Supplementary Information

Be Nice if You Have to - The Neurobiological Roots of Strategic Fairness

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Statistical Models

First Model: Behaviour in the Dictator Game (DG)

To test (i) whether participants act more selfishly when TMS is applied over the right DLPFC compared to sham and TMS over the left DLPFC, transfer decisions of the dictator game without punishment (DG) were regressed on a dummy predictor coding the three TMS conditions (sham condition as baseline). We controlled for the order in which participants experienced the three TMS conditions in two ways. For each observation a session variable coding for the session number was introduced, as well as a dummy variable coding for the condition order (e.g. sham-left-right).

A substantial fraction of the dictator transfers was zero. We therefore treated the data as left censored and fitted a Bayesian random-intercept Tobit regression model to the data using R and JAGS. Non-informative Gaussian priors (m=0, sd=100) were used for each predictor and non-informative uniform distributions (range 0 to 100) for the level-1 and level-2 error term. For the fitting we used three chains. $\hat{R}$ was below 1.1 for all parameters, indicating good mixing of the three chains and thus high convergence (Brooks and Gelman, 1998). Table S1 shows estimated beta coefficients together with the 95% highest density interval (HDI, also called Bayesian confidence interval) for each predictor. Note that, since non-informative priors were used, a 95% HDI that only contains negative or positive values can be interpreted as significant at a p = .05 two-sided threshold in a frequentist framework. However, since the predictors are treated as random variables in the Bayesian framework, the HDI can further be interpreted as the probability distribution of this parameter and the estimate as the point with the highest likelihood.

Table S1

Estimates and 95% interval for the Bayesian random-intercept Tobit regression model testing Hypothesis (i). Dependent variable: Transfer decisions in the dictator game without punishment (DG).

		Estimate	95% HDI
Fixed part			
intercept	Sham TMS	-35.14	-114.41 – 46.00
TMS	left DLPFC	-1.83	-6.86 – 3.14
TMS	right DLPFC	-9.15	-14.37 – -3.92
order	session	4.17	1.66 – 6.68
order	left-right-sham (n = 2)	19.38	-80.21 – 120.99
order	left-sham-right (n = 3)	-24.34	-128.65 – 73.70
order	right-left-sham (n = 4)	-0.80	-98.65 – 93.48
order	right-sham-left (n = 2)	-10.32	-117.01 – 97.41
order	sham-left-right (n = 3)	-21.64	-118.88 – 73.43
order	sham-right-left (n = 3)	34.12	-58.34 – 127.47
Random part			
error-term a		58.67	30.05 – 95.54
error-term y		15.67	14.02 – 17.61

Participants gave significantly less when the right DLPFC was disrupted by TMS compared to sham (TMS right coefficient, see Table S1). When the left DLPFC was disrupted, we did not find evidence for a significant change in transfer rates compared to sham (TMS left coefficient, see Table S1). Examining the posterior distributions of the TMS left and TMS right parameter revealed an estimated difference of -7.3 with a 95% HDI ranging from -10.3 to -4.3. Thus, participants not only gave significantly less to recipients under right TMS compared to sham but also compared to left TMS. Figure S1 shows residual diagnostic plots for the fitted model and a posterior predictive check comparing the actual observed transfer frequencies and the frequencies expected by the fitted model based on 10,000 simulations (Gelman, Meng and Stern, 1996). As can be seen in Figure S1A, transfers above 40 MUs were slightly overestimated by the model.

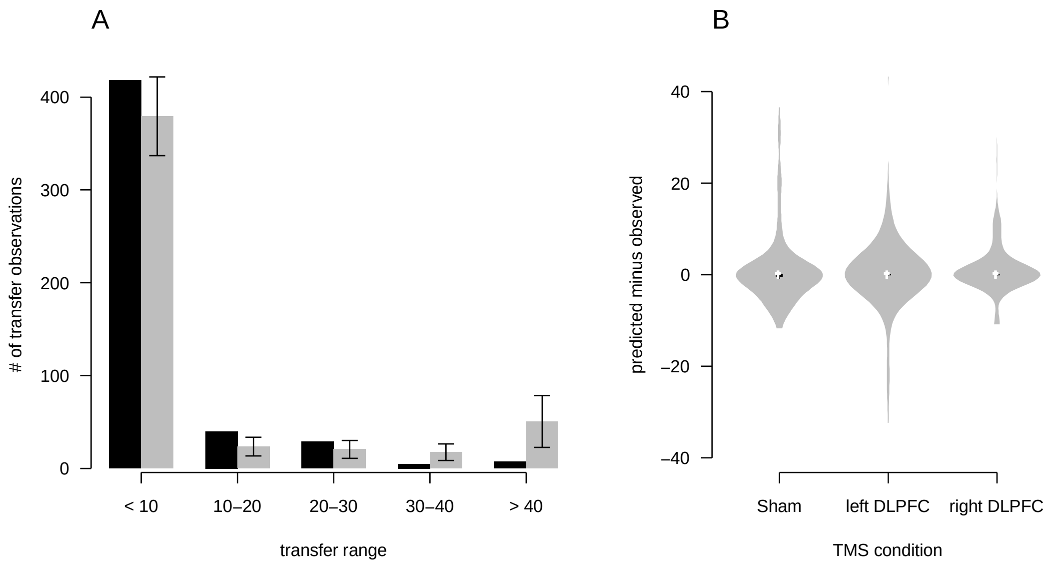


Fig. S1. Posterior predictive check and residual plots of the fitted model. (A) Posterior predictive simulation of transfer frequencies (+/- 1SD, grey bars) compared to actual observed frequencies (black bars) and (B) residual distributions separated by TMS condition. White point shows the median.

