Electronic Supplementary Material

1. Review of relevant literature on social learning

1.1 Conformity

Conformity has been the subject of extensive theoretical research examining the conditions under which it evolves, as well as its impact on the evolution of cooperation and other traits (e.g. 1–10); conformity facilitates the evolution of cooperation (1, 4, 6, 11–13). A multitude of empirical studies from social psychology demonstrate that individuals do tend to copy the majority (e.g. 14–18). However, these studies do not unequivocally measure conformity as it is defined and implemented in cultural group selection models, i.e. the disproportionate tendency to copy the highest frequency behaviour (1, 19, 20). It is only such a disproportionate individual proclivity to acquire the most frequent behaviour that has demonstrable homogenising effects within populations, thus creating variation between them (1, 19); a tendency to simply copy a behaviour with the likelihood of its occurrence in the population does not produce a homogenising effect within a population (13, 19). Furthermore, in the social psychology studies cited above, the experimental task was set up such that an individual experienced no clear benefit from attaining the correct solution to the task, as opposed to adopting the incorrect solution advocated by the majority. An exception is a study (21) which found that in a perceptual task of low difficulty, individuals' tendency to copy the majority decreased when incentives to make accurate judgements were introduced.

Jacobs and Campbell (22) were the first to design experiments that can be used to investigate whether individuals demonstrate conformity as defined in cultural group selection models; these authors formed laboratory "micro-societies" consisting of varying numbers of individuals and demonstrated that the evaluations individuals made in an estimation task were nonlinearly affected by the number of other individuals who had stated a particular estimate. More recent empirical work has been guided directly by theoretical models of cultural transmission in investigating whether individuals demonstrate conformity as defined in cultural group selection models (2, 3, 19, 23–27). Some of these studies were implemented so that an individual's performance in the experimental task translated into proportionate monetary gains (19, 24–27). These empirical studies find mixed support (3, 19, 23, 25–27), or no support (2, 24, 28) for conformist learning.

Many studies have demonstrated that individuals' contributions to a public good correlate positively with the contributions of other individuals (e.g. (29–37); these studies cannot distinguish whether conformity or other strategic considerations explain such "conditional cooperation". Only a small number of studies have investigated whether individuals employ conformist learning in the context of a cooperative dilemma (38–43). Although these studies find some evidence of social learning, they do not unequivocally demonstrate conformist learning as defined and implemented in cultural group selection models. While they show that individuals respond to information about other players' contributions to a PGG, they do not demonstrate that individuals preferentially make contributions that correspond to the most frequent contribution made by other players. Moreover, features of these studies, such as repeated interactions (40–43) and the measurement of conformity as individuals' responses to anticipated rather than real behaviour (43), cannot rule out other mechanisms (e.g. reciprocity) as explanations for the observed behaviour. Carpenter (39) and Bardsley and Sausgruber (38) provide the best evidence for social learning in a PGG. While the authors claim to observe conformity, what they demonstrate instead is that players' contributions in a PGG positively co-vary with those of other players, even when the contributions of other players do not affect their own payoffs; they do not demonstrate that players contribute an amount that equals the contribution value made most frequently by other players. Thus, the current literature does not provide clear evidence that individuals employ conformist learning in the context of a cooperative dilemma.

A few studies have examined the effects on cooperative behaviour of other types of social information. Revealing the behaviour of only one other individual, who participated in a different session of the experiment to the focal individual, has little effect on the focal individual's allocation in the dictator game (44), another economic game used to measure cooperation. Informing individuals playing a two-person PGG of the average contribution made by players in a previous session also does not affect game behaviour (45).

1.2 Payoff biased learning

Payoff biased learning has been extensively investigated in the theoretical literature and studies have examined the conditions under which it evolves, as well as its impact on the evolution of cooperation and other traits (e.g. 1, 4, 6, 7, 11, 25, 46–54); payoff biased learning can facilitate the evolution of cooperation in combination with some levels of conformity and/or punishment of defection (1, 4, 6, 11, 48). Many social psychology studies find evidence that people tend to copy successful, high status or prestigious individuals (reviewed in (20). Recent studies of cultural learning, guided directly by the theoretical literature on cultural evolution, provide evidence that people do employ payoff biased learning to some extent in complex laboratory task environments (24, 25, 55, 56). There is also evidence from the experimental economics literature that payoff biased learning may play a role in determining the behaviour of firms in a market (e.g. 57–60); the extent to which it is employed may vary with informational and environmental parameters (61).

