

Learning Moral Values: Another's Desire to Punish Enhances One's Own Punitive Behavior

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There is little consensus about how moral values are learned. Using a novel social learning task, we examine whether vicarious learning impacts moral values—specifically fairness preferences—during decisions to restore justice. In both laboratory and Internet-based experimental settings, we employ a dyadic justice game where participants receive unfair splits of money from another player and respond resoundingly to the fairness violations by exhibiting robust nonpunitive, compensatory behavior (baseline behavior). In a subsequent learning phase, participants are tasked with responding to fairness violations on behalf of another participant (a receiver) and are given explicit trial-by-trial feedback about the receiver's fairness preferences (e.g., whether they prefer punishment as a means of restoring justice). This allows participants to update their decisions in accordance with the receiver's feedback (learning behavior). In a final test phase, participants again directly experience fairness violations. After learning about a receiver who prefers highly punitive measures, participants significantly enhance their own endorsement of punishment during the test phase compared with baseline. Computational learning models illustrate the acquisition of these moral values is governed by a reinforcement mechanism, revealing it takes as little as being exposed to the preferences of a single individual to shift one's own desire for punishment when responding to fairness violations. Together this suggests that even in the absence of explicit social pressure, fairness preferences are highly labile.

Keywords: moral preferences, learning, punishment, conformity, social norms

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Decades of research have established that moral behavior is dictated by a set of customs and values that are endorsed at the society level in order to guide conduct (Bowles & Gintis, 2011; Chudek & Henrich, 2011; Kouchaki, 2011; Moll, Zahn, de Oliveira-Souza, Krueger, & Grafman, 2005). These culturally normative rules are critically shaped by fairness considerations (Haidt & Kesebir, 2010; Peysakhovich & Rand, 2016; Rai & Fiske, 2011; Spitzer, Fischbacher, Herrnberger, Grön, & Fehr, 2007), which is considered a core foundation of morality (de Waal, 2006; Turiel, 1983). Indeed, there is much evidence that humans are highly motivated to rebalance the scales of justice after experiencing or observing norm violations (Fehr, Bernhard, & Rockenbach, 2008;

Fehr & Fischbacher, 2004; Fehr & Gächter, 2002; Mathew & Boyd, 2011). The degree to which fairness is valued even extends to nonhuman primates, where animals routinely seek out ways to reestablish equality among group members when posed with a fairness infraction (Brosnan & De Waal, 2003; de Waal, 1996, 2006). Although sensitivity to fairness is well established across species, there is little consensus about how these fairness preferences are learned, and whether they are unwavering in their application or vulnerable to social influence.

On one hand, individual fairness preferences are often characterized as stable and fixed (Peysakhovich, Nowak, & Rand, 2014). This dovetails with a long history of research illustrating that moral attitudes (Haidt, 2001; Turiel, 1983)—such as beliefs about justice and honor—are resolutely and sacredly held (Bauman & Skitka, 2009; Skitka, Bauman, & Sargis, 2005; Sturgeon, 1985), resistant to change (Hornsey, Majkut, Terry, & McKimmie, 2003; Luttrell, Petty, Briñol, & Wagner, 2016; Tetlock, 2003), and firmly rooted even in the face of social opposition (Aramovich, Lytle, & Skitka, 2012). And yet research in other domains illustrates how social pressure and influence can swiftly yield conformist behavior (Bardsley & Sausgruber, 2005; Cialdini, 1998; Deutsch & Gerard, 1955; Zaki, Schirmer, & Mitchell, 2011), indicating that individuals desire the approval of others (Baumeister & Leary, 1995; Wood, 2000). There is an equally long history of evidence delin-

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eating how social attitudes are exquisitely attuned to perceived societal milieus (Jones, 1994; Nook, Ong, Morelli, Mitchell, & Zaki, 2016). For instance, perceptions of group consensus can induce compliant behavior, such as altering how readily one estimates or values an object (Asch, 1956; Campbell-Meiklejohn, Bach, Roepstorff, Dolan, & Frith, 2010), or exhibits cooperative behavior in a group setting (Fowler & Christakis, 2010). Early work revealed the force by which social influence could modify decision-making (Cialdini & Goldstein, 2004; Izuma & Adolphs, 2013), demonstrating just how far individuals are willing to go when confronted with overt and forceful instruction (Haney, Banks, & Zimbardo 1973; Milgram, 1963).

Much less is known, however, about the extent to which moral preferences are malleable in the absence of overt social pressure or perception of social consensus. In other words, does learning about another's moral values reveal the existence of a new social norm that bears on how one comes to value certain moral preferences? To examine whether such decisions to restore justice—referred to here as fairness preferences—are indeed susceptible to subtle social influences, we compare how participants respond to fairness violations before learning about another's fairness preferences, to those made afterward, in a series of Internet and laboratory-based experiments. To test and measure these putative behavioral changes, we adapted a dyadic economic task, the Justice Game (FeldmanHall, Sokol-Hessner, Van Bavel, & Phelps, 2014), which measures different motivations for restoring justice.

In the modified Justice Game, Player A is endowed with a sum of money (1) and can make fair or unfair offers by distributing the money as she sees fit between herself ($1 - x$) and Player B (x ; Falk, Fehr, & Fischbacher, 2008). Player B then has the opportunity to restore justice by redistributing the money between the players. Participants partake in three phases of the game, a baseline (1st), learning (2nd), and transfer (3rd) phase (see Figure 1), in which they play both as a second-party (Player B), directly experiencing fairness violations (baseline and transfer phases)—and as a third-party (Player C), making decisions on behalf of another victim, where they can also observe the victim's preferences after each choice (learning phase). This allows us to explore whether observing and then implementing another's preferences during the learning phase influences subsequent responses made for the self during the transfer phase. If responses in the transfer phase significantly differ from responses in the baseline phase (a within-subjects design), it would suggest that preferences for handling fairness violations are indeed malleable, and the degree of behavioral change between these phases would enable us to measure the extent to which moral preferences transmit from one person to another.

Examining behavior in the transfer compared with baseline conditions, further permits us to test two key questions about the malleability of these preferences. First, while a rich economic literature suggests that punishing the perpetrator is the preferred method for restoring justice (Fehr & Fischbacher, 2004; Fehr & Gächter, 2002; Gintis & Fehr, 2012; Henrich et al., 2005), recent work reveals that these punishment preferences are contextually bound (Dreber, Rand, Fudenberg, & Nowak, 2008; Jordan, Hoffman, Bloom, & Rand, 2016), and that when other options are made available, individuals exhibit a resounding endorsement for less punitive and more restorative forms of justice (FeldmanHall et al., 2014). Accordingly, we were primarily interested in understanding

whether punitive preferences can be acquired from learning about others who desire punishment. A robust expression of certain moral values—in this case, that punishment is a preferred form of justice restoration—could signal the existence of an alternative appropriate social norm, and being exposed to this social norm may alter how much people value punishment themselves. Therefore, assuming individuals initially exhibit nonpunitive, compensatory preferences (FeldmanHall et al., 2014), will exposure to an individual who exhibits strong preferences to punish shift how readily one endorses punishment as a means of restoring justice for oneself?