Second Model: Strategic adaption across Dictator Games with (DGp) and without punishment (DG)

To test Hypothesis (ii), whether participants show less strategic fairness when TMS is applied over the right DLPFC compared to sham and TMS over the left DLPFC we first looked at the behaviour of each dictator during sham TMS and classified participants into 'adapters' and 'non-adapters'. Those who gave more to recipients with punishment opportunity over the 20 dictator game rounds during sham were classified as 'adapters' and those who gave less or equal to recipients with punishment opportunity were classified as 'non-adapters'. For each participant we calculated the transfer difference across DG and DGp as a measure for strategic adaption and regressed it on the dummy predictor coding the three TMS conditions (sham condition as baseline) as well as the non-adaption-dummy predictor, which takes value 1 for participant classified as non-adapter and 0 otherwise. Like in the first model we controlled for the order of the TMS treatments.

A random intercept regression was fitted to the data using R and JAGS. Non-informative Gaussian priors (m=0, sd=100) were used for each predictor and non-informative uniform distributions (range 0 to 100) for the level-1 and level-2 error term. For the fitting we used three chains. $\hat{R}$ was below 1.1 for all parameters, indicating good mixing of the chains and thus high convergence (Brooks and Gelman, 1998). Table S2 shows estimated beta coefficients together with the 95% confidence interval for each predictor. Note that predictor coefficients that are not interactions with the non-adapter dummy (fixed part, adapters, see Table S2) can be interpreted as the behaviour of adapters, while the predictor coefficients that do interact with the non-adapter dummy (fixed part, non-adapters, see Table S2) is the change in behaviour of non-adapters compared to adapters.

Table S2

Estimates and 95% interval for the Bayesian random-intercept Poisson regression model testing Hypothesis (ii). Dependent variable: Transfer difference.

		Estimate	95% CI
Fixed part (adapters)			
intercept	Sham TMS, no punishment, adapters	26.69	-50.16 – 103.45
TMS	left DLPFC	2.61	-0.64 – 4.31
TMS	right DLPFC	-6.30	-8.04 – -4.59
Fixed part (non-adapters)			
NA	non-adapters	-26.45	-42.73 – -9.89
NA x TMS	non-adapters, left DLPFC	2.85	-0.04 – 5.73
NA x TMS	non-adapters, right DLPFC	14.58	11.79 – 17.40
order	session	0.01	-0.68 – 0.69
order	left-right-sham (n = 2)	4.18	-74.62 – 82.88
order	left-sham-right (n = 3)	-14.22	-92.36 – 63.83
order	right-left-sham (n = 4)	1.01	-76.70 – 79.51
order	right-sham-left (n = 2)	9.06	-69.21 – 87.65
order	sham-left-right (n = 3)	1.94	-76.01 – 80.78
order	sham-right-left (n = 3)	-5.17	-84.76 – 73.28
Random part			
error term a		13.78	8.63 – 22.99
error term y		10.88	10.49 – 11.29

Participants who adapted during sham did so significantly less when the right DLPFC was disrupted (TMS right, see Table S2). We did not observe a significant change in strategic adaption of adapters during the disruption of the left DLPFC (TMS left, see Table S2). Examining the posterior distributions of the TMS left and TMS right parameter revealed an estimated difference of -8.91 with a 95% HDI ranging from

-9.90 to -7.93. Thus, participants who adapted strategically during sham did so significantly less during TMS over the right DLPFC compared to TMS over the left DLPFC.

Figure S2 shows residual diagnostic plots for the fitted model and a posterior predictive check comparing the actual observed transfer change frequencies and the frequencies expected by the fitted model based on 10,000 simulations (Gelman, Meng and Stern, 1996). As can be seen in Figure S2A, there is no systematic over- or underestimation of transfer change frequencies by the model.