2. Materials and methods

2.1 Study populations

For a detailed ethnographic, geographic and socio-economic description of the study populations see (62).

2.2 Sampling and logistics

For a detailed description of the sampling strategy and logistics see (62).

2.3 Public goods games (PGG)

2.3.1 Anonymity

Participants made all game decisions once and anonymously, and were made explicitly aware of the one-shot, anonymous set-up of each game. A player made her decisions individually at a private location, and apart from the player and SL, no other individual was present while she made her decisions. Player names were not recorded; a player's only identification in the study was a numbered token. Each player retained the same token throughout the study in order to facilitate the comparison of individuals' decisions between the two rounds of the PGG. Players were unaware of the identity of the individuals they played with and remained so even after the study was completed. No village resident could therefore know the decision of a player or what s/he earned in the game, either during or after the study.

2.3.2 Game instructions and testing

Instructions were delivered from a standardized script in Sargujia. Game scripts (available upon request from the author) were first translated from English to Hindi by SL, and then from Hindi to Sargujia by research assistants. The back translation method was used to ensure accuracy of translation. Players were instructed about the game rules and examples both collectively and then individually at the private location where they played the game. The PGG is a more complicated game than the ultimatum game. From prior experience piloting the ultimatum game in similar populations, I estimated that if I explained the PGG rules and examples to each player one at a time only, the total time required to obtain adequate sample sizes in each village would have been in the order of several days. This would have created ample opportunity for individuals who had played the game to discuss it with other village residents who were yet to play. To avoid such inevitable contamination, I first instructed all participants collectively (this usually took about 45 minutes) and then individually, in order to complete the games in one day.

Real money was used to demonstrate game rules and examples, and the instructions explicitly demonstrated the complete anonymity of decisions. Players were tested both collectively and individually for their understanding of the game rules and the anonymity of their decisions. Only players who individually answered a set of test questions correctly played the game. The questions were designed to assess their understanding of the game and features of the experimental set-up such as anonymity.

2.3.3 Administration

All games in all villages were administered by SL. Prior to this study, SL had no contact with any individual from any of the 14 villages included in this study. This protocol minimized experimenter familiarity with the players. On the day of the games, all participants collected at a common location in the village that was usually outdoors. SL then designated three sites; the first for players who were waiting to play the game, the second for those who had played, and the third as a private location where the players made their game decisions. The locations were at least 10-20 m apart from each other, typically further, and always out of earshot. The private location was often in the village school building or a village resident's hut, and on occasion an isolated outdoor site. Individuals who had played the game were prevented from interacting with those who had not yet played the game; participants who had played the game were seated at a separate location to those who had yet to play and research assistants monitored the two groups to ensure there was no discussion about the game. Participants were forbidden from discussing the game during the study period and warned that the games would be discontinued if they did. SL provided rations, which were cooked and consumed on the day of the games, for a full meal for each player. The meal was cooked by the waiting participants themselves; this kept them occupied for a few hours. They prepared a full meal for 25 to 30 people and manufactured plates and bowls from Sal tree leaves for everyone to eat off.

Play order was randomized. Groups of six players were constituted in each round by randomly matching token numbers. Group size was chosen as six because player contributions could assume five possible values (0, 5, 10, 15, 20), so a minimum group size of six was required to ensure that there was a clear mode in every group. Larger group sizes were avoided in order to minimise the likelihood that an individual played again with any of the members of her group from round one, once groups were reconstituted in round two. Of the 49 games played in each round across 14 villages, the total number of players was indivisible by six in seven games; five games had a group size less than six (three or four) and two games had a group size greater than six (seven or eight). These differences in group size do not change the relative payoff structure of the game. Players always thought they were in a group of six players as they were unaware of the number of people who did not play the game due to a failure to answer all test questions correctly.

2.3.4 Payments

All participants received a show-up fee of 30 rupees, which is just under one day's local wages. From demographic data collected on 784 adults I estimated mean local wages in the region at 38.68 ± 12.05 rupees per day.

The stakes of the game were determined as an approximate multiple of mean local wages estimated by sampling several villages in the study region. Individuals across all villages participate in similar economic activities and visit the same markets. Moreover, previous studies suggest that stake size does not significantly affect behavior in the PGG and ultimatum game (63, 64). For all of the above reasons, the stakes were kept constant across villages.

