Supplementary Materials

To support

Developmental emergence of complex prosocial motives and their influence on risky decision making

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I. Supplementary Methods

A. Original expected utility (EU) model

$$EU = pv^{\alpha} \qquad \textit{original model } (1)$$

$$P(choose\ risky) = \frac{1}{1 + \exp\left(\beta\left(EU_{safe} - EU_{risky}\right)\right)} \qquad \textit{decision rule } (2)$$

1. Simulation and recovery

To verify that our parameter of interest (Alpha) is recoverable, we simulated choice data of 10,000 subjects each with 35 trials, with values of each parameter in the model drawn randomly and uniformly from the range of possible parameter values. We chose a range sufficient to explain the range of risk preferences that can be captured by our task for our parameters during simulation (0.02 < Alpha < 3.32, 1e-06 < Beta <10). In particular, we calculated the lower bound (0.035) for α by solving the following equation:

$$0.9 \times 100^{\alpha} = 5^{\alpha}$$

The reasoning is as follows: given our choice set, the most risk averse individual would prefer the safe option ($5 with certainty) to the risky option with the highest expected value (EV) in our choice set, which is winning $100 with 0.90 probability. Under the same logic, the most risk seeking individual would prefer the risky option with the lowest expected value in our choice set ($10 with 0.1 probability) to the certain option ($5). We therefore calculated the upper bound (3.32) for Alpha by solving the following equation:

$$0.1 \times 10^{\alpha} = 5^{\alpha}$$

Alpha for an individual who would not select the lowest EV risky option over the safe option but would select the second lowest from this choice set would solve the following equation:

$$0.25 \times 10^{\alpha} = 5^{\alpha}$$

The resulting Alpha is 2. The choice set could have limited the model's ability to distinguish between Alpha values ranging from 2 to 3.32, as the difference between these two values lies in one choice.

To examine whether parameters were recoverable, we fit simulated data using *fmincon* (*Matlab 2018b; Mathworks*). For parameter recovery, we used the above-mentioned range for Beta (1e-06 < Beta <10) and slightly wider range for Alpha (0 < Alpha < 3.5). By slightly widening the search space, we are able to determine if a person's Alpha is truly unrecoverable by seeing whether their value lies between 3.32 and 3.5; if we had capped fitted Alpha at 3.32 and the fitted Alpha is 3.32, we wouldn't know whether that is really within the bounds or whether the model does not have the option to put it out of bounds. Using similar logic, we tested whether Alpha was less recoverable above vs. below 2, the value at which participants would be indifferent between risky and safe options for the second lowest EV risky choice (as described above).

We fitted the simulated data using the same EU model that generated it. Recoverability of model parameters is defined as the correlation between the parameter that generated the data and the parameter produced through model fitting (Wilson & Collins, 2019). We ran correlations between parameters used to simulate the data ("input parameters") and parameters fit by *fmincon* ("fitted parameters"). Although Beta recovery was mediocre (r = .400; Alpha <= 2: r = .594; Alpha > 2: r = .057), recovery for Alpha was quite reliable (r = .922) with a drop after Alpha exceeds 2 (Alpha <= 2: r = .935; Alpha > 2: r = .049). Values of Alpha were indistinguishable between 2 and 3.5, in line with the notion that such values (mostly) do not yield different choices. Within this range, there was not a difference in recoverability above vs. below the Alpha necessary to explain the range of risk preferences in the task (3.32). Together, these results suggest that the model is limited in its ability to distinguish small differences among the most risky-seeking participants, likely due to the limited choice set. Reassuringly, input values of Alpha above 2 did not yield recovered values below 2, so participants who are in this more risk seeking range are nearly always identified as such based on their Alpha (except where Beta was very low, such that participants frequently do not choose the option with higher EU) (Figure S1).