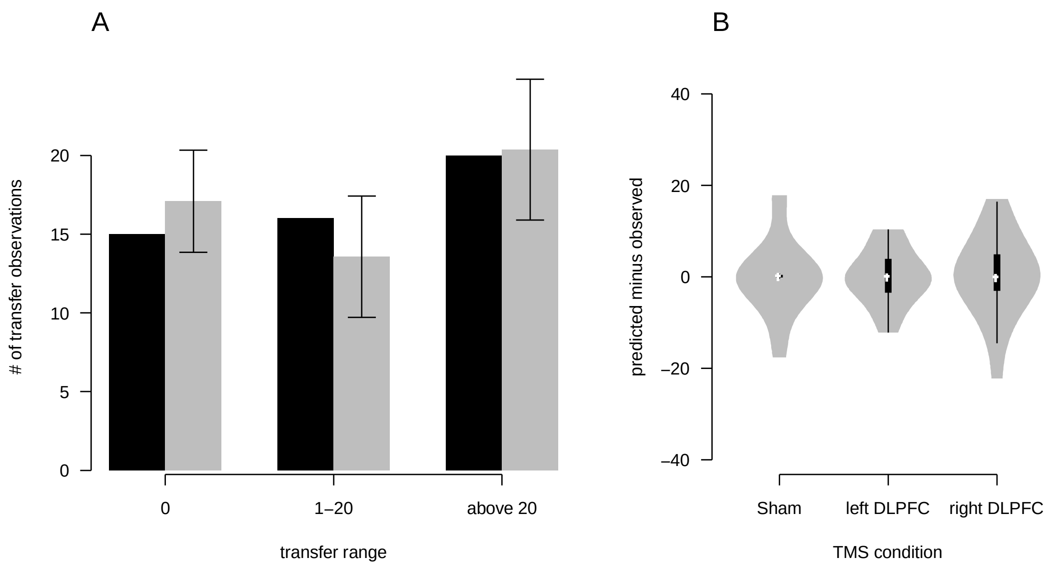


Fig. S2. Posterior predictive check and residual plots of the fitted model. (A) Posterior predictive simulation of transfer change frequencies (+/- 1SD, grey bars) compared to actual observed frequencies (black bars) and (B) residual distributions separated by TMS condition. White point shows the median.

Third Model: Transfer change across Dictator Games with (DGp) and without punishment (DG)

We also fitted a model on the individual trial level by using the transfers in each round and regressed it on all TMS condition x punishment condition x non-adaption interaction terms. We controlled for the order of the TMS treatments and treated the data as left censored. In this model, a change in strategic adaption (TMS condition x punishment condition predictor) due to TMS can be analysed while controlling for a possible change in selfishness in the DG due to TMS (TMS condition predictor).

Non-informative Gaussian priors (m=0, sd=100) were used for each predictor and non-informative uniform distributions (range 0 to 100) for the level-1 and level-2 error term. For the fitting we used three chains. $\hat{R}$ was below 1.1 for all parameters, indicating good mixing of the three chains and thus high convergence (Brooks and Gelman, 1998). Table S3 shows estimated beta coefficients together with the 95% confidence interval for each predictor. Note that predictor coefficients that are not interactions with the non-adapter dummy (fixed part, adapters, see Table S3) can be interpreted as the behaviour of adapters, while the predictor coefficients that do interact with the non-adapter dummy (fixed part, non-adapters, see Table S3) is the change in behaviour of non-adapters compared to adapters.

Participants who adapted during sham did so significantly less when the right DLPFC was disrupted (TMS right x DG coefficient, see Table S3). We did not observe a significant change in strategic adaption of adapters during the disruption of the left DLPFC (TMS left x DG coefficient, see Table S3). Examining the posterior distributions of the TMS left x Punishment and TMS right x Punishment parameter revealed an estimated difference of -8.90 with a 95% HDI ranging from -13.40 to

-6.49. Thus, participants who adapted strategically during sham did so significantly less during TMS over the right DLPFC compared to TMS over the left DLPFC.

Figure S3 shows residual diagnostic plots for the fitted model and a posterior predictive check comparing the actual observed transfer frequencies and the frequencies expected by the fitted model based on 10,000 simulations (Gelman, Meng and Stern, 1996). As can be seen in Figure S3A, there is no systematic over- or underestimation of transfer-frequencies by the model.

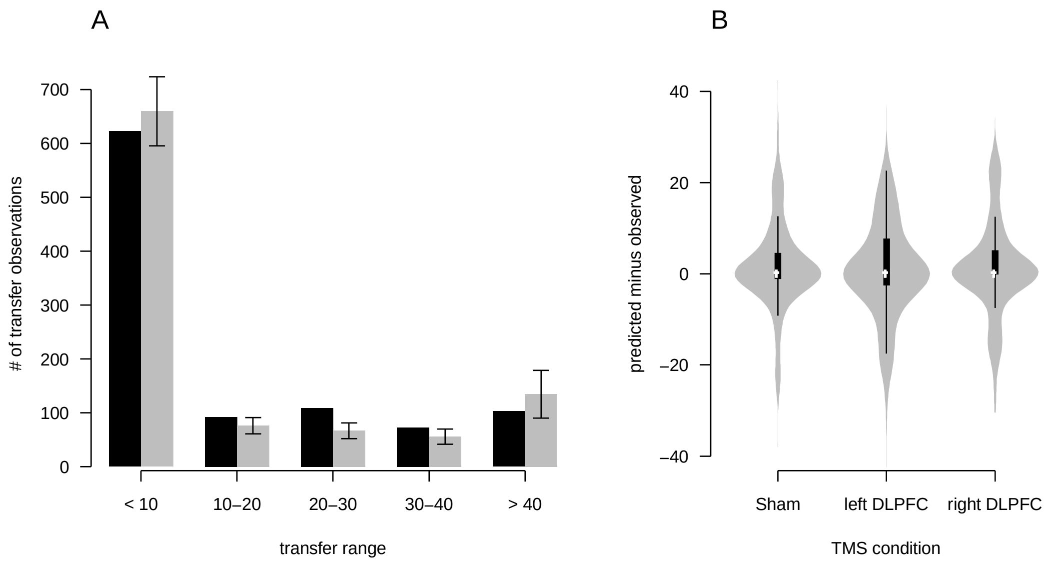


Fig. S3. Posterior predictive check and residual plots of the fitted model. (A) Posterior predictive simulation of transfer frequencies (+/- 1SD, grey bars) compared to actual observed frequencies (black bars) and (B) residual distributions separated by TMS condition. White point shows the median.

