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Supplemental Information

Reciprocal Exchange Patterned by Market Forces Helps Explain Cooperation in a Small-Scale Society

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Table S1, related to Table 1: List of fixed effects included in each candidate model for meat given from A to B; in each row only new fixed effects not included in previous models are listed. For other types of cooperation (produce A to B, labor A to B, childcare A to B, sick care A to B), the in-kind reciprocity and in-kind market forces change to the respective other currency (e.g. Produce B to A) and their supply and demand (e.g. Horticultural Production A, Field Size A, Horticultural Production B, Field Size B) as mentioned in the text (see also Table S2), otherwise the candidate models are the same.

Model	**New fixed effects compared to previous model**
Null	-
Kinship and controls	Distance A-B, Need A, Age A, Age B, N sampling days A, Mean R * Need B[a]
In-kind reciprocity	Meat B to A
Full exchange	Produce B to A, Labor B to A, Childcare B to A, Sick care B to A
In-kind market forces	Meat Production A * Meat B to A, CV Meat Production A * Meat B to A, Meat Production B, CV Meat Production B
Full exchange market forces	Hort. Production A * Produce B to A, Field Size A* Produce B to A, Family Size A * Labor B to A, Field Size A * Labor B to A, Family Size A * Childcare B to A, Field Size A * Childcare B to A, Family Size A * Sick care B to A

[a] Interaction terms imply the presence of both main effects

Table S2, related to Table 1, Figures 1 and 2: Table of coefficients for the best-fit models (and the averaged model in the case of childcare). Predictors showing statistical trend or significance are bolded (where pMCMC is the proportion of samples that cross 0). Standardized coefficients (*β*) are given in italics