Second, we can address the way in which this putative behavioral transfer occurs. That is, how might an alternative social norm become assimilated into an individual's moral calculus? For example, if the difference between how one individual values punishment compared with how another values punishment (i.e., a prediction error between what one prefers and what another prefers) biases one's own taste for punishment, it would suggest that a reinforcement mechanism governs the acquisition of moral preferences (Sutton & Barto, 1998). Moreover, we can also test what type of learning subserves this process. It is possible that simply observing another's fairness preferences is enough to influence one's own preferences (i.e., a contagion effect; Chartrand & Bargh, 1999; Suzuki, Jensen, Bossaerts, & O'Doherty, 2016). Alternatively, transmission of moral preferences may demand successful implementation of the victim's preferences. Here we leverage a task paradigm traditionally used to study reward learning (i.e., reinforcement learning) to elucidate the cognitive mechanisms underlying how moral preferences come to be valued.

Experiment 1

Method

Participants. In Experiment 1, 300 participants (147 females, mean age = 34.37 $SD \pm 10.07$) were recruited from the United States using the online labor market Amazon Mechanical Turk (AMT; Buhrmester, Kwang, & Gosling, 2011; Horton, Rand, & Zeckhauser, 2011; Mason & Suri, 2012; Paolacci, Chandler, & Ipeirotis, 2010; one participant from the reverse condition, two participants from the indifferent condition, and five participants from the compensate condition failed to complete the entire task and therefore their responses were not logged). Participants were paid an initial \$2.50 and an additional monetary bonus accrued during the task from one randomly realized trial from either the baseline or transfer phases (ranging from \$.10 to \$.90). Informed consent was obtained from each participant in a manner approved by New York University's Committee on Activities Involving Human Subjects. All participants had to complete a comprehension quiz before beginning the task (Crump, McDonnell, & Gureckis, 2013). We also ran initial pilot experiment on AMT to assess the necessary levels of reinforcement (150 participant, 71 females, mean age = 33.68 $SD \pm 10.01$). Results fully replicate but are not reported here for succinctness.

Justice game. The Justice Game (FeldmanHall et al., 2014) was adapted to comprise three phases. In phase one—the baseline phase (Figure 1A)—Player A has the first move and can propose any division of a \$1 or \$10 pie (initial endowment for Player A depended on the experiment) with Player B, the participant (Player

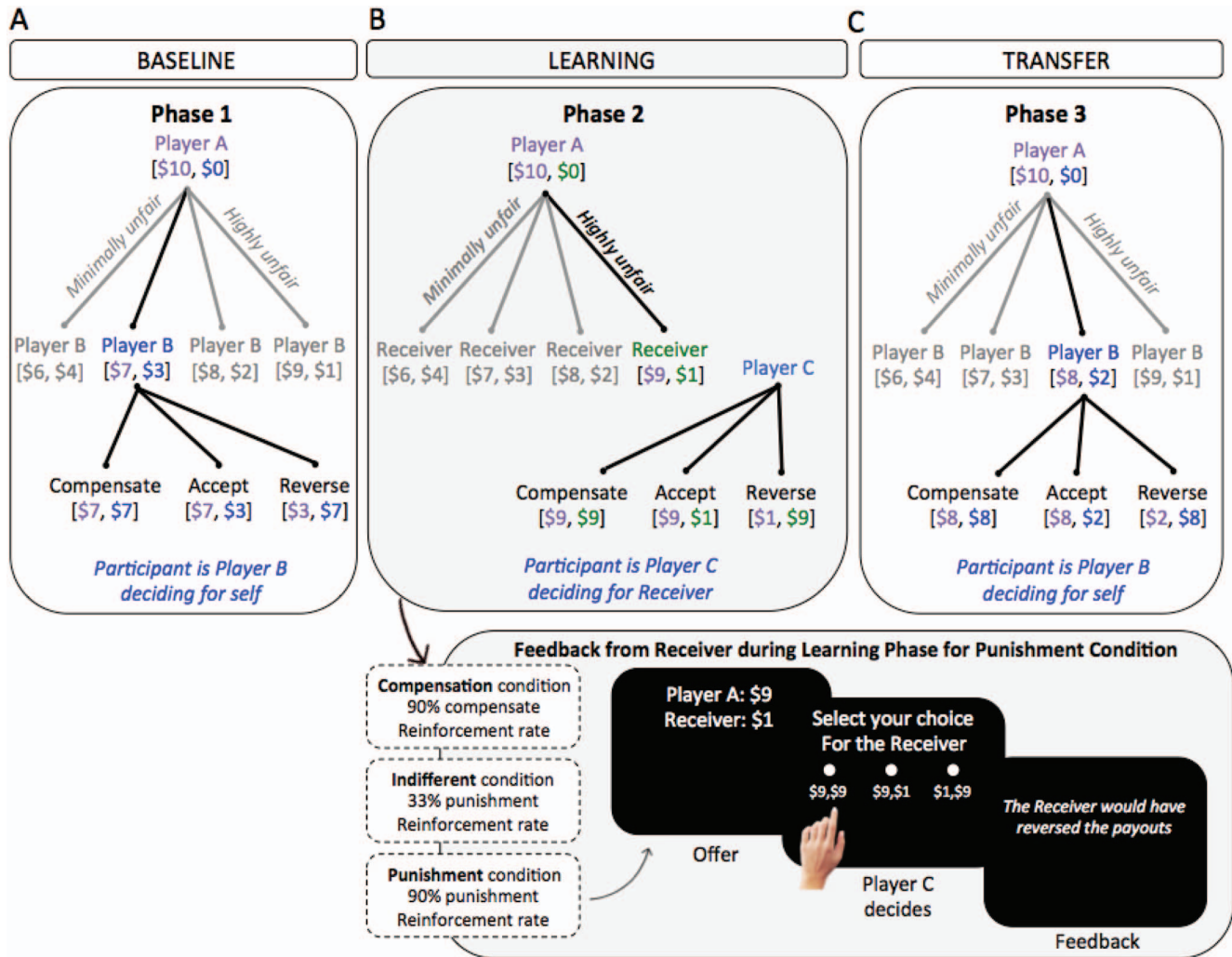


Figure 1. Experimental set-up of justice task. (A) Baseline phase. Player A is the first mover and endowed with a sum of money, in this case \$10 (monetary amounts in the brackets denote the payouts for each player at every stage in the decision tree: A's payout is always on the left, B's payout is always on the right). After receiving an offer from Player A, in this case [\$7, \$3], participants—who take the role of Player B—are presented with three options to restore justice: they can “accept” the offer as is, “compensate” themselves and not punish player A by only increasing their own payout to match that of Player A, or punish Player A by reversing the payouts (simultaneous punishment of Player A and compensation for the self, known as the “reverse” option). Splits from Player A were made out of \$1 in the online experiments and \$10 in the laboratory experiment. (B) Learning phase. In the next phase of the task, participants change roles and make decisions as a nonvested third party (Player C). On each trial, participants observe Player A making an offer, in this case [\$9, \$1] to another participant (the receiver) and can respond on behalf of the receiver. After making a decision about how to reapportion the money, participants receive feedback about how the receiver would have responded. In the example given, the participant, who is in the punishment condition, choose the option to compensate (denoted by \$9, \$9) and then received feedback that the receiver would have preferred the reverse option (the highly punitive response). Participants are randomly selected to be in one of three conditions, where they receive feedback from a highly punitive receiver (punishment condition), a nonpunitive receiver (compensate condition), or a receiver who exhibited no strong preferences (indifferent condition). Participants observe many different Player As making offers to the same Receiver. (C) Transfer phase. In the third phase of the task, participants again take the role of Player B, directly receiving offers from various Player As, in this case an [\$8, \$2] offer. See the online article for the color version of this figure.