Table S3

Estimates and 95% interval for the Bayesian random-intercept Tobit regression model testing Hypothesis (ii). Dependent variable: Transfer decisions.

		Estimate	95% CI
Fixed part (adapters)			
intercept	Sham TMS, no punishment, adapters	-0.27	-67.34 – 62.73
TMS	left DLPFC	-2.86	-5.86 – 1.13
TMS	right DLPFC	-3.86	-6.87 – -0.87
DG	with punishment	25.97	22.95 – 28.94
TMS x DG	with punishment, left DLPFC	3.53	-0.65 – 7.77
TMS x DG	with punishment, right DLPFC	-5.37	-9.56 – -1.12
Fixed part (non-adapters)			
NA	non-adapters	0.66	-10.30 – 11.67
NA x TMS	non-adapters, left DLPFC	7.87	2.89 – 12.90
NA x TMS	non-adapters, right DLPFC	2.25	-2.72 – 7.26
NA x DG	non-adapters, with punishment	-29.36	-34.29 – -24.30
NA x TMS x DG	non-adapters, with punishment, left DLPFC	-3.83	-10.96 – 3.13
NA x TMS x DG	non-adapters, with punishment, right DLPFC	13.62	6.54 – 20.62
order	session	0.71	-0.13 – 1.56
order	left-right-sham (n = 2)	-2.23	-74.25 – 46.86
order	left-sham-right (n = 3)	-15.96	-86.60 – 32.12
order	right-left-sham (n = 4)	-0.81	-72.26 – 47.73
order	right-sham-left (n = 2)	-4.19	-76.12 – 45.32
order	sham-left-right (n = 3)	-6.98	-78.98 – 41.24
order	sham-right-left (n = 3)	-2.72	-74.36 – 46.96
Random part			
error term a		8.88	5.49 – 14.84
error term y		11.11	10.63 – 11.62

Fairness Judgements

After each dictator game in each TMS session, participants made fairness judgements about five hypothetical transfers (from 0 to 50 MUs in steps of 10) on a scale from 1 ("very unfair") to 7 ("very fair").

To test whether fairness judgements were systematically influenced by TMS we regressed the responses on a dummy predictor coding the three TMS conditions (sham condition as baseline), as well as a predictor coding for the different hypothetical offers in increasing order, the non-adaption dummy already used in the above model, and control variables for the order. Non-informative Gaussian priors (m=0, sd=100) were used for each predictor and non-informative uniform distributions (range 0 to 100) for the level-1 and level-2 error term. For the fitting we used three chains. $\widehat{R}$ was below 1.1 for all parameters, indicating good mixing of the three chains and thus high convergence (Brooks and Gelman, 1998). Table S4 shows estimated beta coefficients together with the 95% confidence interval for each predictor. Note again, that predictor coefficients that are not interactions with the non-adapter dummy (fixed part, adapters, see Table S4) can be interpreted as the behaviour of adapters, while the predictor coefficients that do interact with the non-adapter dummy (fixed part, non-adapters, see Table S4) is the change in behaviour compared to adapters.

As can be expected, fairness judgements significantly increased with the hypothetical offer during sham for adapters (offer coefficient, see Table S4). For adapters, this increase in fairness judgements was not significantly altered by the TMS manipulations (TMS left x offer coefficient and TMS right x offer coefficient, see Table S4). Interestingly, non-adapters rated offers to be more fair compared to adapters (non-adaption coefficient, see Table S4) but with increased offer showed a significantly lower slope in rating higher offers as more fair (non-adaption x offer, see Table S4). This indicates that their fairness judgements were less influenced by the size of the offer. This relative insensitivity to changes in the offer could explain why they did not adapt in the first place. Since they did not perceive higher offers as fairer (at least not as much as observed for adapters), it could be that they did not feel an obligation to make higher offers when under the threat of punishment.

Figure S4 shows residual diagnostic plots for the fitted model and a posterior predictive check comparing the actual observed transfer frequencies and the frequencies expected by the fitted model based on 10,000 simulations (Gelman, Meng and Stern, 1996). As can be seen in Figure S4A, fairness judgements in the center were slightly over- or underestimated, while judgements at the end of the scale were neither systematically over- nor underestimated by the model. Overall, the model captured the general frequency trend of judgements.

Table S4

Estimates and 95% interval for the Bayesian random-intercept regression model testing the influence of TMS on fairness judgements. Dependent variable: fairness judgements.