	Meat A to B [cals] b (lower, upper 95% CI)	**Produce A to B [cals]** b (lwr, uppr 95% CI)	**Labor A to B [days]** b (lwr, uppr 95% CI)	**Childcare A to B [y/n]** b (lwr, uppr 95% CI)	**Sick care A to B [y/n]** b (lwr, uppr 95% CI)
R_m^2 / R_c^2	0.24 / 0.99	0.08 / 0.94	0.09 / 0.96	0.33/0.99[b]	0.42/0.84[b]
Zero-inflation intercept	**0.84 (-2.28, 4.00)*****				
Intercept	3.21 (2.88, 3.54)	**-8.74 (-15.93, -1.14)***	**-6.64 (-11.09, -2.38)****	**-43.87 (-77.86, -11.25)****	**-23.35 (-36.17, -12.3)*****
Meat B to A [cals]	**0.03 (0.02, 0.04)***** ***β = 0.11***	0.02 (-0.01, 0.04) *β = 0.06*	-0.02 (-0.05, 0.01) *β = -0.07*	-0.02 (-0.05, 0.02) *β = -0.03*	0.01 (-0.00, 0.015) *β = 0.05*
Produce B to A [cals]	**0.01 (0.01, 0.02)***** ***β = 0.23***	-0.01 (-0.03, 0.01) *β = -0.14*	**-0.02 (-0.04, -0.00)*** ***β = -0.29***	-0.01 (-0.01, 0.00) *β = -0.04*	-0.00 (-0.00, 0.00) *β = -0.01*
Labor B to A [days]	0.07 (-0.10, 0.25) *β = 0.01*	-0.02 (-0.55, 0.46) *β = 0.00*	**0.28 (-0.09, 0.60)[t]** ***β = 0.02***	**1.20 (-0.08, 2.46)[t]** ***β = 0.05***	0.22 (-0.11, 0.55) *β = 0.04*
Childcare B to A [yes/no]	-0.03 (-1.32, 1.49) *β = 0.00*	1.60 (-1.39, 4.53) *β = 0.01*	**2.11 (-0.22, 4.49)[t]** ***β = 0.02***	**38.97 (17.19, 62.80)**** ***β = 0.19***	**2.99 (0.03, 6.07)*** ***β = 0.06***
Sick Care B to A [yes/no]	-0.00 (-1.41, 1.46) *β = 0.00*	0.96 (-2.36, 4.12) *β = 0.01*	0.83 (-1.57, 3.24) *β = 0.01*	**-10.79 (-21.32, -1.25)*** ***β = -0.05***	0.05 (-3.80, 3.84) *β = 0.00*
Relatedness A-B [mean R]	**8.84 (3.97, 13.81)***** ***β = 0.03***	**17.26 (7.86, 27.09)***** ***β = 0.05***	**16.69 (9.07, 24.55)***** ***β = 0.05***	**107.57 (69.75, 147.46)***** ***β = 0.18***	**44.93 (26.76, 64.17)***** ***β = 0.33***
Log Distance A-B [km]	**-1.43 (-1.83, -1.06)***** ***β = -0.07***	**-2.51 (-3.42, -1.64)***** ***β = -0.13***	**-0.44 (-0.93, 0.04)[t]** ***β = -0.02***	**-8.29 (-16.41, -1.48)***** ***β = -0.24***	**-1.65 (-3.36, -0.27)*** ***β = -0.21***
Need A [cals]	0.00 (-0.00, 0.00) *β = 0.02*	0.00 (-0.00, 0.00) *β = 0.00*	-0.00 (-0.00, 0.00) *β = -0.01*	-0.00 (-0.01, 0.00) *β = -0.18*	0.00 (-0.00, 0.00) *β = 0.01*
Need B [cals]	0.00 (-0.00, 0.00) *β = 0.01*	-0.00 (-0.00, 0.00) *β = 0.00*	0.00 (-0.00, 0.00) *β = 0.01*	0.00 (-0.00, 0.00) *β = 0.08*	-0.00 (-0.00, 0.00) *β = -0.09*
Midparent Age A [years]	-0.02 (-0.05, 0.02) *β = -0.03*	-0.05 (-0.14, 0.03) *β = -0.03*	-0.02 (-0.06, 0.023) *β = -0.01*	0.15 (-0.27, 0.58) *β = 0.06*	-0.03 (-0.13, 0.07) *β = -0.05*
Midparent Age B [years]	0.00 (-0.03, 0.03) *β = 0.00*	0.00 (-0.06, 0.07) *β = 0.00*	-0.05 (-0.13, 0.02) *β = -0.03*	-0.22 (-0.68, 0.20) *β = -0.08*	0.01 (-0.07, 0.09) *β = 0.01*
Sampling Days A	0.00 (-0.01, 0.02) *β = 0.01*	0.01 (-0.04, 0.05) *β = 0.02*	0.00 (-0.02, 0.02) *β = 0.00*	-0.17 (-0.45, 0.10) *β = -0.12*	**0.07 (0.01, 0.14)*** *β =* ***0.22***
Avge Meat Production A [cals/d]	**0.53 (0.18, 0.92)**** ***β = 0.02***	0.26 (-0.81, 1.35) *β = 0.01*	0.37 (-0.09, 0.84) *β = 0.02*	-1.55 (-7.61, 4.53) *β = -0.04*	-0.53 (-1.92, 0.80) *β = -0.06*
Variance Meat Production A [CV]	-0.41 (-0.90, 0.15) *β = -0.02*	-0.81 (-2.20, 0.54) *β = -0.04*	0.25 (-0.32, 0.77) *β = 0.01*	3.97 (-3.59, 11.82) *β = 0.10*	0.10 (-1.55, 1.78) *β* = 0.01
Avge Horticultural Production A [cals/d]	0.12 (-0.28, 0.56) *β = 0.00*	0.62 (-0.65, 1.75) *β = 0.03*	0.13 (-0.41, 0.70) *β = 0.01*	-0.48 (-8.10, 6.78) *β = -0.01*	-0.82 (-2.68, 1.00) *β = -0.09*
Field Size A [tareas]	0.19 (-0.27, 0.63)	0.66 (-0.79, 1.91)	-0.368 (-0.97, 0.21)	5.99 (-2.20, 14.51)	1.42 (-0.36, 3.31)