A: $1 - x$, Player B: x ; Figure 1A illustrates only unfair offers ranging from [\$60, \$40] to [\$90, \$10]). Player B can then reapportion the money by choosing from the following three options; (1) *accept*: agreeing to the proposed split ($1 - x, x$; Güth,

Schmittberger, & Schwarze, 1982); (2) *compensate*: increasing Player B's own payout to match Player A's payout, thus enlarging the pie and maximizing both players' outcomes ($1 - x, 1 - x$; Lotz, Okimoto, Schlosser, & Fetchenhauer, 2011); or (3) *reverse*:

reversing the proposed split so that Player A is maximally punished and Player B is maximally compensated ($x, 1 - x$; Pillutla & Murnighan, 1996; Straub & Murnighan, 1995), a highly retributive option that punishes the perpetrator proportionate to the wrong committed (Carlsmith, Darley, & Robinson, 2002). In other words, reversing the players' payouts results in Player A receiving what was initially assigned for Player B, and vice versa—a direct implementation of the “just deserts” principle. Importantly, the compensate option is entirely nonpunitive and highly prosocial, since Player A is not punished with a reduced payout for behaving unfairly. In contrast, the reverse option provides the opportunity to punish for free, since Player B's payout remains the same in either the compensate or reverse options (see SI for a more in-depth explanation of each option).

Past research illustrates that choosing to nonpunitively compensate is the most frequently endorsed option when responding to fairness violations (FeldmanHall et al., 2014). To ensure that Player B perceives an offer of [\$.90, \$.10] as unfair, participants were told that one trial would be randomly selected to be paid out, and that half of the time it would be paid out according to Player A's split (like a dictator game), and half the time according to Player B's decision. This incentive structure means that an unfair offer signals Player A's desire to maximize and enrich their payout at the expense of Player B's payout (e.g., a selfish decision).

During this baseline phase, participants were told that they were preselected to be Player B and completed four trials, one for each level of fairness transgression (i.e., offer type), ranging from a relatively fair [\$.60, \$.40] split to a highly unfair [\$.90, \$.10] split (NB: participants were told that any offer was possible, which included a highly fair offer of [\$.50, \$.50], although participants were never presented with this amount as we were only interested in fairness transgressions). The varying types of offers from Player A were randomly presented to each participant. The baseline phase enabled us to record behavior prior to any social manipulations. In phase two—the learning phase—participants were told they would be playing the game as Player C, a nonvested third party (Figure 1B). Accordingly, participants were asked to make decisions on behalf of two other players, such that payoffs would be paid to Players A and another player—denoted as the receiver. As Player C, participants first observed Player A making an offer to the receiver. Player C could then redistribute the money between Player A and the receiver with the same three options described above (accept, compensate, reverse). Once a decision was made, Player C was informed of what the receiver would have preferred to do (e.g., feedback). This feedback was given on every trial so that Player C could learn the justice preferences of the receiver they were deciding for.

In one condition participants received feedback from a highly retributive receiver, who reported that she would have wanted the initial split from Player A to be reversed (punishment condition: across 80 trials there was 90% reinforcement rate of reverse, 5% reinforcement rate of accept, and 5% reinforcement rate of compensate). Effectively, by providing this trial-by-trial feedback, the receiver signals that she not only values increasing her own payout, but she also prefers that Player A is punished for making unfair splits. In a second condition, participants received feedback from highly compensatory (nonpunitive) receiver (compensate condition: across 80 trials there was 90% reinforcement rate of compensate, 5% reinforcement rate of accept, and 5% reinforcement

rate of reverse). In this case, participants learned that the receiver did not value punishment, and instead preferred that only her own payout be increased to match that of Player A. In a third condition, participants received feedback from a receiver who was indifferent in their preferences, preferring to compensate themselves, reverse the outcomes, or accept the offer at equal reinforcement rates (indifferent condition: 33% for each type of feedback). These reinforcement feedback rates in each of the three conditions were predetermined by the experimenter to signal robust preferences that were highly punitive, not punitive at all, or completely random with an aim to ensure that participants could learn another player's judicial preferences, even during varying levels of fairness violations. Participants were randomly assigned to be in one of the three conditions such that each participant received feedback from only one receiver (between-subjects design). As in the baseline phase, offers from Player A ranged from minimally unfair to highly unfair.

In the third phase of the experiment—the transfer phase—participants played the same justice game but this time as the victim (Player B) again. The transfer phase was the same as the baseline phase except there were 20 trials, where various unfair offer types were randomly presented. Following the experiment, participants were asked to report their strategies given these offer types (see online supplemental materials for participants' reported strategies).

Learning. To examine candidate learning processes involved in implementing another's preferences, we fit a family of computational reinforcement learning models that differently account for how feedback is incorporated, the magnitude of the fairness violation, and whether one's own initial fairness preferences influence learning rates (see SI). These models—which allowed us to examine various different psychological notions for how learning might unfold—were then fit to participants' behavior and tested via model comparison.

Results

Baseline behavior. Replicating earlier findings (FeldmanHall et al., 2014), behavior in the baseline phase revealed that participants overwhelmingly prefer to compensate themselves and not punish Player A, even if punishment is free and costs nothing to implement (i.e., the reverse option). Because up until this point all conditions (e.g., compensate, indifferent, punishment) had identical experiences, we reasoned that the rate at which compensate (or reverse) was endorsed should not vary across conditions. Indeed, decisions to compensate were endorsed on average 70% in all conditions, and extremely punitive decisions, which reverse the players' payouts, were only endorsed on average 21%—regardless of condition (Figure 2A). These robust baseline nonpunitive preferences were the same across conditions ($ReverseRate_{i,t} = \beta_1 Condition + \epsilon$, Table 1; same nonsignificant results are found for $CompensateRate_{i,t} = \beta_1 Condition + \epsilon$). Moreover, paralleling past work (FeldmanHall et al., 2014), these highly compensatory, nonpunitive decisions were observed even after very unfair offers are made (67% mean endorsement of compensation for highly unfair offers across conditions).

Transfer effects. To test whether exposure to another's preferences to restore justice results in the transmission of fairness preferences, we examined whether responses in the transfer phase

