjects + 
                         as.numeric(Order) + scale(age) + male, 
                        random=~PID:GroupNum, 
                       data=dat[dat$Cond=="BG",])
```
Results

Table S9. MCMC GLMM regression on raw, unstandardized bribe.

Table S10. MCMC GLMM regression on z-score of bribe to calculate standardized coefficients.

We can graph these effects:

Figure S17. Comparison of bribes in the BG for weak vs strong leaders by poor vs rich economic potential. As predicted, when leaders are stronger, we see an increase in bribes.

Summary

As predicted, we find that stronger leaders extract larger bribes. Surprisingly, we find some possible evidence that this effect is stronger in richer economic potential than poorer. If these results generalize, one possible explanation for this is that Leader's and players have a non-zero norm for prosocial contributions. Leader's use punishment to achieve this minimum contribution. Since this contribution is more likely to be met in a richer economic potential context, leaders use more of their punitive power to extract bribes.

Next, we look at what predicts when Leaders will punish. If this hypothesis about leader's expecting a minimum contribution to the pubic good is correct, then we should see contributions predict punishment in the BG (not just bribes).

Frequentist

```
Model
model <- lmer(cBribe ~ factor(MPCR) + factor(LeaderPower) + 
                          Period + factor(Version) + Subjects + 
                         as.numeric(Order) + scale(age) + male +
                         (1|PID) + (1|GroupNum),
                        data=dat[dat$Cond=="BG",])
```


Table S11. Multilevel model regressing raw, unstandardized bribe with random effects for participants within groups. The variance explained by both fixed and random factors10,11 is $R^2 = 0.70$.

Table S12. Multilevel model regressing z-score of contribution to calculate standardized coefficients, with random effects for participants within groups. The variance explained by both fixed and random factors^{10,11} is $R^2 = 0.70$ **.**

Punishment

Based on our theory, we predict that more punishments will be allocated to bribes and that Leader's will be less tolerant of small bribes when they have more power (they'll punish small bribes more).

Bayesian

Model

```
model <- lmer(cBribe ~ cPunishment ~ factor(MPCR) * cBribe + 
factor(LeaderPower) * cBribe + factor(MPCR) * cContribution + 
factor(LeaderPower) * cContribution + Period + factor(Version) + 
Subjects + as.numeric(Order) + scale(age) + male,
                       data=dat[dat$Cond=="BG",])
```
Results

Table S13. MCMC GLMM regression on raw, unstandardized punishment.

Table S14. MCMC GLMM regression on z-score of punishment to calculate standardized coefficients.

We can graph contributions and bribes against punishment (this is the actual data, not controlling for effects):

(a)

(b)

Figure S18. Punishment plotted against (a) Bribes and (b) Contribution. Loess curve to show pattern. High contributions, and certainly high bribes, are rare, but the overall pattern suggests more punishments allocated for both low contributions and low bribes.

Summary

As predicted, we find that more powerful leaders are more punitive towards smaller bribes (though this effect is marginally significant). Surprisingly, even in the BG, more powerful leaders are also more likely to punish smaller contributions. These results suggest that Leader's possess either a prosocial or anti-corruption norm. Curiously, smaller bribes and contributions both receive smaller punishments when in a richer economic context. It is possible that in this richer economic context, contributions are more in line with Leader expectations, based purely on the norm and economic potential. If this is the case, we should expect that Leaders are more likely to do nothing or to accept bribes when economic potential is greater.

Frequentist

```
Model
model <- lmer(zPunishment ~ factor(MPCR) *zBribe +
factor(LeaderPower)*zBribe + factor(MPCR)*zContribution + 
factor(LeaderPower)*zContribution +
                 Period + factor(Version) + Subjects + 
                 as.numeric(Order) + scale(age) + male + 
                 (1|PID) + (1|GroupNum),
               data=dat[dat$Cond=="BG",])
```
Results

Table S15. Multilevel model regressing raw, unstandardized punishment with random effects for participants within groups. The variance explained by both fixed and random $factors^{10,11}$ is $R^2 = 0.76$.

Table S16. Multilevel model regressing raw, unstandardized punishment with random effects for participants within groups. The variance explained by both fixed and random $factors^{10,11}$ is $R^2 = 0.34$.

Leader Decisions

Based on the theory, we predict that stronger leaders should accept more bribes.

Bayesian

Model