	β = 0.01	*β = 0.03*	*β = -0.02*	*β = 0.15*	*β =* 0.16
Family Members A	**0.54 (-0.10, 1.16)^{t}** ***β = 0.02***	0.59 (-1.04, 2.02) *β = 0.03*	0.26 (-0.42, 1.01) *β = 0.01*	**-8.97 (-20.63, 1.51)^{t}** ***β = -0.22***	-0.19 (-2.36, 1.91) *β = -0.02*
Family Members B			**-0.46 (-1.60, 0.69)^{t}** ***β = -0.02***	-2.22 (-9.95, 5.63) *β = -0.05*	**-1.48 (-3.03, 0.02)*** ***β = -0.16***
Avge Meat Production B [cals/d]	0.11 (-0.26, 0.45) *β = 0.00*				
Variance Meat Production B [CV]	0.31 (-0.14, 0.76) *β = 0.01*				
Avge Horticult. Production B [cals/d]		0.03 (-0.82, 0.82) *β = 0.00*			
Field Size B [tareas]		-0.31 (-1.18, 0.53) *β = -0.01*	0.85 (-0.06, 1.80) *β = 0.04*	-2.18 (-8.57, 3.89) *β = -0.06*	
Relatedness A-B * Need B	-0.00 (-0.00, 0.00) *β = 0.00*	-0.00 (-0.00, 0.00) *β = -0.01*	-0.00 (-0.00, 0.00) *β = 0.00*	**-0.02 (-0.04, -0.01)**** ***β = -0.11***	0.00 (-0.00, 0.01) *β = 0.05*
Meat B to A * Avge Meat Production A	0.01 (-0.00, 0.01) *β = 0.04*	**-0.02 (-0.03, 0.00)*** ***β = -0.10***	0.00 (-0.01, 0.02) *β = 0.01*	-0.01 (-0.03, 0.01) *β = -0.04*	0.00 (-0.00, 0.01) *β = 0.06*
Meat B to A * Variance Meat Production A	0.00 (-0.01, 0.02) *β = 0.00*	-0.00 (-0.03, 0.03) *β = -0.01*	0.00 (-0.03, 0.03) *β = 0.00*	**-0.08 (-0.13, -0.02)***** ***β = -0.13***	-0.01 (-0.02, 0.00) *β = -0.07*
Produce B to A * Avge Horticult. Production A	-0.00 (-0.00, 0.01) *β = 0.01*	0.01 (-0.01, 0.03) *β = 0.15*	0.00 (-0.02, 0.02) *β = 0.03*	**0.01 (0.00, 0.02)*** ***β = 0.08***	0.00 (-0.00, 0.00) *β = 0.06*
Produce B to A * Field Size A	0.00 (-0.00, 0.01) *β = 0.00*	-0.00 (-0.02, 0.01) *β = -0.05*	0.00 (-0.02, 0.02) *β = 0.00*	**0.01 (0.00, 0.02)*** ***β = 0.08***	-0.00 (-0.00, 0.00) *β = -0.04*
Labor B to A * Family Members A	0.16 (-0.05, 0.37) *β = 0.01*	**-0.53 (-1.11, 0.06)^{t}** ***β = -0.05***	0.13 (-0.32, 0.56) *β = 0.01*	-0.03 (-2.00, 1.77) *β = 0.00*	-0.02 (-0.46, 0.38) *β = 0.00*
Labor B to A * Field Size A	-0.08 (-0.36, 0.21) *β = 0.00*	0.33 (-0.35, 1.02) *β = 0.02*	-0.20 (-0.87, 0.45) *β = -0.01*	-0.86 (-2.87, 1.21) *β = -0.03*	-0.08 (-0.67, 0.53) *β = -0.01*
Childcare B to A * Family Members A	-1.43 (-3.42, 0.67) *β = 0.00*	-0.54 (-3.96, 3.20) *β = 0.00*	1.53 (-1.26, 4.39) *β = 0.01*	11.70 (-15.19, 39.11) *β = 0.05*	1.48 (-2.55, 5.46) *β = 0.03*
Childcare B to A * Field Size A	-0.69 (-1.71, 0.40) *β = 0.00*	**3.01 (0.54, 5.53)*** ***β = 0.02***	-0.17 (-2.29, 1.85) *β = 0.00*	13.46 (-7.63, 36.58) *β = 0.06*	1.49 (-1.26, 4.19) *β = 0.03*
Sick Care B to A * Family Members A	0.10 (-1.44, 1.72) *β = 0.00*	-2.49 (-5.85, 0.79) *β = -0.02*	**-2.73 (-5.24, -0.34)*** ***β = -0.02***	**-23.63 (-36.85, -11.25)***** ***β = -0.12***	-2.84 (-7.22, 1.38) *β = -0.06*