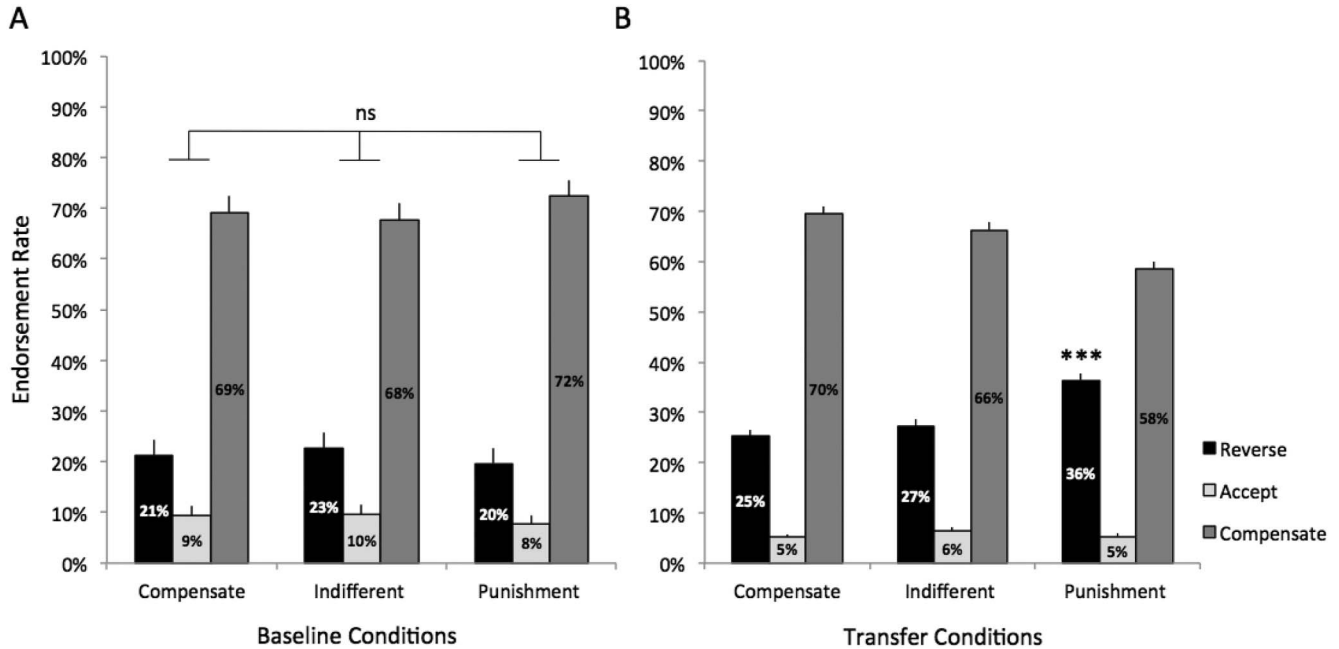


Figure 2. Responses to fairness violations as the victim in Experiment 1. (A) Behavior in the baseline phase for each condition reveals participants overwhelmingly endorsed the nonpunitive option to compensate themselves and not punish Player A for making an unfair offer (70% endorsement of the compensate option across three conditions). Participants equally endorsed decisions to compensate, reverse, and accept at the same rate across conditions. (B) Behavior in the transfer phase. After engaging with a receiver with highly punitive preferences (punishment condition), participants significantly altered how they responded to fairness violations, increasing their endorsement of decisions to punish Player A (i.e., choosing reverse) in the transfer phase. Significant enhancement of choosing to punish was only observed in the punishment condition ($p < .001$). Error bars reflect 1 SEM.

changed from those made during the baseline phase. We computed the difference in the proportion of times an option (compensate, reverse, accept) was endorsed between the baseline versus transfer phases for each participant (not accounting for the magnitude of fairness violation). Given that the baseline phase revealed highly compensatory and nonpunitive behavior, we speculated that the greatest transmission of fairness preferences should be observed for participants in the punishment condition, as this is where the receiver's preferences will differ most dramatically from participants' default, nonpunitive preferences (Figure 2A). In contrast, participants in the indifferent condition should exhibit small transfer effects, as the receiver's feedback did not systemically endorse

one response type, and those in the compensate condition should show no behavioral changes as there was no conflict between judicial preferences the participant made for herself and what she observed the receiver desired.

As predicted, the indifferent condition—where participants received feedback from a receiver who did not show a strong singular preference (albeit slightly stronger punitive preferences than a typical participant)—did not manifest a significant transmission of fairness preferences. Participants endorsed the reverse option 23% in the baseline phase, and 27% in the transfer phase (a 4% increase, Figure 2B), which statistically revealed no evidence of a significant transfer effect (rm analysis of variance; ANOVA; DV = endorsement of reverse, IV = Phase: $F(1, 97) = 1.64, p = .20$). In the compensate condition, where participants learned about a receiver who strongly preferred the nonpunitive, compensatory option, participants increased their endorsement of compensate by 1% in the transfer phase (rmANOVA DV = endorsement of compensate; IV = Phase: $F(1, 94) = 0.01, p = .90$), while decisions to reverse were endorsed at similar same rates in both baseline and transfer phases. In other words, exposure to a receiver who endorses compensatory measures more often than oneself results in effectively no transmission of preference, which is likely due to the fact that there was little conflict or prediction error between what the receiver and participant valued when deciding to restore justice.

Table 1

Mixed Effects Logistic Regression Predicting Endorsement of Reverse Option, $\text{Reverse Rate}_{i,t} = \beta_1 \text{Condition} + \epsilon$

DV	Coefficient (β)	Estimate (SE)	z	p
Reverse	Intercept	−2.58 (.39)	−6.69	<.001***
	Indifferent condition	.18 (.46)	.41	.68
	Punish condition	−.07 (.46)	−.17	.86

Note. DV = endorsement of reverse. Where reverse (1 = reverse, else-wise 0) is indexed by subject and trial and condition is an indicator variable, such that the compensate condition serves as the intercept.

*** $p < .001$.

In contrast, for those in the punishment condition, exposure to the receiver's fairness preferences exerted marked effects upon participants' own decisions to restore justice (Figure 2B). Participants significantly bolstered their endorsement of the punitive reverse option for themselves after learning about a receiver who preferred highly retributive measures (16% increase: rmANOVA DV = endorsement of reverse, IV = Phase, $F(1, 98) = 31.29$, $p < .001$, $\eta^2 = .24$).

To compare if these observed transfer effects in the punishment condition are significantly different from the effects observed in the compensate and indifferent conditions, we computed response Δ scores as the difference between endorsement rates for a particular response between the transfer phase and the baseline phase (averaging across all types of fairness violations). In the punishment and indifferent conditions, the response Δ is computed with respect to the reverse response, while for participants in the compensate condition, the response Δ is computed for the compensate response (note in the indifferent condition we compute response Δ for reverse given that the reinforcement rate is the same for each option). Thus, response Δ s were calculated as a function of condition, such that every participant's unique score is contingent on the condition in which they participated. Statistically, participants in the punishment condition exhibited significantly greater transfer effects (mean response $\Delta = .16$ $SD \pm .27$) compared with those in the other two conditions (Figure 3: Compensate condition mean response $\Delta = .003$ $SD \pm .30$, indifferent condition mean response $\Delta = .04$ $SD \pm .35$; ANOVA: $F(2, 289) = 6.14$, $p = .002$; post hoc LSD tests against punishment condition: all p values < 0.01).

Learning about another's moral preferences. These findings indicate that decisions to restore justice can be altered after

learning about another's preferences, specifically when another person holds markedly different moral values. To understand how individuals modify their choices in response to feedback in the learning phase, we leveraged reinforcement learning (RL) models, which provide a useful computational framework for understanding how trial-by-trial learning unfolds. These RL models formalize how individuals adapt their behavior to recently observed outcomes. In particular, we modeled participant choice during the learning phase as a function of feedback presented from the receiver on the previous trial, allowing the influence of feedback to decay over time. A strength of this approach is that it allows us to test different psychological assumptions about how learning might occur. In the present study, we used these models to understand what aspects of the decision space (e.g., unfairness levels) guide learning processes. Furthermore, our modeling approach makes no assumptions about the correct action—which ensures that we can use it across the three learning conditions—and places no constraints on what the participant's initial preferences are (which can often be problematic in the interpretation of delta-type measures).

The simplest model considered, termed the basic model, assumes that people learn the values of the candidate actions (accept, compensate, or reverse) based on direct experience with the actions and the feedback they experience (see the online supplemental materials for model details), but are agnostic to the fairness level of the offer at hand. In other words, the basic model assumes that people are insensitive to the magnitude of the fairness infraction and will therefore respond in similar ways, despite the severity of violation. However, given that past research suggests that people deeply care about the magnitude of the fairness violations (Cameron, 1999), we also explored whether learning is contingent on how unfairly the receiver was treated. Thus, the next model considered—termed the fairness model—assumes that people are sensitive to the fairness infraction (Camerer, 2003). If it is the case that social learning is sensitive to the extent of the fairness infraction, then such a model should do a better job of reflecting actual behavior than the basic model.