2.4 Demographic and individual data

Demographic and other data on individuals were collected via a standardized questionnaire administered by a research assistant. Once all games in a village had been completed, a population census was conducted and the geographic coordinates for every house in the village were recorded using a global positioning system (Garmin GPS 12XL). Geographic information systems (GIS) data were processed and analyzed in ArcGIS (version 9.2; Environmental Systems Research Institute).

Lamba & Mace (2011) (62; Table S5) provides descriptions of all the demographic and individual data collected. Five village descriptors were included in this study. The village descriptors 'population size' and 'proportion of migrants' (a measure of migration rates between populations) are of interest because they are directly linked to the evolutionary stability of cooperation in a population; the theoretical literature demonstrates that large populations and high rates of migration work against the evolution of cooperation (reviewed in 13, 65). The village descriptor 'proportion of non-Korwas' is used to examine whether any variation between villages is explained by the co-residence of other ethnic groups; theoretical and empirical studies demonstrate that inter-group competition can promote within-group cooperation (e.g. (66, 67). The variables 'household dispersion' and 'distance from major town' allow investigation of whether residence patterns show an association with levels of cooperation.

Individual descriptors included in this study were chosen in five domains; two of these domains, namely, 'basic individual descriptors' and 'wealth, markets and social networks', provide essential information on socio-economic characteristics of individuals, such as age, sex, household size, education, marital status and wealth, that may affect their behavior. These domains also include measures of individual market contact since recent studies propose that market integration has a major impact on levels of cooperation (68, 69). Variables in the domain 'residence and migration' capture the migratory history of each individual and thus allow analyses of whether or not, and to what extent, migrating to another population affects the behavior of an individual. The domain 'children and grandchildren' measures the numbers of living offspring individuals have. Finally, the domain 'kin' measures the numbers of living relatives that an individual has and also records how many of these relatives reside in the same village as the individual. Variables in the latter two domains are used to investigate whether there is any support for kin selection (70) models of cooperation in these populations. Note that due to an oversight, data on the number of kin who participated in the PGG were not collected in the first three villages visited namely villages 8, 1 and 6.

2.5 Analyses

2.5.1 Multilevel models

Multilevel models are used to analyze hierarchically clustered units of analysis, for instance individuals within villages within cultural groups. These models account for the possibility that units within a cluster, such as individuals from a village, may be more alike than units across clusters, such as individuals across villages. Ignoring the potential correlation of units within a cluster, i.e. the multilevel structure of data, can result in an underestimation of standard errors. Multilevel models correct for such non-independence of clustered data, reducing the likelihood of type I errors. They also allow us to accurately estimate the effects of groups along with group-level predictors.

Analyses proceeded in four stages. In the first stage, null models (with intercept terms only) were constructed with and without a multilevel structure and these were compared to establish whether the multilevel model provided a significantly better fit to the data. The Deviance Information Criterion (DIC) was used to compare models (71). The DIC is a Bayesian measure of model fit and complexity; it accounts for the change in degrees of freedom between nested models. Models with a lower DIC value provide a better fit to the data and a difference in DIC values of 5-10 units or more is considered substantial (71, 72). In the second stage, a series of multilevel univariate models were constructed to explore the relationship between each explanatory variable in the dataset and the outcome variable. A Wald test (73) was used to establish the statistical significance level of an explanatory variable. In the third stage, a series of domain-wise (sets of related variables such as those measuring wealth, kin etc. described in (62); Table S1) models were produced to identify the important explanatory variables within each domain. Once again, the Wald test was used to establish the statistical significance of variables.

The full model was constructed in the fourth stage, implementing a step-wise procedure with four serially entered blocks of variables. The first block entered contained all those variables from the domains of village descriptors, basic individual descriptors, residence and migration, wealth, markets and social networks that reached significance at $p<0.10$ within their domains (in the third stage domain-wise analyses); the block additionally contained age and sex even if they did not reach significance. The model obtained was then reduced by a backwards procedure, comparing reduced and non-reduced models for fit using their DIC values and eliminating predictor terms that did not significantly improve model-fit. All variables that were not discarded at this stage were carried forward and the next block of variables was added into this model. The second block added contained all those variables from the domain of children and grandchildren that reached significance at $p<0.10$ within this domain. The backward stepwise procedure was repeated with the new block of variables. The third block added contained all those variables from the domain of kin that reached significance at $p<0.10$ within this domain. The fourth block contained two predictor variables, the values of a player's group one MC and HEC. The variables age and sex were always carried forward to the last block. They were only eliminated at the very end if they did not significantly improve model-fit. Hence, the four blocks of variables were always added in the same order in a forward step-wise procedure, but within each block variables were eliminated in a backward step-wise procedure to obtain the full model.