^{t} P<0.1, * P<0.05, ** P<0.01, *** P<0.001

[a]These variables were all z-score transformed such that 0 is the population average; the main effects of receiving are thus estimated at the population average for supply and demand, and the main effects of supply and demand are estimated at 0 receiving.

[b]Note that the residual variance for binary models was fixed [S1, S2]

Table S3, related to Figure 3: Model summary predicting total cooperation given

	Total Help A to B b (upper, lower 95% CI)
R_m^2 / R_c^2	0.20 / 0.33
Intercept	**-1.43 (-1.96, -0.85)*** **
Total Help B to A	**0.57 (0.49, 0.66)***** ***β* = 0.14**
Relatedness A-B	**3.66 (2.56, 4.84)***** ***β* = 0.07**
Log distance A-B	**-0.12 (-0.22, -0.01)*** ***β* = -0.04**
Need A	0.00 (-0.00, 0.00) *β* = -0.02
Need B	0.00 (-0.00, 0.00) *β* = 0.02
Age A	**-0.01 (-0.02, -0.001)*** ***β* =-0.04**
Age B	-0.00 (-0.01, 0.01) *β* = -0.01
Relatedness : Need B	0.00 (-0.00, 0.00) *β* = 0.00

Table S4, related to Experimental Procedures: Descriptive statistics of variables used in analyses

Variable name	Type [units]	Mean	SD	Range
Meat sharing	Numeric [cals/d]	12.2	77.9	0-1534
Produce sharing	Numeric [cals/d]	48.2	313.9	0-6527
Labor sharing	Numeric [d/y]	0.3	1.7	0-38
Childcare	Binary [yes/no]	0.04	0.2	0-1
Sick care	Binary [yes/no]	0.04	0.2	0-1
Mean relatedness	Numeric [R]	0.04	0.07	0-0.34
Distance	Numeric [log km]	0.01	1.2	-6.9 – 1.8
Meat production[a]	Numeric [cals/d]	6.0	1.2	-0.9-8.5
Variance in meat production[a]	Numeric [CV]	3.0	1.0	1.3-7.5
Horticultural production[a]	Numeric [cals/d]	8.1	1.0	5.3-10.0
Total size of fields[a]	Numeric [tareas[b]]	18.7	13.3	0-71
Midparent age	Numeric [years]	42.8	15.6	16-86
Family size[a]	Numeric	5.9	3.0	1-15
Net need	Numeric [cals]	-102.4	3017.7	-9692 - 8687
Sampling days	Numeric [d]	102.5	29.6	8-166

[a] These variables were entered into the analysis as z-scores
[b] 1 tarea = 628.9 m^2

Supplemental Experimental Procedures

Data collection and preparation

Food sharing, production, and consumption: From January 2005 to December 2009, adults (n=1245) from 11 communities were interviewed once or twice per week about all production activity during the previous two days. Each family was interviewed an average of 45.5 times (SD = 20.4). Quantities produced and shared were estimated through the use of locally understood standard measures and project data on mean weights for common resources, and converted into calories using standard nutritional tables. Here we included the total meat/produce calories produced and transferred as well as variance in meat production. Age-specific production and consumption curves were used to calculate a household's estimated net need, i.e. total production minus consumption. For more details see [S3–S5].

Horticultural fields and labor: Data on number and size of fields and labor sharing were obtained from annual field interviews (n=780) conducted from 2005-2009, the period overlapping with the food production and sharing interviews [S3, S4]. Household heads were asked about all fields they had made this year, as well as from whom they had received any help in field clearance, tree chopping, burning, weeding, or harvesting, and for how many days. Help given to others in field labor was recorded in the same fashion. Payment for labor was recorded as money, food, harvest share, labor, labor debt, or unpaid. Here we included the average number of unpaid labor days given from household A to household B per year as well as the total size of fields a household made per year.