The last model we considered is termed the extended fairness model. This model builds upon the fairness model, but with the addition of a separate learning rate for each offer type, which are used to perform updates based on the fairness violation on the present trial. We conceived of this model based on the idea that depending on how sensitive people are to fairness violations, they may be differently reactive to feedback depending on the magnitude of the transgression. Since higher learning rates allow estimates to reflect the consequences of more recent outcomes and lower learning rates reflect longer outcome histories—which leads to more stable estimates—having separate learning rates for each infraction level allows us to test whether the severity of the violation might hasten learning. In other words, people may be attuned to how unfairly one is being treated, and this might lead to faster learning depending on how egregious the infraction is. Together, these three models capture a range of how sensitive people are to various fairness violations, and afford an understanding of how an individual's preferences change from trial-to-trial in response to feedback from the receiver.

This formal model based approach supported the behavioral findings that people acquire the punitive preferences of another. First, we found that the fairness model best fit participants' learning patterns (see Table 2): it consistently had the lowest average

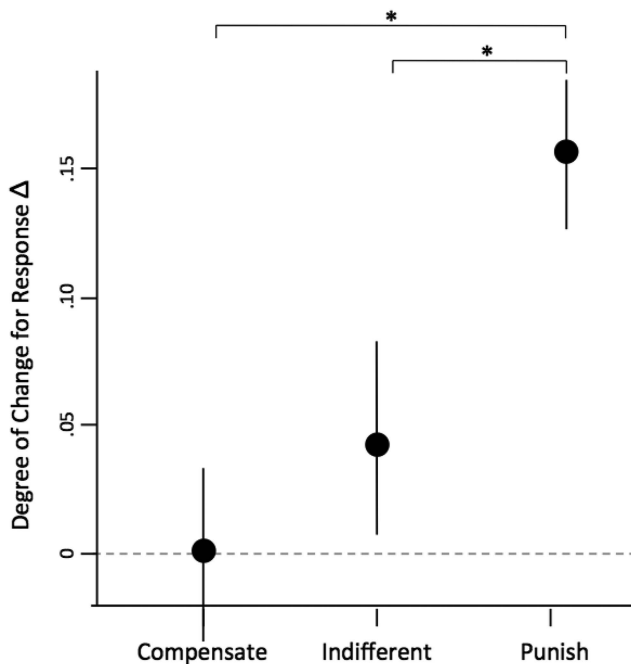


Figure 3. Degree of transfer effect in Experiment 1. Amount of change in participants' responses from baseline to transfer phase in the three conditions. Results indicate the greatest transfer effects were unique to the punishment condition. Error bars reflect 1 SEM. ** $p = .01$.

Bayesian Information Criterion (BIC) scores—which quantifies model goodness of fit, penalizing for model complexity—indicating that participants were sensitive to the extent of the fairness infraction, but did not exhibit different learning rates (i.e., how efficiently they updated) across each offer type. Simply put, when learning about the moral preferences of others, people are sensitive to how unfairly another is treated.

Second, this reinforcement-learning mechanism seems to accurately describe moral learning in this task. Comparing model goodness-of-fit across the punishment, indifferent, and compensate conditions revealed that participants in the compensate condition were best characterized by this learning account (insofar as having the best model fit), while participants in the punishment condition had the worst model fit (see Table 2). While at first blush this pattern of results may appear to conflict with the robust transfer effects observed in the punishment condition, it should be noted that participants in the compensate condition were receiving feedback that already aligned with their behavior. Thus, there was little to learn (i.e., small prediction errors) in the compensate condition as the receiver's feedback already reflected the participant's own preferences. In contrast, there was much to learn and implement in the punishment condition, as the receiver's preferences significantly differed from participants' initial preferences. In the indifferent condition, receivers were expressing slightly more punitive preferences (33%) compared with participants' baseline punitive preferences (23%), which amounts to a smaller learning gap and thus slightly better model fits compared to the punishment condition.

Experiment 2

Given that the transfer effects were specific to the punishment condition, our goal in Experiment 2 was to probe the generality of these acquired punitive preferences within a laboratory setting. Accordingly, in the next experiment we only tested the punishment condition.

Method

Participants. For Experiment 2, we recruited 37 participants (23 females, mean age = 23.4 $SD \pm 4.56$) from New York University and the surrounding New York City community to serve as a within laboratory replication of the condition of interest—the punishment condition. Our aim was to recruit 35 participants (sample size determined from previous work; Murty, FeldmanHall, Hunter, Phelps, & Davachi, 2016) on the assumption that some participants would fail to believe the experimental structure and should be removed before analysis. While two participants reported high disbelief during funnel

debriefing, because the results remain robust with or without their inclusion, we report behavior from all 37 participants. Participants were paid an initial \$15 and an additional monetary bonus accrued during the task from one randomly realized trial from either the baseline or transfer phases (between \$1–\$9). Informed consent was obtained from each participant in a manner approved by the University Committee on Activities Involving Human Subjects.

Task. Experiments 1 and 2 were the same in their structure and aim, with only two key differences. First, Experiment 2 was run within the laboratory. This demanded a slightly more comprehensive cover story of who the other players were (see SI), which reduced the perception of anonymity compared with the players in the online version of the task (Experiment 1). Second, in Experiment 2, unfair offers made to participants were of much larger monetary value—all splits were made out of \$10—eliciting justice violations of greater magnitude.

Results

Baseline behavior. Participants exhibited a remarkably similar pattern of baseline behavior as those in Experiment 1, forgoing the free punitive option and instead choosing to compensate 70% of the time (Figure 4A). As before, participants endorsed accept 9% of the time, and reverse 21% of the time during the baseline phase.

Transfer effects. After learning about another who strongly prefers to punish the perpetrator, participants demonstrated a 15% increase in endorsing the punitive option when deciding as the victim (rmANOVA DV: endorsement of reverse, IV: phase, $F(1, 36) = 7.35$, $p < .01$, $\eta^2 = .17$, Figure 4B)—replicating the findings from Experiment 1. Finally, as we had done in Experiment 1, by comparing model fits, we again found evidence that the fairness model best characterizes overall learning (lowest BIC scores, Table S3).

Experiment 3

To further test the generalizability of our findings, we next investigated these transfer effects in a different social context. In the ultimatum game—which leverages a classic game theoretic setting—the only way to restore justice is to punish Player A. Thus, punishment rates are typically higher in the ultimatum game compared with the justice game. If under these circumstances individuals still learn to acquire the punitive preferences of another, it would provide converging evidence across contexts that a reinforcement mechanism governs how people learn to value moral preferences. In addition, given the task structure of the justice game, we wanted to be sure that our participants perceived

Table 2
Summary of Model Goodness-of-Fit Metrics for Experiment 1

RL models	Mean (SE) BIC scores by condition			
	Compensate	Indifferent	Punishment	Average
Basic model	137.61 (3.94)	180.81 (3.01)	154.75 (6.38)	157.92 (2.89)
Fairness model	87.68 (6.04)	118.56 (4.90)	132.20 (5.36)	113.1 (3.31)
Extended fairness model	98.71 (6.07)	129.57 (4.87)	143.29 (5.44)	124.18 (3.32)

Note. RL = reinforcement learning; BIC = Bayesian information criterion.