		Estimate	95% CI
Fixed part (adapters)			
intercept	Sham TMS, adapters, zero offer	4.18	-38.86 – 33.45
TMS	left DLPFC	0.23	-0.86 – 1.35
TMS	right DLPFC	-0.18	-1.31 – 0.95
offer	hypothetical offer	0.13	0.10 – 0.15
offer x TMS	offer, left DLPFC	-0.02	-0.05 – 0.02
offer x TMS	offer, right DLPFC	0.00	-0.04 – 0.03
Fixed part (non-adapters)			
NA	non-adapters	3.25	1.61 – 4.87
NA x offer	non-adapters, offer	-0.14	-0.18 – -0.10
TMS x NA	left DLPFC, non-adapters	-0.84	-2.61 – 0.91
TMS x NA	right DLPFC, non-adapters	-0.74	-2.52 – 1.03
TMS x offer x NA	hypothetical offer, left DLPFC, non-adapters	0.05	-0.01 – 0.10
TMS x offer x NA	hypothetical offer, right DLPFC, non-adapters	0.03	-0.03 – 0.08
order	session	-0.01	-0.24 – 0.23
order	left-right-sham (n = 2)	-2.73	-32.16 – 40.27
order	left-sham-right (n = 3)	-3.98	-33.25 – 39.20
order	right-left-sham (n = 4)	-3.68	-32.95 – 39.51
order	right-sham-left (n = 2)	-3.62	-32.90 – 39.60
order	sham-left-right (n = 3)	-4.56	-34.06 – 38.48
order	sham-right-left (n = 3)	-3.43	-32.78 – 39.66
Random part			
sigma a		0.87	0.33 – 1.52
sigma y		1.63	1.48 – 1.79

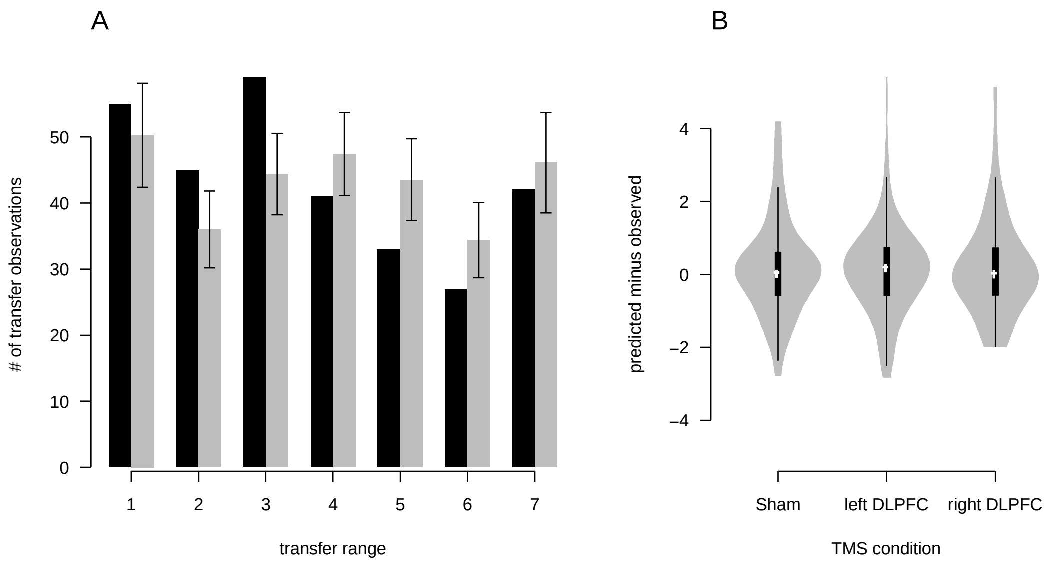


Fig. S4. Posterior predictive check and residual plots of the fitted model. (A) Posterior predictive simulation of transfer frequencies (+/- 1SD, grey bars) compared to actual observed frequencies (black bars) and (B) residual distributions separated by TMS condition. White point shows the median.

Expected punishment

Next to fairness evaluations, participants were asked about how many MUs (from 0 to 25) they believed the receivers would on average spent on punishment for a given hypothetical offer (from 0 to 50 MUs in steps of 10).

To test whether punishment expectations were systematically influenced by TMS we regressed the responses to dummy predictors coding the three TMS conditions (sham condition as baseline), as well as a predictor coding for the hypothetical offer, the non-adaption dummy already used in the above models, and predictors coding for the session and TMS order.

Again, the data was treated as left-censored and non-informative Gaussian priors (m=0, sd=100) were used for each predictor and non-informative uniform distributions (range 0 to 100) for the level-1 and level-2 error term. For the fitting we used three chains. $\hat{R}$ was below 1.1 for all parameters, indicating good mixing of the three chains and thus high convergence (Brooks and Gelman, 1998). Table S5 shows estimated beta coefficients together with the 95% confidence interval for each predictor. Note again, that predictor coefficients that are not interactions with the non-adapter dummy (fixed part, adapters, see Table S5) can be interpreted as the behaviour of adapters, while the predictor coefficients that do interact with the non-adapter dummy (fixed part, non-adapters, see Table S5) is the change in behaviour of non-adaptors compared to adapters.