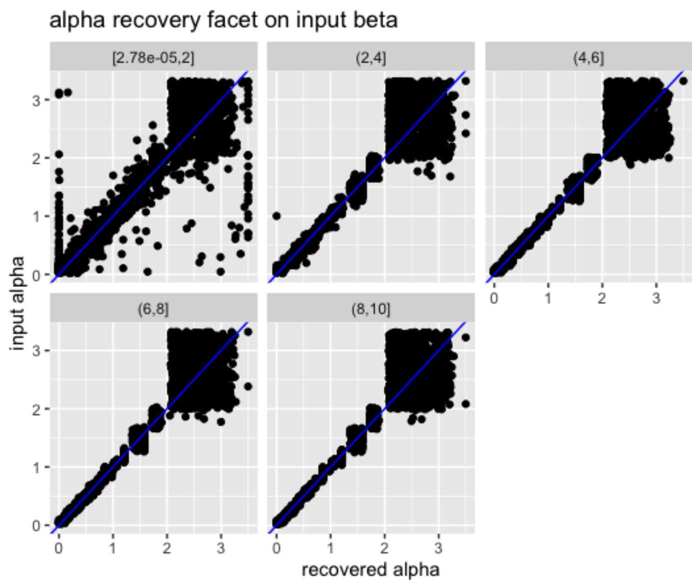

Figure S1. Recovery of Alpha based on different thresholds of input (simulated) Beta. *x*-axes denote recovered (fitted) Alpha. *y*-axes denote input (simulated) Alpha. The range on top of each panel denotes the range of input Beta that was used to generate the simulated data.

2. Comparing EU model with prospect theory models

According to prospect theory and past research (Tversky & Kahneman, 1992; e.g., Gonzalez & Wu, 1999; Hsu et al., 2009) nonlinear weighting of probabilities is an important bias in decision making. Although our choice set was designed according to an expected utility framework (Tymula et al., 2012) and not a prospect theory framework, we nevertheless fit two additional models in the latter framework to determine whether incorporating a probability weighting function could improve the model fit. The first prospect theory model is constructed by combining the expected utility function and the following single-parameter weighting function:

$$w(p) = \frac{p^{\gamma}}{\left(p^{\gamma} + (1-p)^{\gamma}\right)^{\frac{1}{\gamma}}} \qquad \textit{first prospect theory model}\ (3)$$

Therefore, this prospect theory model includes three free parameters: Alpha, Beta, and Gamma, where Gamma (γ) controls the weighting of probabilities (p). The second prospect theory model we fitted included only Beta and Gamma, i.e., where EU = *pv*, implying that the decision maker is risk neutral. We examined the parameter recoverability of the two prospect theory models before fitting them to real data using the aforementioned procedure. These correlations between input and fitted parameters are displayed in Table S1, indicating poor parameter recovery for the prospect theory models. We conclude that it is not feasible to incorporate prospect theory into our computational approach and which is likely due to limitations of the choice set.

Table S1. Parameter recovery for competing models.

	Alpha, Beta (EU model)	Alpha, Beta, Gamma (prospect theory model)	Beta, Gamma (prospect theory model)
Alpha correlation (fitted, simulated input)	0.922 (when Alpha<=2: 0.935; when Alpha>2: 0.049)	0.206 (when Alpha<=2: 0.204; alpha > 2: 0.024)	
Beta correlation (fitted, simulated input)	0.400 (when Alpha<=2: 0.594; when Alpha>2: 0.057)	0.138 (when Alpha<=2: 0.222; when Alpha>2: 0.006)	0.52

Gamma correlation (fitted, simulated input)		0.003 (when Alpha<=2: 0.005; when Alpha> 2: -0.0004)	0.028

3. Decisions on model usability by condition

We decided we would not use the original model if a given condition had more than 30 participants with a negative log likelihood (LL) that exceeded the value of negative LL for an agent who chose randomly for all 35 trials:

$$-ln\ (0.5)\ \times 35 = 24.26$$

According to the criterion, which translates to an AIC of 52.52, we decided not to use the original model for the Opposite context conditions (Table S2).

Table S2. Number of participants that the original model failed to predict better than random choices according to AIC values.

Conditions	*N*
Baseline	0
Friend Predicted	0
Opposite	39
Desired Opposite	57

4. Model-based exclusions

The criteria described in the “Methods - Model-based exclusion” section resulted in the following exclusions (Table S3). We conducted sensitivity analyses including and excluding participants whose Alpha is theoretically possible but exceeds 2, due to simulations showing poor recovery of Alpha in this range. See Sensitivity Analyses.