```
mcmcmodel.bribe <- MCMCglmm(LeaderDec Bribe ~
factor(MPCR)+factor(LeaderPower) + Period + factor(Version) + Subjects 
+ as.numeric(Order) + scale(age) + male, 
                       random=~PID:GroupNum, data=dat[dat$Cond=="BG",], 
family = "categorical", burnin=50000, nitt=1000000, thin=5000)
mcmcmodel.punish <- MCMCglmm(LeaderDec Punish ~
factor(MPCR)+factor(LeaderPower) + Period + factor(Version) + Subjects 
+ as.numeric(Order) + scale(age) + male, 
                       random=~PID:GroupNum, data=dat[dat$Cond=="BG",], 
family = "categorical", burnin=50000, nitt=1000000, thin=5000)
mcmcmodel.nothing <- MCMCglmm(LeaderDec Nothing ~
factor(MPCR)+factor(LeaderPower) + Period + factor(Version) + Subjects 
+ as.numeric(Order) + scale(age) + male, 
                       random=~PID:GroupNum, data=dat[dat$Cond=="BG",], 
family = "categorical", burnin=50000, nitt=1000000, thin=5000)
```
Results

Table S17. MCMC GLMM categorical regression (equivalent to logistic regression) of each leader decision against the other two decisions.

Summary

In line with our theoretical predictions, the only robust effect is that more powerful leaders are almost twice as likely to accept bribes and more than 2.5 times less likely to do nothing.

Yet, since leaders are also punishing for low contributions, our results suggest that something other than pure rational behavior as captured by our model is at play. Cultural evolutionary models suggest that people may internalize norms, which then influence their behavior. Next we test the effect of exposure to norms on player and Leader behaviors.

Frequentist

Model

```
model.bribe <- multinom(LeaderDec Bribe ~
factor(MPCR)+factor(LeaderPower) + 
                           Period + factor(Version) + Subjects + 
                          as.numeric(Order) + scale(age) + male, 
                           random=~ 1|LeaderID/GroupNum, 
                          data=dat[dat$Cond=="BG",], family = binomial)
```


Table S18. Multilevel logistic regression of each leader decision against the other two decisions, with random effects for players within groups.

Exposure to Norms

Here we test how exposure to corruption norms affect behavior in our game. We do so by using our exposure score (a mean of the corruption perceptions of the countries the participant has lived in) and the heritage corruption score (a mean of the corruption perceptions of the countries the participant has an ethnic heritage). Since there is no incentive to offer bribes or contribute, except when compelled to do so by punishment, our theory predicts that exposure to norms should primarily affect Leader decisions. Nonetheless, internalized norms may also affect the behavior of players in contributing and bribing.

We want to test the effect of direct exposure to corruption norms, but we would also like to control for heritage exposure (i.e. do these norms affect individuals who have lived in these countries, but are not natives to these corrupt countries). Similarly, we want to see the effect of heritage norms, but also look at the effect on second generation migrants and beyond, by controlling for actual direct exposure by having lived in a more corrupt country. The correlation between the direct exposure and heritage measures of corruption is $r = 0.67$, $p < .001$. To check if we can include both variables in our model, we check the Variance Inflation Factor on a fixed effect version of our model. These are reported for all models below.

We are interested in the effect norms have on player behavior as well as leader behavior. In each case, we run a model with player norms, with leader norms, and with both player and leader norms.

Summary

All the analyses tell a consistent story—the participants in our experiment whose families came from countries with high corruption, were themselves less likely to engage in corruption. We see no effect of direct exposure to corruption, until we control for these individuals. Then we see that direct exposure to corruption norms results in increased corrupt behavior—i.e. in our Canadian sample, those who have lived in corrupt countries from which they do not derive their heritage behave in more corrupt ways. These data are consistent with second generation migrants acculturating to local Canadian norms and also with selection in the previous generation for low corruption—i..e. those who preferred less corruption moved to Canada in the previous generation. Our data do not allow us to distinguish between these explanations, however, assuming no differential selection pressures between generations, the behavior of Canadians with direct exposure to corruption norms suggests this might be a case of acculturation (that is those with direct exposure behave in a more corrupt mannner, suggesting that the parents of those with a heritage that included corrupt nations were also more corrupt, but their children are less corrupt).

Contributions

Do corruption norms affect contributions? We look at the effect of corruption norms in the BG.

VIF