Iterative Generalized Least Squares (IGLS) estimation with a 2^{nd} order predictive (or penalized) quasi-likelihood (PQL) approximation was used to fit all univariate (second stage) and domain-wise models (third stage). The null (first stage) and full models (fourth stage) were fitted using Markov Chain Monte Carlo (MCMC) estimation (74) run for 5,000 iterations and a burn-in period of 500 iterations.

The small sample sizes in some villages are a reflection of the small populations in these villages (e.g. village 1 had only 12 adults, all of whom participated in this study). Multilevel models account for sample size differences between populations when computing the variance components and parameter estimates. 70-100% of households had at least one household member participate in the games in all villages except villages 14, 13 and 9, where this proportion was 17%, 55% and 55% respectively. The latter three villages are among those with the largest populations in our dataset (Table 1). Although I estimated how many households were represented by at least one individual once all games had been completed, I did not collect data on which household each individual belonged to in order to avoid compromising players' anonymity. Hence, I cannot include households as an additional level in our models.

2.5.2 GIS analyses

Geographic Information Systems (GIS) data were processed and analyzed in ArcGIS version 9.2 (75). All maps were created and analyzed using the WGS 1984 Geographic Coordinate System with a Transverse Mercator Projection. A 30m Digital Elevation Model (ASTER Global Digital Elevation Model V001) was used for the relevant map area; this was obtained from the NASA Land Processes Distributed Active Archive Center (https://wist.echo.nasa.gov). The nearest neighbor index (76), calculated for households in each village, is used as the measure of household dispersion for each village.

3. References

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4. Supporting Tables

Table S1 Results of chi-squared tests comparing frequencies of players' tendency to conform and be payoff-biased for individuals from 14 villages pooled together. Each test is reported in a similarly coloured block of rows and compares frequencies of all categories listed under 'comparison categories' in the same block. Separate tests are reported for each of four sets of players as indicated in the column 'Set of players'.

Set of players	Comparison categories	χ^2	df	Monte Carlo simulated p
Not coordinated with MC in round one	Anti-conformist No change Conformist	41.695	2	<0.05
	Anti-conformist No change	35.836	1	<0.017[a]
	Conformist No change	0.295	1	>0.017[a]
	Anti-conformist Conformist	41.438	1	<0.017[a]
Coordinated with MC in round one	Anti-conformist Conformist	0.026	1	>0.05
Not coordinated with HEC in round one	Anti-payoff-biased No change Payoff-biased	26.600	2	<0.05
	Anti-payoff-biased No change	24.858	1	<0.017[a]
	Payoff-biased No change	0.225	1	>0.017[a]
	Anti-payoff-biased Payoff-biased	20.645	1	<0.017[a]
Coordinated with HEC in round one	Anti-payoff-biased Payoff-biased	5.568	1	<0.05

[a] Bonferroni adjusted significance level is 0.05/3 = 0.017.

Table S2 (A) Associations of each predictor term (fixed effect) with player tendency to conform in the null (intercept only) and full models for individuals who were not coordinated with the MC in round one. **(B)** Village and individual level variance components for player tendency to conform in the null and full models.[1] The variance partition coefficient [VPC = village level variance/ (village level variance + individual level variance)] is 0.007 ± 0.017 (95% BCI[2] = 0.000, 0.056) in the null model, and 0.006 ± 0.011 (95% BCI[2] = 0.000, 0.039) in the full model.