Table S3. Percentage of participants excluded by condition.

Conditions	Number of participants excluded	Number of analyzed participants	Percentage of participants excluded
Baseline	1	127	0.78%
Friend Predicted	0	128	0.00%
Opposite	10	118	7.81%
Desired Opposite	5	120	4.00%

These exclusions apply to analyses of Alpha and $\text{Weight}_{\text{friend}}$ as dependent variables only, as they were derived from computational models. No participant was excluded for analyses using simulated earnings or proportion of risky choices.

B. Revised model for Opposite context conditions

$$EU = (1-w)p_{self}{v_{self}}^{\alpha} + w\left(p_{friend}{v_{friend}}^{\alpha_{friend}}\right) \qquad revised\ model\ (4)$$

Through the same process outlined for our original model, we determined that our revised model was recoverable in its parameter of interest within the following bounds: Alpha ([0,2]).

1. Parameter recovery

Table S4. Parameter recovery for $\text{Weight}_{\text{friend}}$ and Alpha from Revised model (equation 4).

	$\text{Weight}_{\text{friend}}$	Alpha
correlation between simulated input and fitted value	*r*=.73	*r*=.78

2. Model Recovery with the revised (equation 4) vs. the original model (equation 1)

Like the process outlined for the original model, we simulated data using the original and revised model respectively, and fitted the resulting simulated data with both models respectively. Our revised model outperformed the original model for the following bounds for $Weight_{friend}$ [1e-06,1].

Table S5. Given what the generating model is (row), percentage of times that AIC suggests (column) is a better model.

Fit model / Data generating model	original	revised
original	88.7%	11.3%
revised	37.7%	62.3%

II. Supplementary Results

A. Distributions of actual and simulated random earnings

Figure S1. Distributions of actual and simulated random earnings. The blue area represents simulated earnings, and the red area represents actual data. We simulated 10,000 participants choosing at chance (50%) with 35 trials each in the Baseline condition, and compared this distribution to that of the actual data from the Baseline condition (Mean of simulated random earnings vs. actual data: \$406.06 vs. \$614.52; Standard deviation of simulated random earnings vs. actual data: 72.14 vs. 63.75.

B. **Distribution of trials and participants across age for analyses on relinquishing preferred option**

1. Distribution of all trials with conflicting self- and friend-preference

A. B.

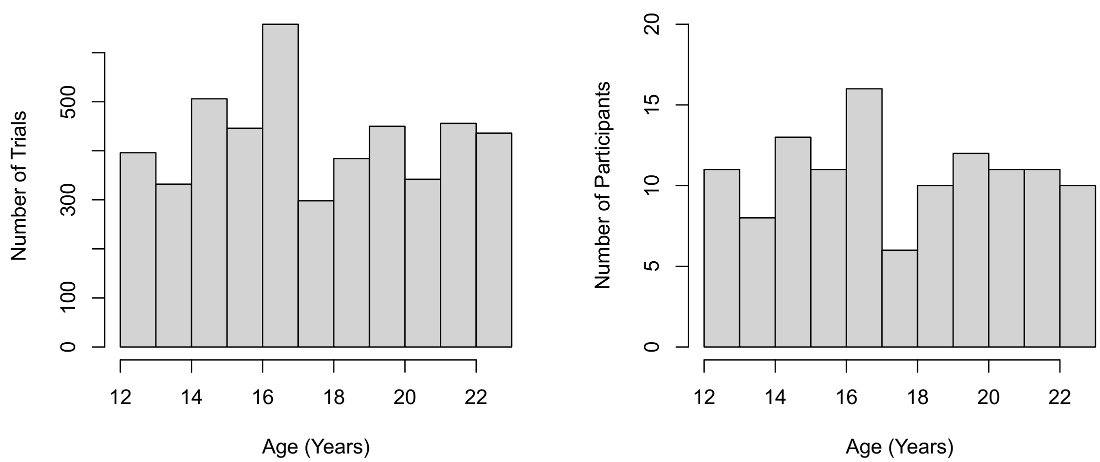

Figure S2. Histograms of the distribution of trials with conflicting self- and friend-preferences across the age range. *X*-axis: age in years. A. Distribution of 4730 trials included. *Y*-axis: number of trials. B. Distribution of 120 participants included. *Y*-axis: number of participants.