```
model \leq - \ln(zContribution \sim factor (MPCR) +
                factor(LeaderPower)+ 
                zPlayerExposureCorruption +
                zPlayerHeritageCorruption +
                zLeaderExposureCorruption +
                zLeaderHeritageCorruption +
                Period + factor(Version) + Subjects + 
                as.numeric(Order) + scale(age) + male, 
              data=dat.norms[dat.norms$Cond=="BG",])
```
All corruption norm variables have VIF<2.5.

Variable	VIF
Player Exposure Corruption Score	1.83
Player Heritage Corruption Score	1.87
Leader Exposure Corruption Score	1.62
Leader Heritage Corruption Score	1.68

Table S19. VIF Scores for OLS regression on contribution.

Bayesian

Effect of Norms on Contributions

Table S20. MCMC GLMM regression on z-score of contribution.

We find no evidence that leader corruption norms affect contributions. We find a small effect suggesting that players with a heritage that includes countries with high corruption norms actually contribute more and players with direct exposure to corruption contribute less, but this effect is not significant. Note that leadership is randomly assigned, so the effect of leaders must occur via shaping the norms of the groups they are in. We can test this by checking if mean contributions are higher in groups where heritage corruption scores are higher.

How do corruption norms in groups affect mean of contributions?

We calculate the mean contribution within each group and predict this with the mean of corruption norms.

Table S21. MCMC GLMM regression of mean of z-score of contributions in each group on mean corruption scores of players in the group.

No clear patterns emerge at the group level. Next we look at how corruption norms affect bribing behavior.

Frequentist

Table S22. Multilevel model regressing z-score of contribution.

Table S23. OLS regression of mean of z-score of contributions in each group on mean corruption scores of players in the group.

Bribes

VIF

Table S24. VIF Scores for OLS regression on bribes.

Effect of Norms on Bribes

Table S25. MCMC GLMM regression on z-score of bribe.

How do corruption norms in group affect bribe behavior in group

	Coefficient	95% CI		p-value	
High Economic Potential	0.33	$-0.07,$	0.74	.132	
Strong Leader	0.47	0.02,	0.89	.044	
Exposure Corruption Score	-0.02	$-0.58,$	0.56	.936	
Heritage Corruption Score	-0.06	$-0.63,$	0.50	.832	
Version	-0.37	$-0.84,$	0.06	.098	
Subjects	0.01	$-0.18,$	0.21	.956	
Order	-0.10	$-0.30,$	0.08	.344	
Mean Age	-0.19	$-0.40,$	0.02	.088	
Percent Male	0.03	$-0.73,$	0.87	.914	
(Intercept)	0.20	$-1.11,$	1.49	.764	
Obs.	1396				
N	175				
Group Num.		45			
$_{\rm DIC}$	107.33				

Table S26. MCMC GLMM regression of mean of z-score of bribes in each group on mean corruption scores of players in the group.

Again, similar to contributions and not statistically significant, we find that direct exposure results in higher bribes, but heritage lower bribes.

Frequentist

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
High Economic Potential	0.29	0.30	0.30	0.29	0.30	0.30	0.31
Strong Leader	$0.58**$	$0.60**$	$0.60**$	$0.58**$	$0.59**$	$0.59**$	$0.61**$
Player Exposure Corruption Score	-0.02		0.04				0.04
Player Heritage Corruption Score		-0.07	-0.10				-0.10
Leader Exposure Corruption Score				-0.10		0.02	0.02
Leader Heritage Corruption Score					-0.03	-0.04	-0.04
Period	$0.02**$	$0.02**$	$0.02**$	$0.02**$	$0.02**$	$0.02**$	$0.02**$
Version	$-0.59**$	$-0.60**$	$-0.60**$	$-0.60**$	$-0.60**$	$-0.61**$	$-0.61**$
Subjects	-0.03	-0.02	-0.02	-0.03	-0.02	-0.02	-0.02
Order	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10	-0.10
Age	0.01	0.02	0.02	0.01	0.01	0.01	0.02
Male	-0.08	-0.09	-0.09	-0.08	-0.08	-0.08	-0.09
(Intercept)	0.42	0.39	0.38	0.42	0.39	0.39	0.35
Obs.	1396	1396	1396	1396	1396	1396	1396
N	175	175	175	175	175	175	175
Groups	45	45	45	45	45	45	45
R^2	0.70	0.70	0.70	0.70	0.70	0.70	0.70

Table S27. Multilevel model regressing z-score of bribe.

Table S28. OLS regression of mean of z-score of bribes in each group on mean corruption scores of players in the group.

Leader Decision

Players have no incentive to offer bribes, other than to avoid punishment. If exposure to norms affect bribery, we should expect that leader's who have been directly exposed to more corrupt norms accept more bribes (rather than punishing or doing nothing).

VIF

Variable	VIF
Player Exposure Corruption Score	1.84
Player Heritage Corruption Score	1.89
Leader Exposure Corruption Score	1.64
Leader Heritage Corruption Score	1.72

Table S29. VIF Scores for logistic regression on leader decision to accept bribe compared to not accepting bribe.

Variable	VIF
Player Exposure Corruption Score	1.81
Player Heritage Corruption Score	1.83
Leader Exposure Corruption Score	1.67
Leader Heritage Corruption Score	1.70

Table S30. VIF Scores for logistic regression on leader decision to punish compared to not punishing.

Variable	VIF
Player Exposure Corruption Score	1.66
Player Heritage Corruption Score	1.69
Leader Exposure Corruption Score	1.62
Leader Heritage Corruption Score	1.71

Table S31. VIF Scores for logistic regression on leader decision to do nothing compared to not doing nothing.

Bayesian