Childcare and sick care: Information on childcare and sick care among households came from interviews conducted in 2005 and 2006 (n=671), asking heads of households about common forms of shocks such as illness, accidents, theft, crop failure, or social conflict, and their buffers against them [S4, S6]. During this interview, people were asked to nominate up to three individuals who normally provide them with childcare through questions like 'who looks after your children when you go foraging?', 'who feeds your children when you go foraging?', and 'where do your children sleep when you go foraging?', with questions about four contexts (foraging, town visits, illness ego, illness spouse) resulting in a large number of possible nominations. While this ensured that anyone providing regular childcare was nominated, the questions do not capture frequency of care. Therefore, we used a binary measure of childcare measured as any nomination of a member of one household by a member of another (except when calculating the ordinal measure used to compile the total helping score; in this case total nominations were used to determine whether A gave household B more or less childcare than A gave to the average other household). Data on sick care were obtained by asking participants whether they or their spouse had experienced illness or accidents in the past three months, or, if not, the last time they did. They were then asked to name people who had given them medicinal plants, medicine, money to buy medicine or go to the hospital, fed them or their family, or provided any other form of help during these episodes. Similar to childcare, this resulted in a binary measure of sick care among households.

Other variables: Ages were recorded during regular censuses and medical visits as well as demographic interviews [S7]. Average degree of relatedness among households was obtained from demographic interviews as well as by asking about the relationship between donor and receiver for each instance of help given in the interviews described above [S3]. Distance between households (in kilometers) was calculated by applying the spherical law of cosines to latitude and longitude coordinates measured with a handheld GPS unit [S3].

Modeling zero-inflation

All count data (meat/produce/labor sharing) had a larger number of zeroes than expected under a regular poisson process given their means. We therefore initially modeled count data as zero-inflated Poisson distributed (with log link), wherein a zero-inflation intercept (with logit link) captures excess zeroes that cannot be modeled as part of the Poisson distribution [S8]; the inverse logit of this zero-inflation intercept thus indicates the proportion of 'false zeroes' due to methodological biases, in our case interpretable as dyads that were never observed to cooperate but perhaps would have been given a longer sampling period. Interestingly, this proportion of false zeroes was very high (~95%) for meat sharing, but diminishingly low (<0.1%) for produce and labor sharing, indicating that our sampling period was adequate for the latter but not the former (consistent with the greater variance and unpredictability of meat production). Thus, we re-fit produce and labor models using regular Poisson, which is what we report.

Model equations

The full zero-inflated poisson model with random slopes for count commodities (meat, produce, labor) given by household *i* to household *j* in community *c* is given by:

$$Y_{ijc} \sim ZIP\ (\mu_{ijc}, \zeta)$$

$\log(\mu_{ijc}) = b_0 + b_1 * meat_{jic} + b_2 * produce_{jic} + b_3 * labor_{jic} + b_4 * childcare_{jic} + b_5 * sick\ care_{jic} + \cdots + r_{i1} * (1 + r_{i2} * meat_{jic} + r_{i3} * produce_{jic} + r_{i4} * labor_{jic} + r_{i5} * childcare_{jic} + r_{i6} * sick\ care_{jic}) + r_j + r_{c1} * (1 + r_{c2} * distance_{jic}) + e$

$$logit(\zeta) = \gamma$$
$$r_i \sim Norm\ (0, \textstyle\sum_{donor})$$
$$r_j \sim Norm\ (0, \sigma^2_{recipient})$$
$$r_c \sim Norm\ (0, \textstyle\sum_{community})$$
$$e \sim Norm(0, \sigma^2_e)$$