2. Distribution of the subset of conflicting trials with equal expected value (EV) of risky and safe options across age

A. B.

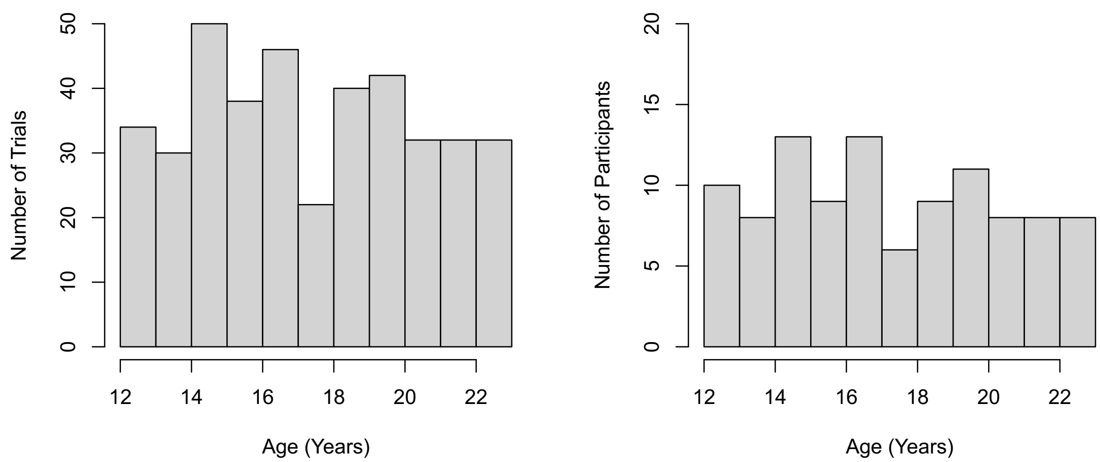

Figure S3. Histogram of the distribution of trials in which the expected value (EV) of the safe and risky options are equivalent across the age range. *X*-axis: age in years. A. Distribution of 398 trials included in this set of analysis: y-axis: number of trials. B. Distribution of 103 participants included in this set of analysis: y-axis: number of participants.

C. Supplementary results for relinquishing preferred options on trials with different EV for risky and safe options

In the main manuscript, we report findings charting age related differences in the tendency to relinquish an originally preferred option to peers, when the risky and safe choice options have an equal EV. Here, we explore more complex scenarios: when the risky options were advantageous ($EV_{risky\ option} > EV_{safe\ option}$ on a given trial) and disadvantageous ($EV_{risky\ option} < EV_{safe\ option}$ on a given trial). See section C.1 for distribution of trials and participants included for these analyses across age.

1. Distributions of trials and participants across age

1) When risky options were advantageous ($EV_{risky} > EV_{safe}$)