```
Model
mcmcmodel.bribe <- MCMCglmm(LeaderDec Bribe ~
factor(MPCR)+factor(LeaderPower) + 
                                zPlayerExposureCorruption +
                               zPlayerHeritageCorruption +
                               Period + factor(Version) + Subjects + 
as.numeric(Order) + 
                               scale(age) + male, random=~LeaderID:GroupNum, 
data=dat.norms[dat.norms$Cond=="BG",], family = "categorical", 
burnin=50000,nitt=1000000,thin=5000)
mcmcmodel.bribe <- MCMCglmm(LeaderDec Punish ~
factor(MPCR)+factor(LeaderPower) + 
                                zPlayerExposureCorruption +
                               zPlayerHeritageCorruption +
                               Period + factor(Version) + Subjects + 
as.numeric(Order) + 
                               scale(age) + male, random=~LeaderID:GroupNum, 
data=dat.norms[dat.norms$Cond=="BG",], family = "categorical", 
burnin=50000,nitt=1000000,thin=5000)
mcmcmodel.bribe <- MCMCglmm(LeaderDec Nothing ~
factor(MPCR)+factor(LeaderPower) + 
                                zPlayerExposureCorruption +
                               zPlayerHeritageCorruption +
                               Period + factor(Version) + Subjects + 
as.numeric(Order) + 
                               scale(age) + male,
                              random=~LeaderID:GroupNum, 
data=dat.norms[dat.norms$Cond=="BG",], family = "categorical",
```