A

Fixed effect	Tendency to conform [|PGG1-MC|-|PGG2-MC|] (Indian rupees)		DIC[3]
	β ± SD	95% BCI[2]	
Null models			
Intercept (single level)	2.979 ± 0.414	2.171, 3.812	780.967
Intercept (multilevel)	2.979 ± 0.418	2.150, 3.794	781.425
Full model (multilevel)			762.046
Intercept	3.005 ± 0.538	1.948, 4.055	
People invited to harvest festival from own village	0.107 ± 0.033	0.041, 0.171	
Father living in village: yes (ref: no)	-3.672 ± 0.841	-5.310, -1.988	

B

	Village level		Individual level	
	Variance ± SD	95% BCI[2]	Variance ± SD	95% BCI[2]
Null model (multilevel)	0.168 ± 0.398	0.001, 1.303	22.563 ± 2.853	17.663, 28.869
Full model (multilevel)	0.109 ± 0.228	0.001, 0.775	19.162 ± 2.435	14.967, 24.423

[1] For the two multilevel models (null and full), fixed effect parameters in each model are specified in Table S2A, while Table S2B presents the village and individual level variances in player tendency to conform for each model respectively. For instance, in Table S2A, the full model (multilevel) has three fixed effects including the intercept; for each fixed effect (column 1), the associated β value (column 2) and its 95% BCI[2] (column 3) can be read in the corresponding row. The DIC[3] value (see Section 2.5.1 for details) for the model is presented in column 4 of Table S2A. The variance components for the full model (multilevel) can be read in the last row of Table S2B; column 2 represents the village level variance in player tendency to conform with its 95% BCI[2] (column 3), and column 4 represents the individual level variance in player tendency to conform with its 95% BCI[2] (column 5). The fixed effect parameters for the single level null model are presented in Table S2A; this model does not have variance components.

[2] Bayesian Credible Interval. Calculated from the posterior distribution, a k% interval contains k% of possible values of a parameter (77).

[3] Deviance Information Criterion.

Table S3 (A) Associations of each predictor term (fixed effect) with player tendency to conform in the null (intercept only) and full models for individuals who were already coordinated with the MC in round one. **(B)** Village and individual level variance components for player tendency to conform in the null and full models.[1] The variance partition coefficient [VPC = village level variance/ (village level variance + individual level variance)] is 0.011 ± 0.019 (95% BCI[2] = 0.000, 0.063) in the null model, and 0.017 ± 0.029 (95% BCI[2] = 0.000, 0.104) in the full model.

A			
Fixed effect	**Tendency to conform [|PGG1-MC|-|PGG2-MC|] (Indian rupees)**		**DIC[3]**
	β ± SD	**95% BCI[2]**	
Null models			
Intercept (single level)	-3.174 ± 0.309	-3.753, -2.539	849.883
Intercept (multilevel)	-3.185 ± 0.339	-3.848, -2.466	850.390
Full model (multilevel)			819.108
Intercept	1.577 ± 0.872	-0.069, 3.392	
Number of monthly visits to nearest town	-0.158 ± 0.069	-0.298, -0.035	
MC	-0.391 ± 0.072	-0.538, -0.253	

B				
	Village level		**Individual level**	
	Variance ± SD	**95% BCI[2]**	**Variance ± SD**	**95% BCI[2]**
Null model (multilevel)	0.160 ± 0.298	0.002, 0.931	14.430 ± 1.677	11.520, 18.022
Full model (multilevel)	0.200 ± 0.372	0.001, 1.275	11.609 ± 1.372	9.180, 14.533

[1] For the two multilevel models (null and full), fixed effect parameters in each model are specified in Table S3A, while Table S3B presents the village and individual level variances in player tendency to conform for each model respectively. For instance, in Table S3A, the full model (multilevel) has three fixed effects including the intercept; for each fixed effect (column 1), the associated β value (column 2) and its 95% BCI[2] (column 3) can be read in the corresponding row. The DIC[3] value for the model is presented in column 4 of Table S3A. The variance components for the full model (multilevel) can be read in the last row of Table S3B; column 2 represents the village level variance in player tendency to conform with its 95% BCI[2] (column 3), and column 4 represents the individual level variance in player tendency to conform with its 95% BCI[2] (column 5). The fixed effect parameters for the single level null model are presented in Table S3A; this model does not have variance components.

[2] Bayesian Credible Interval.

[3] Deviance Information Criterion.