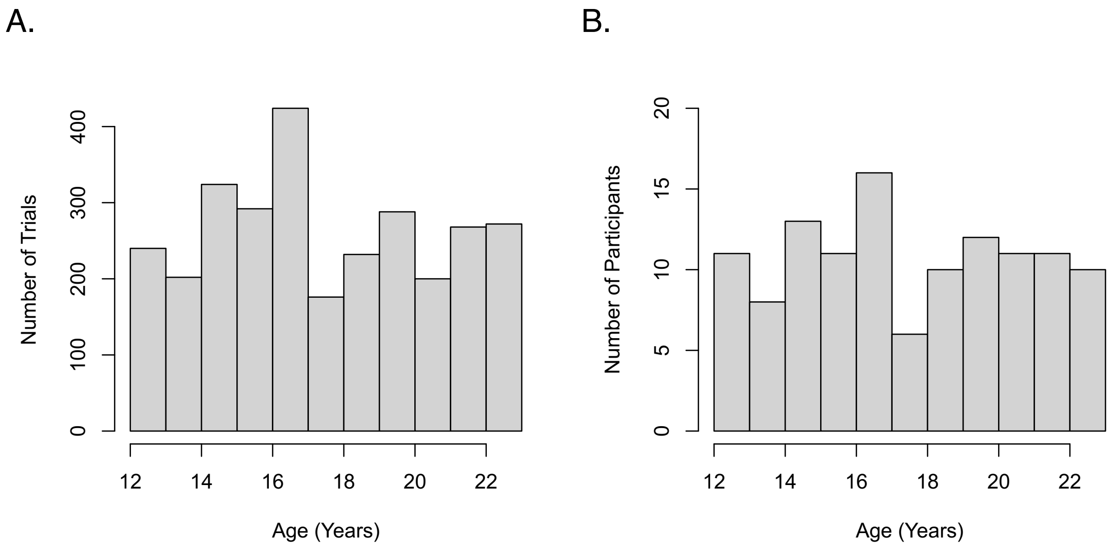

Figure S5. Histogram of the distribution of trials in which the expected value (EV) of the safe and risky options are equivalent across age. *x*-axis: age in years. A. Distribution of 2918 trials included in this set of analysis: y-axis: number of trials. B. Distribution of 119 participants included in this set of analysis: y-axis: number of participants.

2) When risky options were disadvantageous ($EV_{risky} < EV_{safe}$)

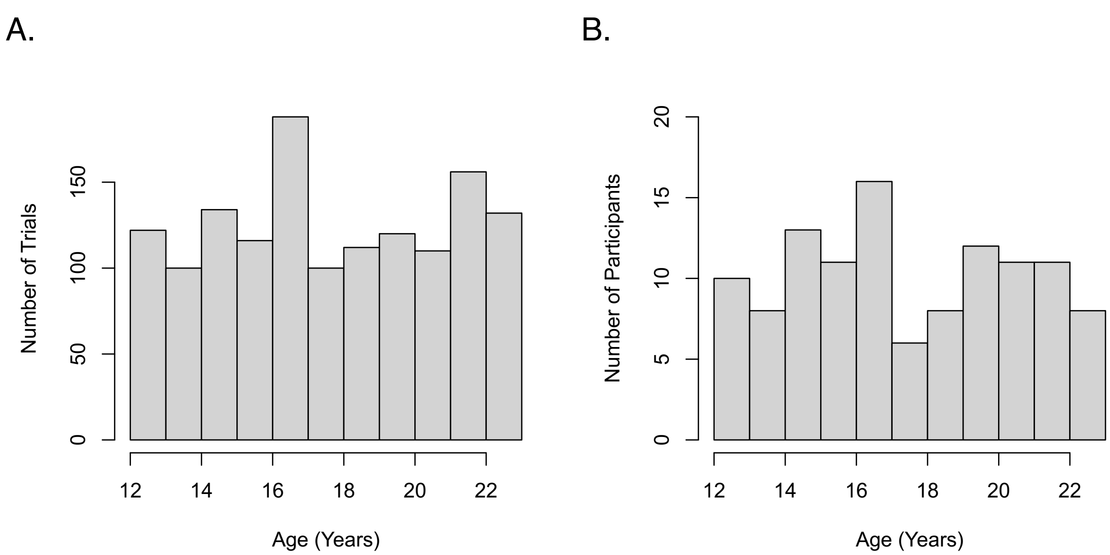

Figure S6. Histogram of the distribution among trials in which the expected value (EV) of the safe and risky options are equivalent across age. *x*-axis: age in years. A. Distribution of 1390 trials included in this set of analysis: y-axis: number of trials. B. Distribution of 114 participants included in this set of analysis: y-axis: number of participants.