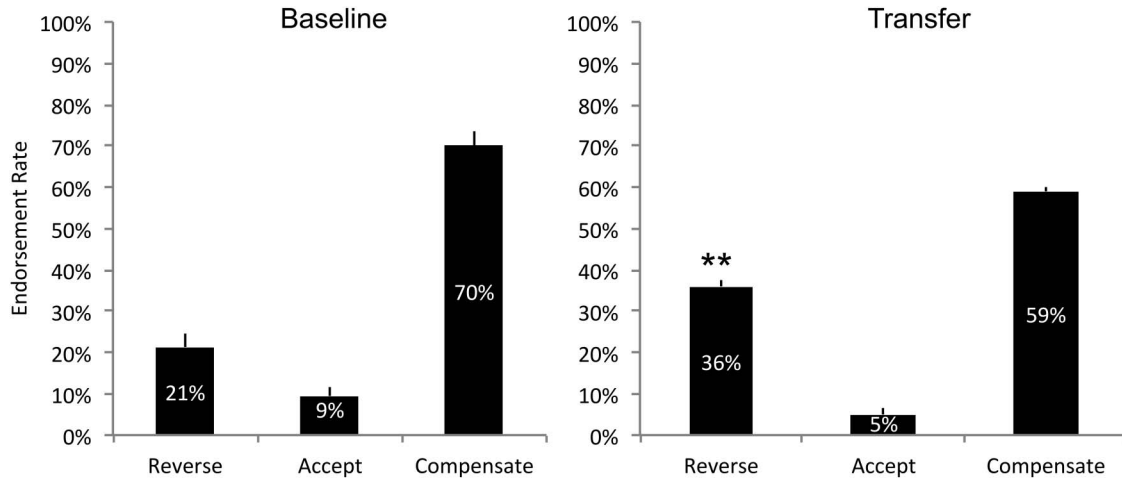


Figure 4. Baseline and transfer behavior in Experiment 2. Results reveal that participants significantly increased their endorsement of reverse after learning about another person that values punishment. Error bars reflect 1 SEM. ** $p = .01$.

a [\$9, \$1] or [\$90, \$.10] split from Player A as a truly unfair split. Because offers consisting of 10% of the pie are clearly—and unambiguously—intended to maximize Player A's payout in the ultimatum game, this additional test-bed would ensure that in our previous experimental set-ups Player B was perceiving Player A's splits as unfair.

Method

Participants. In Experiment 3, 51 participants (21 females, mean age = $34.06 \text{ SD} \pm 9.73$) were recruited from AMT. Participants were paid an initial \$2.50 and an additional monetary bonus accrued during the task from one randomly realized trial from either the baseline or transfer phases. Informed consent was obtained from each participant in a manner approved by the University Committee on Activities Involving Human Subjects.

Task. The ultimatum game followed the same task parameters as those described in the previous experiments, only this time Player A acted as a proposer and Player B (the participant) acted as the responder. As in traditional ultimatum games, Player B could either accept the offer as is, or, reject the offer (with no option to compensate), which ensures that neither player receives a payout (Figure 5A). Effectively, rejecting is formalized as a way of enacting costly punishment on Player A.

Results

The pattern of results in this ultimatum game replicate the other experiments. After learning about a receiver (another Player B in the learning phase) who strongly prefers to reject the offer and punish the perpetrator, participants exhibited a 12% increase in endorsing the punitive option when deciding for the self in the transfer phase (mean response $\Delta = .12 \text{ SD} \pm .40$; rmANOVA DV = endorsement of reverse, IV = phase, $F(1, 50) = 9.01$, $p < .004$, $\eta^2 = .15$, Figure 5B). A comparison of the reinforcement learning models revealed the fairness model again outperformed the other models (SI) indicating that participants were sensitive to

the extent of fairness violation, but did not exhibit different learning rates for each offer type.

These findings, together with the results from Experiments 1–2, illustrate that people significantly increase their willingness to endorse the punitive option after learning about another individual who prefers highly retributive responses to fairness violations. Compellingly, this effect appears to be so robust that, even when punishment is costly (as it is in the ultimatum game), people still modify how they respond to fairness violations by increasing their endorsement of the punitive option and forgoing their own monetary self benefit. Simply put, acquiring the moral preferences of another who has a strong taste for punishment surpasses one's own desire for self-gain.

Experiment 4

In Experiments 1–3, we found that learning about another who strongly prefers punishment as a means of restoring justice changes how readily one endorses punitive measures when they themselves are the victim. It is less clear, however, whether the acquisition of another's preferences requires active learning (i.e., implementation of the receiver's preferences) or whether passive, observational learning (i.e., mere exposure to the receiver's preferences) is enough to elicit a similar pattern of behavioral acquisition (i.e., a contagion effect). To examine this question, we ran a fourth experiment where participants either completed an active learning task (akin to those described in the previous experiments) or a passive learning task, in which participants simply observed a receiver punitively responding to fairness violations.

In addition, an open question is whether certain phenotypic trait profiles result in greater acquisition of moral preferences. It is possible, for example, that the more receptive and empathic an individual is (Preston, 2013), the more likely one is to acquire another's moral values (Hoffman, 2000). By this logic, those who are better at perspective taking or feeling empathic concern may be more readily able and motivated to simulate the desires of another (Hastings, Zahn-Waxler, Robinson, Usher, & Bridges, 2000),

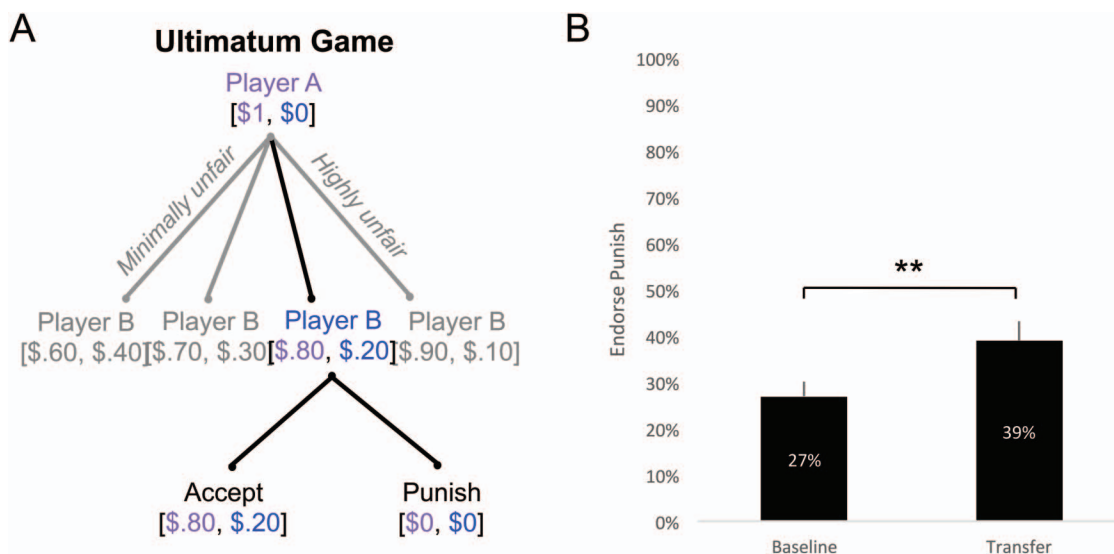


Figure 5. Experiment 3. (A) The same task structure described in the previous experiments—a baseline, learning, and transfer phase—was also employed in Experiment 3; however, here subjects completed the ultimatum game, where they could either choose to accept the offer from Player A as is, or reject the offer, thereby enacting costly punishment on Player A. (B) Replicating the previous experiments, we found that after learning about a receiver who wanted Player A to be punished, participants increased their own desire to punish by 12%. Error bars reflect 1 SEM. ** $p = .01$. See the online article for the color version of this figure.

which in turn could enable better learning and greater acquisition of another's desire to punish. In Experiment 4 we tested this theory, positing that those high in trait empathy would demonstrate greater behavioral modification than those who are low in trait empathy.