Table S4 (A) Associations of each predictor term (fixed effect) with player tendency to be payoff-biased in the null (intercept only) and full models for individuals who were not coordinated with the HEC in round one. **(B)** Village and individual level variance components for player tendency to be payoff-biased in the null and full models.[1] The variance partition coefficient [VPC = village level variance/ (village level variance + individual level variance)] is 0.006 ± 0.013 (95% BCI[2] = 0.000, 0.043) in the null model, and 0.017 ± 0.032 (95% BCI[2] = 0.000, 0.114) in the full model.

A

Fixed effect	**Tendency to be payoff-biased [(PGG1-HEC)-(PGG2-HEC)] (Indian rupees)**		**DIC[3]**
	β ± SD	**95% BCI[2]**	
Null models			
Intercept (single level)	2.180 ± 0.404	1.393, 2.975	1196.512
Intercept (multilevel)	2.173 ± 0.448	1.299, 3.047	1196.966
Full model (multilevel)			1178.252
Intercept	-2.746 ± 1.241	-5.191, -0.323	
MC	0.278 ± 0.090	0.102, 0.454	
HEC	0.481 ± 0.124	0.243, 0.726	

B

	Village level		**Individual level**	
	Variance ± SD	**95% BCI[2]**	**Variance ± SD**	**95% BCI[2]**
Null model (multilevel)	0.399 ± 0.869	0.001, 2.878	31.491 ± 3.289	25.615, 38.424
Full model (multilevel)	0.512 ± 1.015	0.001, 3.568	28.137 ± 2.935	22.818, 34.441

[1] For the two multilevel models (null and full), fixed effect parameters in each model are specified in Table S4A, while Table S4B presents the village and individual level variances in player tendency to be payoff-biased for each model respectively. For instance, in Table S4A, the full model (multilevel) has three fixed effects including the intercept; for each fixed effect (column 1), the associated β value (column 2) and its 95% BCI[2] (column 3) can be read in the corresponding row. The DIC[3] value for the model is presented in column 4 of Table S4A. The variance components for the full model (multilevel) can be read in the last row of Table S4B; column 2 represents the village level variance in player tendency to be payoff-biased with its 95% BCI[2] (column 3), and column 4 represents the individual level variance in player tendency to be payoff-biased with its 95% BCI[2] (column 5). The fixed effect parameters for the single level null model are presented in Table S4A; this model does not have variance components.

[2] Bayesian Credible Interval.

[3] Deviance Information Criterion.

Table S5 (A) Associations of each predictor term (fixed effect) with player tendency to be payoff-biased in the null (intercept only) and full models for individuals who were already coordinated with the HEC in round one. **(B)** Village and individual level variance components for player tendency to be payoff-biased in the null and full models.[1] The variance partition coefficient [VPC = village level variance/ (village level variance + individual level variance)] is 0.508 ± 0.131 (95% BCI[2] = 0.245, 0.756) in the null model, and 0.487 ± 0.152 (95% BCI[2] = 0.194, 0.775) in the full model.

A			
Fixed effect	**Tendency to be payoff-biased [(PGG1-HEC)-(PGG2-HEC)] (Indian rupees)**		**DIC[3]**
	β ± SD	**95% BCI[2]**	
Null models			
Intercept (single level)	-2.269 ± 0.517	-3.275, -1.263	575.836
Intercept (multilevel)	-2.834 ± 1.193	-5.260, -0.227	539.108
Full model (multilevel)			513.979
Intercept	-7.867 ± 2.105	-11.801, -3.573	
Sex: female (ref: male)	2.243 ± 0.844	0.578, 3.862	
Percentage of non-Korwas	-0.070 ± 0.073	-0.266, 0.068	
Education: literate (ref: illiterate)	-0.838 ± 1.232	-3.267, 1.542	
some schooling (ref: illiterate)	2.787 ± 0.830	1.243, 4.447	
Household size (individuals)	0.337 ± 0.147	0.062, 0.626	
HEC	0.447 ± 0.135	0.172, 0.721	

B				
	Village level		**Individual level**	
	Variance ± SD	**95% BCI[2]**	**Variance ± SD**	**95% BCI[2]**
Null model (multilevel)	17.562 ± 10.020	5.476, 43.896	15.029 ± 2.477	10.989, 20.513
Full model (multilevel)	12.327 ± 8.339	2.957, 33.840	10.973 ± 1.903	7.839, 15.280