As can be expected, with increased offer, adapting participants expected the receivers to punish less. This expectation was not significantly altered by TMS in adapters. Interestingly, non-adapters not only expected significantly less punishment in general (NA coefficient, see Table S5) but also expected that punishment does not increase with increasingly unfair offers (slope of 0.06 for increasing offers; coefficient NA x offer plus offer). This could explain why they did not adapt to the punishment threat in the first place. It could also mean that they did not believe that punishment would actually take place.

Table S5

Estimates and 95% interval for the Bayesian random-intercept regression model testing the influence of TMS on expected punishment. Dependent variable: expected punishment.

		Estimate	95% CI
Fixed part (adapters)			
intercept	Sham TMS, adapters, zero offer	11.72	-46.92 – 77.46
TMS	left DLPFC	-3.45	-7.12 – 0.20
TMS	right DLPFC	-3.55	-7.22 – 0.14
offer	hypothetical offer	-0.46	-0.56 – -0.37
TMS x offer	left DLPFC, offer	0.09	-0.04 – 0.22
TMS x offer	right DLPFC, offer	0.08	-0.05 – 0.22
Fixed part (non-adapters)			
NA	non-adapters	-28.66	-43.87 – -15.29
NA x offer	non-adapters, offer	0.52	0.34 – 0.70
TMS x NA	left DLPFC, non-adapters	14.88	7.69 – 22.13
TMS x NA	right DLPFC, non-adapters	8.21	-0.98 – 15.68
TMS x offer x NA	hypothetical offer, left DLPFC, non-adapters	-0.33	-0.57 – 0.09
TMS x offer x NA	hypothetical offer, right DLPFC, non-adapters	-0.17	-0.42 – 0.07
order	session	0.85	-0.06 – 1.77
order	left-right-sham (n = 2)	7.04	-60.81 – 67.75
order	left-sham-right (n = 3)	6.43	-61.93 – 66.21
order	right-left-sham (n = 4)	4.64	-61.41 – 63.96
order	right-sham-left (n = 2)	6.98	-60.57 – 66.89
order	sham-left-right (n = 3)	5.50	-61.16 – 65.16
order	sham-right-left (n = 3)	13.21	-55.39 – 74.16
Random part			
error term a		10.32	5.64 – 19.37
error term y		5.78	5.20 – 6.44

Figure S5 shows residual diagnostic plots for the fitted model and a posterior predictive check. As can be seen in Figure S5A, expected punishment in the range from 0-25 MUs was slightly overestimated by the model.

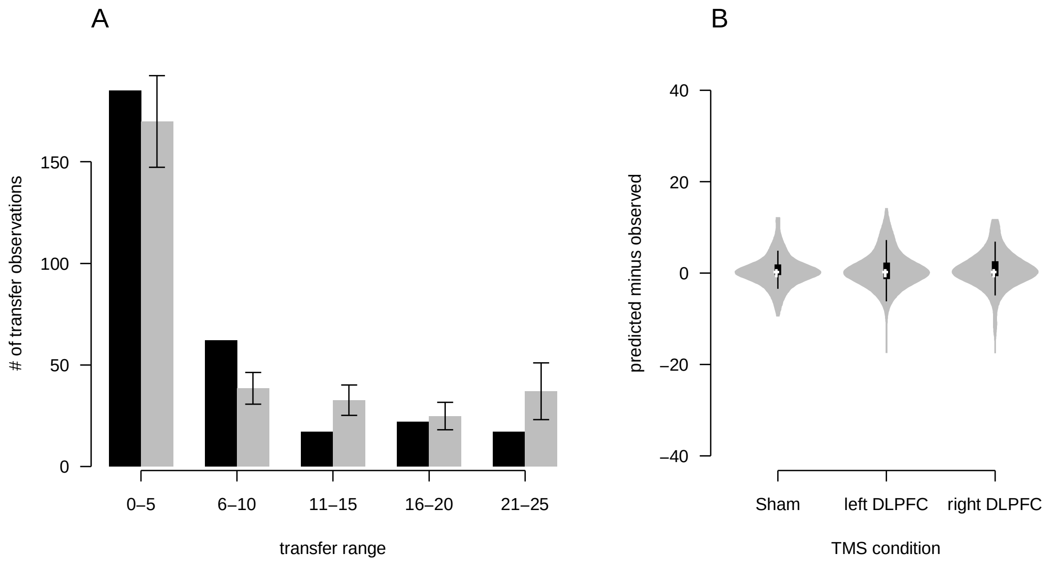


Fig. S5. Posterior predictive check and residual plots of the fitted model. (A) Posterior predictive simulation of transfer frequencies (+/- 1SD, grey bars) compared to actual observed frequencies (black bars) and (B) residual distributions separated by TMS condition. White point shows the median.

Own imagined punishment

Lastly, participants where asked how many MUs (from 0 to 25) they would spent on punishment were they in the shoes of a receiver receiving hypothetical offers from 0 to 50 MUs in steps of 10.