```
burnin=50000,nitt=1000000,thin=5000)
```
Results

Accept Bribe

Table S32. MCMC GLMM categorical regression (equivalent to logistic regression) for leader decision to accept bribe compared to not accepting bribes.

Punish

Table S33. MCMC GLMM categorical regression (equivalent to logistic regression) for leader decision to punish compared to not punishing.

Do Nothing

Table S34. MCMC GLMM categorical regression (equivalent to logistic regression) for leader decision to do nothing compared to not doing nothing.

Frequentist

Model

```
model <- multinom(LeaderDec Bribe ~ factor(MPCR)+factor(LeaderPower) +
                            zPlayerExposureCorruption +
                           zPlayerHeritageCorruption +
                           Period + factor(Version) + Subjects + 
                           as.numeric(Order) + scale(age) + male, 
                          random=~ 1|LeaderID/GroupNum, 
                         data=dat.norms[dat.norms$Cond=="BG",], family 
= binomial)
model <- multinom(LeaderDec_Punish ~ factor(MPCR)+factor(LeaderPower) 
+ 
                            zPlayerExposureCorruption +
                           zPlayerHeritageCorruption +
                           Period + factor(Version) + Subjects + 
                           as.numeric(Order) + scale(age) + male, 
                          random=~ 1|LeaderID/GroupNum,
```

```
 data=dat.norms[dat.norms$Cond=="BG",], family 
= binomial)
model <- multinom(LeaderDec_Nothing ~ factor(MPCR)+factor(LeaderPower) 
+ zPlayerExposureCorruption +
                           zPlayerHeritageCorruption +
                           Period + factor(Version) + Subjects + 
                           as.numeric(Order) + scale(age) + male, 
                          random=~ 1|LeaderID/GroupNum, 
                         data=dat.norms[dat.norms$Cond=="BG",], family
```
= binomial)

Results

Accept Bribe

Table S35. Multilevel logistic regression of each leader decision to accept bribe compared to not accepting bribe, with random effects for players within groups.

Punish

Table S36. Multilevel logistic regression of each leader decision to punish compared to not punishing, with random effects for players within groups.

Do Nothing

Table S37. Multilevel logistic regression of each leader decision to do nothing compared to not doing nothing, with random effects for players within groups.

Next, we look at whether anti-corruption measures can return contributions to the levels seen in the IPGG, when bribery is not a option.

Cures for Corruption

Here we report the full regression discussed in the main text. Consistent with the theory we have developed, partial transparency may work by revealing or establishing contribution norms and full transparency may work by revealing contribution and bribe norms, as well as the leader's punitive preferences. Leader investment can only work by increasing a leader's tendency to punish for lack of contributions rather than lack of bribes, but this is only likely to work when economic potential is high.

Table S38. The coefficients in Figure 1 of the main text are derived from this MCMC GLMM regression on the z-score of contribution. The coefficients of interest can be calculated by changing the reference groups, changing the meaning of the "main effects" in the model. For example, the the coefficient of bribery game in this table is the difference

between the BG treatment and the IPGG when Economic Potential and Strong Leader are zero.

Frequentist

Table S39. Multilevel model regressing z-score of contribution, with random effects for participants within groups. . The variance explained by both fixed and random factors10,11 is $R^2 = 0.68$.

Preferences for characteristics of the game world

Questions

One more question - after having played several different versions of this game, if you were to play one more game where you chose the rules, what would you do?

In my version of the game...

We gave participants a survey at the end of the experiment to see what kind of world they would prefer were they allowed to change the parameters. We assume that this is also the kind of world they would migrate to given the opportunity. Looking only at majorities where greater than 50% agreed on something, most people want to live in a world with:

A pool with institutional punishment, but where players can offer bribes and leaders can accept these bribes. Economic potential would be rich (unsurprisingly) and there would be transparency (players expressed strong preference for both transparency types).

There is some disagreement, but a small plurality of people would prefer to choose to contribute rather than be forced to contribute, and would prefer the leader to be less powerful and forced to invest in the public good.

Graphs

Figure S19. Distribution of answers for each end of survey question regarding preferences for the characteristics of the game.

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