[1] For the two multilevel models (null and full), fixed effect parameters in each model are specified in Table S5A, while Table S5B presents the village and individual level variances in player tendency to be payoff-biased for each model respectively. For instance, in Table S5A, the full model (multilevel) has six fixed effects including the intercept; for each fixed effect (column 1), the associated β value (column 2) and its 95% BCI[2] (column 3) can be read in the corresponding row. The DIC[3] value for the model is presented in column 4 of Table S5A. The variance components for the full model (multilevel) can be read in the last row of Table S5B; column 2 represents the village level variance in player tendency to be payoff-biased with its 95% BCI[2] (column 3), and column 4 represents the individual level variance in player tendency to be payoff-biased with its 95% BCI[2] (column 5). The fixed effect parameters for the single level null model are presented in Table S5A; this model does not have variance components.
[2] Bayesian Credible Interval.
[3] Deviance Information Criterion.

5. Supporting Figures

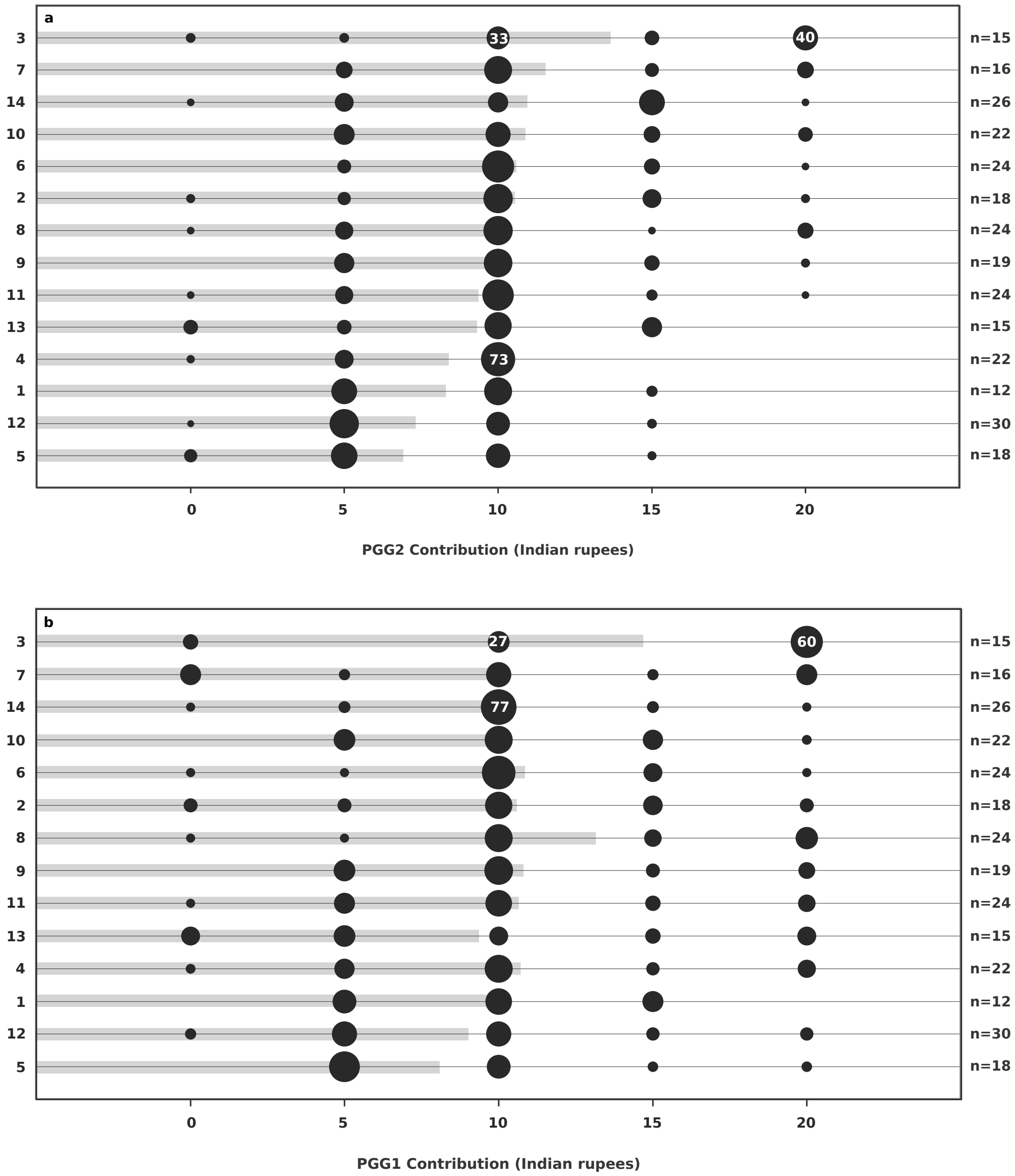