Method

Participants. In Experiment 4, 200 participants (96 females, mean age = 35.4 $SD \pm 10.5$) were recruited from AMT and randomly selected to partake in either the active or passive learning task (a between-subjects design with $N = 100$ per task, although five participants in the active learning condition failed to complete the experiment, resulting in $N = 95$ for the active learning condition). Participants were paid an initial \$2.50 and an additional monetary bonus accrued during the task from one randomly realized trial from either the baseline or transfer phases. Informed consent was obtained from each participant in a manner approved by the University Committee on Activities Involving Human Subjects.

Task. The active learning condition was the same as the punishment condition described in Experiment 1, with the addition of the Interpersonal Reactivity Index (Davis, 1983) administered at the end of the experiment. This enabled us to collect individual trait measures of how well each participant typically engages in empathic concern (EC) and perspective taking (PT). The passive learning condition followed a similar structure as described in Experiment 1, with the following differences: during the learning phase of the task, participants observed a receiver making their own decisions about how to reapportion the money. For example, in the first trial of the learning phase, Player A might offer the receiver a [\$90, \$10] split. The receiver—who adhered to an

algorithm of selecting the reverse option 90% of the time (as was done in all the previous experiments)—would then typically choose to reverse the outcomes, such that Player A received [\$10] and the receiver [\$90]. After watching the receiver make her choice, the participant was asked what the receiver had just decided. By having the participant key in a response, we were able to structurally match the passive learning condition to the active learning condition, while ensuring that participants were also engaged across the learning phase. How well a participant attended to and reported the receiver's decisions was denoted as accuracy, such that accuracy was computed by comparing the participant's response on a given trial with what the receiver had actually selected on that trial. Thus, feedback in the passive learning condition is akin to how well a participant paid attention to what the receiver was deciding (rather than implementing what the receiver desired, as was indexed in all previous experiments). At the end of the passive learning task, we also collected the Interpersonal Reactivity Index measure.

Results

Baseline behavior. As expected, we observed no differences in baseline behavior between the active and passive learning conditions (Table 3, Figure 6). As in the previous experiments, regardless of the condition, participants choose to compensate at high rates (active learning: 72% endorsed compensate, 17% endorsed reverse, and 11% endorsed accept; passive learning: 70% endorsed compensate, 21% endorsed reverse, and 9% endorsed accept).

Transfer effects. In the active learning condition, learning about another who strongly prefers to punish the perpetrator resulted in a 12% increase in endorsing the punitive option

Table 3

Mixed Effects Logistic Regression Predicting Endorsement of Reverse Option in Experiment 4, $\text{Reverse Rate}_{i,t} = \beta_1 \text{Condition} + \varepsilon$

DV	Coefficient (β)	Estimate (SE)	z	p
Reverse	Intercept	.168 (.02)	6.78	<.001***
	Passive learning	.04 (.02)	1.76	.08

Note. DV = endorsement of reverse. Where reverse (1 = reverse, else 0) is indexed by subject and trial and condition is an indicator variable, such that the active learning condition serves as the intercept.

*** $p < .001$.

(rmANOVA DV = endorsement of reverse, IV = phase, $F(1, 94) = 14.2$, $p < .001$, $\eta^2 = .13$, Figure 6), and we again found evidence that the fairness model best characterized overall learning (Table S6). In the passive learning condition, observing another person respond to offers with punishment also resulted in a 12% increase in endorsing the punitive option (rmANOVA DV = endorsement of reverse, IV = phase, $F(1, 99) = 14.3$, $p < .001$, $\eta^2 = .13$, Figure 6). To directly assess whether there were any significant differences in how readily one acquires preferences to punish during active learning versus mere exposure, we ran an independent samples t test on response Δ scores across the two tasks. We observed no differences in overall acquisition (independent t test between active and passive learning tasks, $t(193) = -0.07$, $p = .94$; Figure 6B) nor any differences at each level of fairness

infracton (all p values $> .25$), suggesting that mere exposure without implementation also results in acquiring the punitive preferences of another.

Effects of empathy on learning. As anticipated, participants in the active and passive learning conditions exhibited similar empathic abilities—both in taking the perspective of another (active learning mean PT = $18.4 \text{ SD} \pm 6.15$; passive learning mean PT = $19.1 \text{ SD} \pm 5.27$, independent t test, $t(193) = -.82$, $p = .42$), and in feeling empathic concern (active learning mean EC = $19.3 \text{ SD} \pm 6.12$; passive learning mean EC = $19.1 \text{ SD} \pm 6.97$, independent t test, $t(193) = -.27$, $p = .79$). We also probed whether those low in empathic concern might be less likely to select the nonpunitive compensate option during the baseline phase compared with those high in empathic concern (using a median split of empathic concern scores across both the active and passive conditions). We found that while those with low empathic tendencies were slightly less likely to choose the compensate option (67% of the time) compared with those high in empathic concern (76% of the time), this difference failed to reach significance ($p = .11$). Furthermore, we surprisingly did not find evidence that either perspective taking or empathic concern abilities resulted in greater acquisition of another's preferences (correlations between Response $\Delta \times$ IRI subscales in both the active and passive conditions, all p values $> .30$), suggesting that empathic abilities may not act as a proximal mechanism for conformist behavior under these circumstances.