As above, own imagined punishment expenses were regressed on a dummy predictor coding the three TMS conditions (sham condition as baseline), as well as a predictor coding for the hypothetical offer, the adaption dummy already used in the above models, and predictors coding for the session and TMS order. The data was treated as left-censored and non-informative Gaussian priors (m=0, sd=100) were used for each predictor and non-informative uniform distributions (range 0 to 100) for the level-1 and level-2 error term. For the fitting we used three chains. $\hat{R}$ was again below 1.1 for all parameters, indicating good mixing of the three chains and thus high convergence (Brooks and Gelman, 1998). Table S6 shows estimated beta coefficients together with the 95% confidence interval for each predictor.

Adapting participants indicated that they would spent less MUs on punishment the fairer the offer is (offer coefficient, see Table S6) and non-adapting participants did not significantly differ (NA x offer coefficient, see Table S6). However, non-adapters indicated to spent significantly less on punishment (non adapters coefficient, see Table S6). Adapting participants reported that they would spent less MUs on punishment while under the influence of TMS over the right DLPFC (TMS right coefficient, see Table S6).

Figure S6 shows residual diagnostic plots for the fitted model and a posterior predictive check. As can be seen in Figure S6A, expected punishment in the range from 0-25 MUs was slightly overestimated by the model.

Table S6

Estimates and 95% interval for the Bayesian random-intercept regression model testing the influence of TMS on imagined punishment. Dependent variable: own imagined punishment expenses.

		Estimate	95% CI
Fixed part (adapters)			
intercept	Sham TMS, adapters, zero offer	3.15	-49.32 – 60.14
TMS	left DLPFC	0.23	-3.70 – 4.18
TMS	right DLPFC	-3.71	-7.84 – -1.30
offer	hypothetical offer	-0.47	-0.58 – -0.37
offer x TMS	offer, left DLPFC	0.04	-0.10 – 0.18
offer x TMS	offer, right DLPFC	0.08	-0.06 – 0.22
Fixed part (non-adapters)			
NA	non-adapters	-31.05	-60.11 – -4.92
NA x offer	non-adapters, offer	0.21	-0.02 – 0.43
TMS x NA	left DLPFC, non-adapters	-2.15	-10.66 – 6.35
TMS x NA	right DLPFC, non-adapters	6.97	-1.32 – 15.38
TMS x offer x NA	hypothetical offer, left DLPFC, non-adapters	0.15	-0.15 – 0.45
TMS x offer x NA	hypothetical offer, right DLPFC, non-adapters	-0.02	-0.32 – 0.29
order	session	1.45	0.40 – 2.51
order	left-right-sham (n = 2)	13.72	-47.47 – 68.92
order	left-sham-right (n = 3)	2.35	-58.11 – 62.34
order	right-left-sham (n = 4)	14.78	-45.69 – 73.35
order	right-sham-left (n = 2)	-8.15	-74.45 – 49.58
order	sham-left-right (n = 3)	22.18	-37.28 – 79.96
order	sham-right-left (n = 3)	17.44	-42.22 – 76.78
Random part			
error term a		19.06	9.36 – 40.11
error term y		5.75	5.08 – 6.53

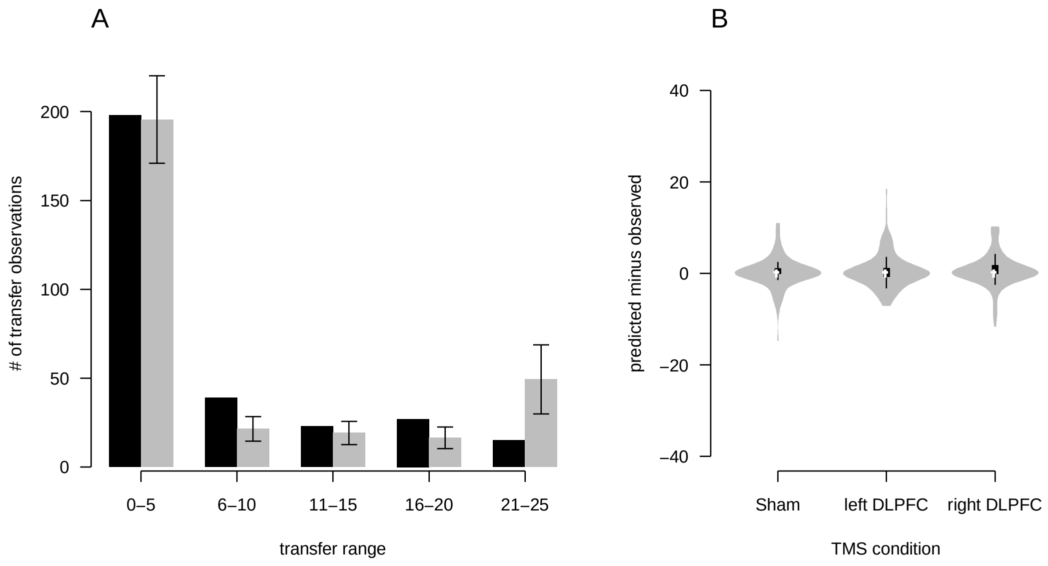


Fig. S6. Posterior predictive check and residual plots of the fitted model. (A) Posterior predictive simulation of transfer frequencies (+/- 1SD, grey bars) compared to actual observed frequencies (black bars) and (B) residual distributions separated by TMS condition. White point shows the median.