Figure S1 Distributions of (a) PGG2 contributions and (b) PGG1 contributions, across 14 villages. For each village on the y-axis, the areas of the black bubbles represent the proportion of individuals from the village who made a contribution of the value on the x-axis. To indicate scale, the numbers in some bubbles are the percentage proportions represented by those bubbles. Grey horizontal bars indicate the mean contributions for villages. Counts on the right (n) represent the number of players from each village (total n = 285). Villages in both graphs are ordered by their mean PGG2 contributions; village 5 has the lowest mean PGG2 contribution. The overall mode across villages is 10 rupees for both PGG2 (mean ± SD = 9.81 ± 4.60) and PGG1 (mean ± SD = 10.51 ± 5.44) contributions.

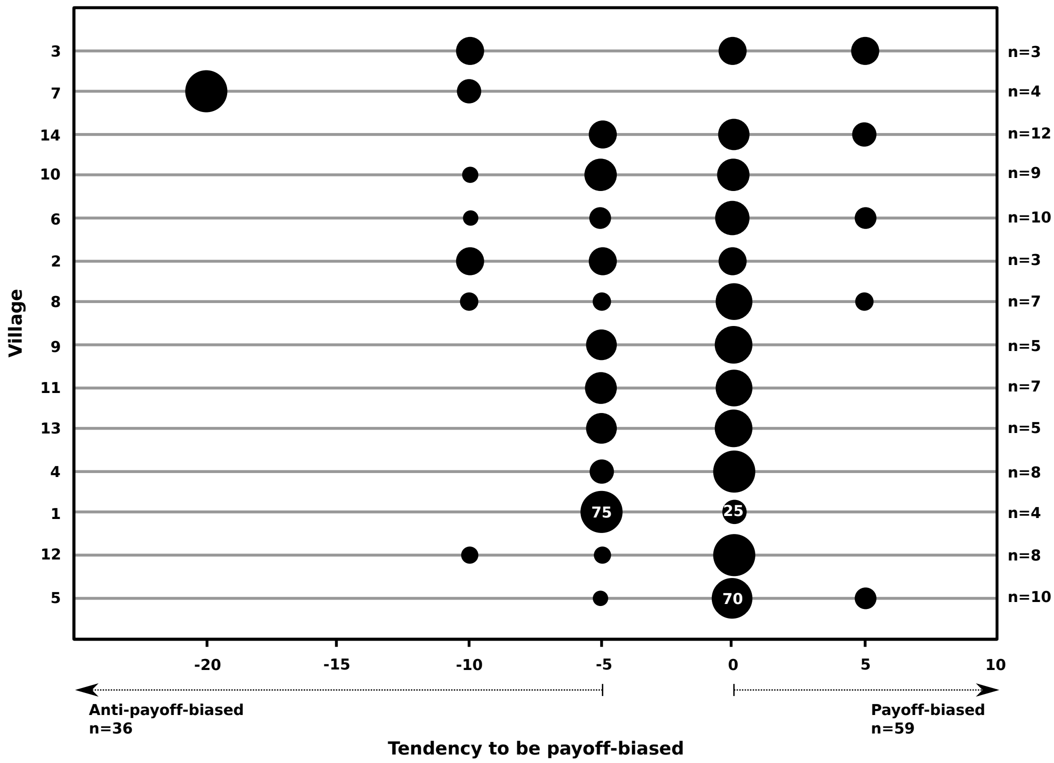

Figure S2 Distributions of tendency to be payoff-biased for individuals who were already coordinated with the HEC in round one across 14 villages. For each village on the y-axis, the areas of the black bubbles represent the proportion of individuals from the village with the value of the tendency to be payoff-biased on the x-axis. To indicate scale, the numbers in some bubbles are the percentage proportions represented by those bubbles. Counts on the right (n) represent the number of players from each village (total n = 95). Villages are ordered by their mean PGG2 contributions; village 5 has the lowest mean.