Herein ζ is the probability of measuring a false zero (see above, [S8]), μ_{ijc} the expected value for the count process for dyad *ij* in community *c*, the subscript *ji* denotes commodities received, and all random effects r_x follow a normal distribution with mean 0 and variance σ^2, covariances are estimated between the random intercept and random slopes for donor household *i* and community *c* in their respective variance-covariance matrices $\sum_{donor}$ and $\sum_{community}$, and residual variance is soaked up by the additive overdispersion term e, which is modeled as a random intercept for each datapoint [S1, S8]. The regular poisson model is the same but without the zero-inflation intercept:

$$Y_{ijc} \sim Pois\ (\mu_{ijc})$$

The binomial model for binary data uses the logit link function:

$$Y_{ijc} \sim Bin\ (p_{ijc})$$
$$\text{logit}(p_{ijc}) = b_0 + \cdots$$

with the rest being the same as for the ZIP model. R code for fitting these models with MCMCglmm is available from the first author upon request.

Model fitting

Prior to analysis, collinearity of potential predictor variables was assessed using generalized variance inflation factors (gVIF's [S9], all < 3). Nonlinear effects of predictors were assessed visually by plotting each dependent variable against each predictor using a loess smooth [S8]; distance between households had a clear convex effect and was consequently logged. All supply and demand variables were transformed into z scores such that 0's represent the population average.

We placed weak Gaussian priors (mean = 0, variance = 1000) on all fixed effects to improve convergence and guard against overfitting [S10]. Variance-covariance components received standard inverse gamma priors in the (zero-inflated) Poisson models (increasing the degree of belief parameter to 0.02 for models with random exchange slopes) and weak Cauchy priors (variance=1000) in binary models [S1]. As the variances of the zero-inflation intercept and the residual variance in binary models cannot be estimated, they were fixed to 1 and 10, respectively [S1]. Models were run until the Markov chains converged as assessed visually by plotting time series and histograms as well as formally by calculating Potential Scale Reduction Factors (all <1.1) on three runs of the same model using the gelman.diag function [S11]. The respective number of iterations, burnin, and thinning interval varied depending on the complexity of the candidate model and the distribution; the most complex models were run for 250,000 (meat), 100,000 (produce, labor), and 1,000,000 iterations (childcare, sick care) respectively, with a burnin of 50,000/10,000/250,000 and a thinning interval of 20/10/50. Chains were sampled using Gibbs sampling for (zero-inflated) Poisson models and slice sampling for binary models. R code for all analyses is available from the first author upon request.

Standardized coefficients and R^2:

We calculated standardized coefficients for the GLMM's using the method described by Menard [S12], Eq. 5, in which

$$\beta = \frac{b * s_X * R}{s_{link\ (\hat{Y})}}$$

with b being the parameter estimate, s_X the standard deviation of the predictor variable, R the square root of the (marginal) coefficient of determination R_m^2 (see below), and $s_{link\ (\hat{Y})}$ is the standard deviation of the predicted values on the scale of the respective link function (log for poisson, logit for binomial).

We followed Nakagawa and Schielzeth [S2] and the extension by Johnson [S13] for random slope models to calculate coefficients of determination for GLMM's. The marginal coefficient of determination R_m^2, i.e. variance explained by the fixed effects, and the conditional coefficient of determination R_c^2, i.e. the variance explained by the fixed and random effects are:

$$R_m^2 = \frac{\sigma_f^2}{\sigma_f^2 + \overline{\sigma_l^2} + \sigma_e^2 + \sigma_d^2}$$

$$R_c^2 = \frac{\sigma_f^2 + \overline{\sigma_l^2}}{\sigma_f^2 + \overline{\sigma_l^2} + \sigma_e^2 + \sigma_d^2}$$

where σ_f^2 is the variance explained by the fixed effects, $\overline{\sigma_l^2}$ is the mean random effect variance, σ_e^2 is the residual variance, and σ_d^2 is the distribution-specific variance.

Two things are worth noting. First, the residual variance σ_e^2 cannot be estimated for binary models and was therefore fixed to 10 [S1]; this limits the value the denominator can take resulting in relatively high coefficients of determination, and by extension standardized coefficients (see above) for the childcare and sick care models. Second, to our knowledge no one has extended coefficients of determination to zero-inflated poisson models so we applied the regular poisson formula to the meat sharing model.

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