Experimental Instructions

Figure S7 to S10 show the instructions and comprehension questions participants received prior to the experiment.

INSTRUCTIONS

In the following experiment we want to investigate how people behave in an interactive situation. In addition to your show up fee you will earn money based on the decisions you make during the experiment. It is important that you understand the procedure of the experiment. Please read the following instructions carefully and do not hesitate to ask questions if anything remains unclear!

During the experiment you will not earn Euros but money units (MU):

100 MUs = 16€
Thus,
1 MU = 0,16 €

There are 20 rounds. In each round you will play with a different participant. So you will never meet the same person again during the experiment. Of course you can see that right now there are no other people in this room to play with. Instead of bringing 20 different people to the lab now, they have already taken part in the experiment and have given a hypothetical response to every possible decision you can make during this experiment. Attached to the instruction you can find photos of all participants you will interact with during this experiment. The payoffs of these participants depend on your decisions, so they did not receive any money yet, but will receive it after this experiment.

How does one round work?

In every round you will interact with one other participant, we call you participant A and we call the person you interact with participant B. In each round you will interact with a different participant B.

At the beginning of each round you and participant B each receive an endowment of 25 MUs.

You receive an additional endowment of 100 MUs. You can transfer as much of these MUs as you want to participant B (from 0 MUs to 100 MUs in steps of 1 MU). In each round, you simply type in how many MU's you want to transfer to participant B. You can change what you typed in pressing "ß " on the keyboard. If you are confident about your decision press "ENTER" to confirm it and the next round will begin.

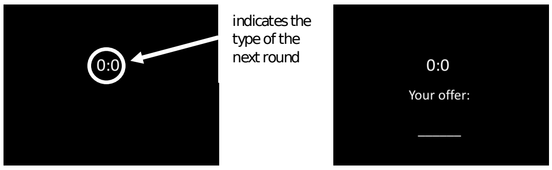
Fig. S7. Written instructions provided to the participants (page 1).

There are two types of rounds, the 5:1 and the 0:0 rounds.

<u>5:1 rounds:</u>

In the 5:1 rounds, he or she can spend his or her MUs to decrease your payoff in a ratio of 5:1. That means that for each MU participant B spends, 5 MU will be subtracted from your final payoff. Since all player B's have given a hypothetical response to every possible decision you can make during this experiment, you can imagine that player B observes your decision and then makes his decision.

<u>0:0 rounds:</u>



In the 0:0 rounds participant B cannot spend any MU's and therefore cannot decrease your payoff. The round is therefore finished after you have decided on an allocation of the 100 MUs and participant B will be informed about this allocation.

After finishing all 20 rounds you will be asked to fill in a short questionnaire.

At the end of the experiment:

At the end of the experiment one out of all rounds will be selected randomly and you and participant B will be paid based on this selected round after the last session.

Fig. S8. Written instructions provided to the participants (page 2).

Trainings questions:

In order to make sure that you understand the procedure of this experiment, we would like you to answer the following questions:

1. How much endowment do you receive at the beginning of each round? ____________________________

2. How much endowment does participant B receive at the beginning of each round? ____________________________

3. In the 5:1 rounds, by how many MUs can participant B decrease your payoff using one of his or her MUs? ____________________________

4. In the 0:0 rounds, by how many MUs can participant B decrease your payoff using one of his or her MUs? ____________________________

5. Does the following picture indicate a round in which participant B can decrease your payoff? ____________________________

6. Does the following picture indicate a round in which participant B can decrease your payoff? ____________________________

7. Has participant B received any payoff yet? ____________________________

8. How many Euros are 100 MUs? ____________________________

9. How many MUs can you maximally transfer to Player B? ____________________________

10. How many MUs can you minimally transfer to Player B? ____________________________

11. With how many other people will you interact throughout 5 rounds in this experiment? ____________________________

3

Fig. S9. Comprehension questions participants had to fill out.

Trainingstrial:

0:0

your offer

____ ← Please indicate a hypothetical offer

The following two questions are related to the offer you have made.

How many MUs would you earn additionally to your 25 MUs endowment? _________

How many MUs would Player B earn additionally to his/her 25 MUs endowment? _________

5:1

your offer

____ ← Please indicate a hypothetical offer

The following five questions are related to the offer you have made.

How many MUs would you earn if Player B would use 25 MUs to decrease your payoff?

____

How many MUs would Player B earn if he/she would use 25 MUs to decrease your payoff?

____

How many MUs would you earn if Player B would use 0 MUs to decrease your payoff?

____

How many MUs would Player B earn if he/she would use 0 MUs to decrease your payoff?

____

4

Fig. S10. Training questions participants had to fill out.

Supplemental References

Brooks, SP. and Gelman, A. (1998). General methods for monitoring convergence of iterative simulations. *Journal of Computational and Graphical Statistics*, **7**, 434-455.

Gelman, A., Meng, X., and Stern, H. (1996). Posterior predictive assessment of model fitness via realized discrepancies. *Statistica Sinica* **6**, 733–807.