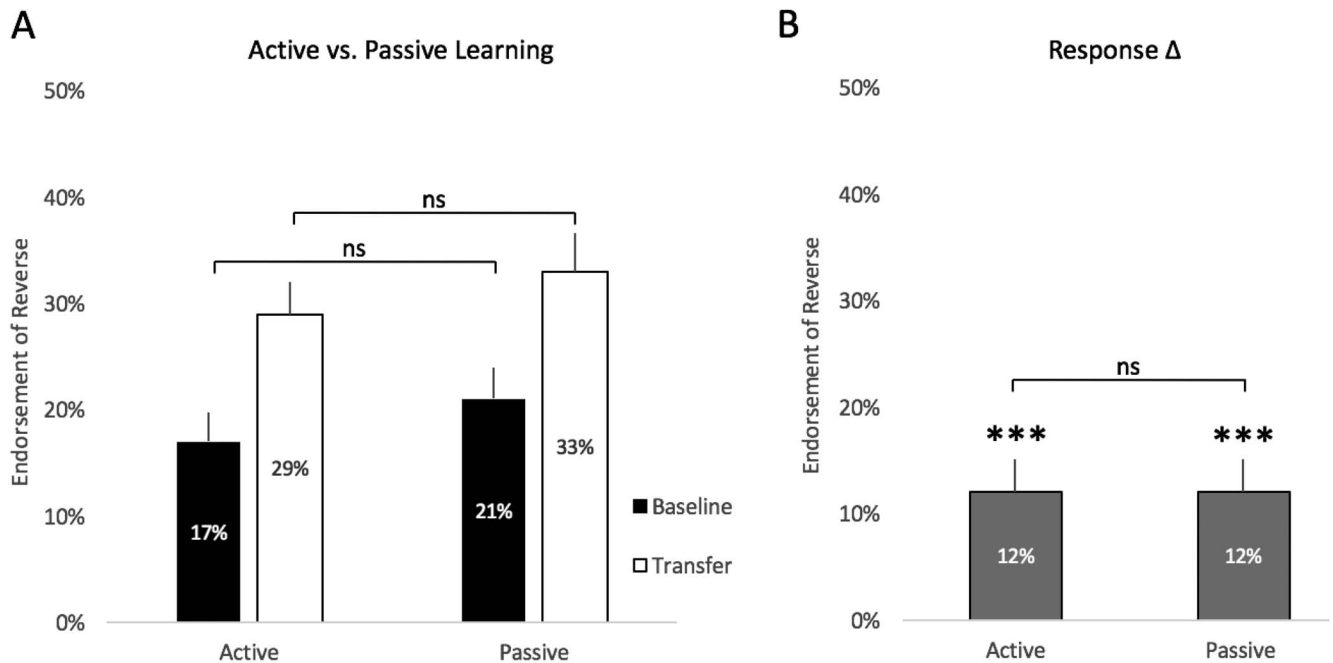


Figure 6. Active versus passive learning during Experiment 3. (A) In the baseline phase of the task, we observed no differences in how readily one endorsed reverse (the punitive response) between the active and passive learning conditions. There were also no differences between conditions for the endorsement of compensate (approximately 70%) or accept (approximately 10%) options. (B) While the overall increase in acquiring another's punitive preferences was significant for both the active and passive conditions (all p values < 0.001), there were no differences in response Δ s across the two conditions—regardless of whether participants were required to actively learn about another's preferences or merely observe another make choices. Error bars reflect 1 SEM. *** $p = .001$.

Discussion

Similar to the old adage—“we are like chameleons, we take our hue and the color of our moral character from those who are around us” (Chartrand & Bargh, 1999; Locke, 1824)—here we found that fairness preferences to restore justice are shaped by the moral preferences of those around us. More specifically, participants who were exposed to another individual exhibiting a strong taste for punishment increased their own endorsement of punishment when later deciding how to restore justice for themselves. The acquisition of another’s fairness preferences was contingent on learning from social feedback and recruited mechanisms akin to those deployed in basic reinforcement learning. The convergent findings of these four experiments highlight the delicate nature of our moral calculus, revealing that preferences for fairness can be remarkably shaped by indirect, peripheral social factors. Rather than employing prescriptive judgments of justice in an absolutist manner (Turiel, 1983), we observed that responses to fairness infractions are malleable even in the absence of social pressure (Milgram, 1974) or perception of social consensus (Asch, 1956; Kundu & Cummins, 2013), and took as little as learning the preferences of one single individual (Latané, 1981).

The fact that we observed behavioral modifications stemming from such subtle social dynamics extends the classic findings of individuals conforming under more obvious social pressure (Cialdini & Goldstein, 2004) and is particularly surprising given that these foundational moral principles are assumed to be resolutely held (Piaget, 1932; Tetlock, 2003). Evidence of increasing one’s own valuation of punishment suggests that learning about how others navigate fairness violations may signal other, more socially accepted routes or prescriptions for restoring justice (Chudek & Henrich, 2011; Rand & Nowak, 2013). Accordingly, learning about another person’s preferences in the absence of explicit social demands appears to be powerful enough to indicate the existence of alternative social norms—which, as research has repeatedly shown—is a key factor in conformist behavior (Cialdini & Trost, 1998; Cialdini & Goldstein, 2004).

That exposure to someone who holds different moral values alters which social norm is relevant to the situation at hand, indicates that people naturally infer which behaviors are socially normative and adjust their own behavior accordingly. Indeed, given that participants interacted with many different unfair players over the course of our task, it is highly unlikely that participants were merely increasing their rate of punishment in the belief that they would be able to change an unfair player’s subsequent actions (and debriefing statements support this, see SI). Our results build on the foundational idea that how others behave—for example, picking up litter or denouncing bullying—can cue the endorsement of a new social norm, which can have pronounced effects on shifting perceptions of what is a desirable behavior (Cialdini, Reno, & Kallgren, 1990; Paluck, Shepherd, & Aronow, 2016). Here, we find that this is the case even within the moral domain: individuals use another’s moral preference as a barometer of what is socially acceptable or appropriate when deciding how to restore justice.

This effect—that when another person’s valuation of punishment is powerfully expressed, individuals readily upwardly adjust how much they value punishment themselves—appeared to be driven by a reinforcement mechanism. This suggests that punitive

preferences are swiftly assimilated when there is a significant difference between another’s moral values and one’s own moral values (Daw & Doya, 2006; Daw & Frank, 2009). These behavioral modifications were influenced both when implementing another’s preferences and through observational learning routes. In other words, active learning and mere exposure seems to similarly guide the acquisition of another’s moral preferences. That both learning processes resulted in the alteration of how punitive value computations are represented and subsequently expressed, intimates that learning from others provides a potent cognitive mechanism by which moral preferences can be developed and shaped.

These results, however, also lay bare a number of lingering questions. First, it is unclear whether the observed behavioral alterations are a result of shifting perceptions of how to appropriately respond when restoring justice, or, simply a product of how fairness violations are being perceived. For instance, it is possible that increases in punishment occurs because people are adjusting what they consider to be a suitable response after witnessing a fairness violation. On the other hand, it is also conceivable that the upward shifts in punishment are the result of reframing what is perceived to be a fairness infraction (e.g., if others are punishing it may be taken as evidence that a more serious transgression has occurred than previously thought). Additional experiments can help tease apart if people become more punitive because they learn that responding punitively is the morally correct response or because they come to recognize that Player A’s behavior is unfair. In addition, it is possible that if an individual were able to more clearly establish a norm of justice restoration before being exposed to the preferences of another—for example, by having the opportunity to respond to more of Player A’s unfair splits during the baseline phase—the influence of another’s punitive preferences on one’s own desire to punish might be attenuated. Future research will be able to more precisely characterize the boundary conditions in which moral norms operate.

Historically, the notion that the human moral calculus should be stable in the face of social demands describes how moral attitudes are taken as ethical blueprints for action (Forsyth, 1980; Kant, 1785; Rawls, 1994). That moral values are believed to play an integral and defining role in shaping a person’s identity (Haidt, 2001; Turiel, 1983), explains why moral attitudes and preferences are often so sacredly held (Tetlock, 2003). And yet the work here illustrates how the human moral experience can also be idiosyncratic and fickle. Continuing to tune our knowledge about how individuals come to understand the difference between right and wrong, acquire principles of fairness and harm, and ultimately make moral decisions, cannot only help shed light on which factors are most influential in guiding moral choice, but also the computational mechanisms underpinning this complex learning process.

Context of Research

This research was born out of our prior work where we observed that when individuals are presented with nonpunitive options for restoring justice, they strongly prefer not to punish the perpetrator—a finding that stood in stark contrast to much of the existing literature (FeldmanHall et al., 2014). Naturally, this led us to wonder which social contexts would spur people to punish. While

there is good evidence that how other people value certain stimuli (e.g., another's attractiveness, food preferences, risk profiles) can influence our own preferences for the same stimuli, much less work has focused on how another's moral preferences can bias our own moral actions. Therefore, this set of experiments aimed to test whether social influence could alter our moral values. We were also interested in whether the process of acquiring another's moral preferences would entail active learning (e.g., implementing the actual preferences of another) or mere exposure to another's moral preferences. By fitting a series of learning models to our data, we were able to directly test whether acquiring a desire to punish can be explained by either learning account.

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