2. Results

When the risky options were advantageous, giving up an originally preferred safe option would maximize payout but would require the individual to overcome their initial preferred level of risk aversion. If maximizing payout were a weaker motive than risk aversion, they would refuse to change their preference. Note that here, being motivated by shielding a friend from undesired risks and payout maximization would yield the same behavior. The analogous analysis to the one in the Equal-EV section in the manuscript revealed that on average, participants were more likely to relinquish their preference if it entailed giving up their originally preferred safe option (Mean proportion of total choices relinquished when originally preferring safe options vs, originally preferring risky options: .456 vs. .234, B=0.99, SE=0.13, Z=7.41, p<.001). This trend was significant in ages 13.6-17.3 and 19.7-22.8 years (Figure 4), We speculate that payout maximization (and/or prosocial motives) were stronger than risk aversion in these individuals and drove them to relinquish their original preferences.

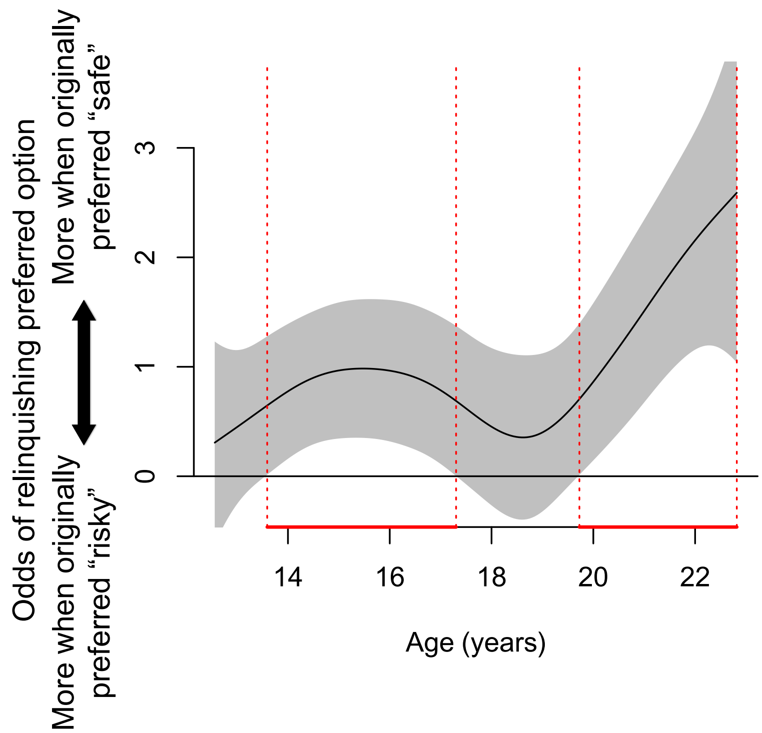

Figure S4. Age-related patterns of odds of relinquishing preferred option on trials where the EV of the risky options exceeded that of the safe options AND there was a conflict between self- and friend preferences. Shaded area represents 95% simultaneous CIs of the difference between fit estimates at each age point. Dotted red lines indicate ages and 13.6-17.3 and 19.7-22.8 years, the 95% simultaneous CIs do not include 0, indicating significant age-related changes. Positive difference indicates participants were more likely to relinquish if they originally preferred the safe option than if they originally preferred the risky option. Negative difference indicates the opposite. Zero indicated there is no difference between the odds of switching in either direction.

When risky options were disadvantageous, relinquishing an originally preferred safe option would be detrimental to payout maximation and contrary to risk aversion. Thus, it could only plausibly be driven by prosocial motives of accommodating one's friend. Analogous analysis to the ones above revealed that on average, participants were more reluctant/unwilling to relinquish their preferred safe option in exchange for a disadvantageous risky option (Mean proportion of total choices relinquished when originally preferring safe options vs. when originally preferring risky options: .167 vs. .395, *B*=-0.39, *SE*=0.19, *Z*=-2.11, *p*=.035). We speculate that prosocial motives were not strong enough to overcome either payout maximization or risk aversion (or both) and motivate behavioral change. There was no age-related difference, as the model did not detect significant difference in the odds of switching in either direction (i.e., the simultaneous CI included 0 at all ages).

3. Discussion

When relinquishing the safe option was advantageous in terms of EV, this trend was observed in early-to-mid adolescence and young adulthood but not during mid-to-late adolescence. At a glance, this suggests they were not more likely to relinquish preferred risky or safe options, setting them apart from the clear directional switch of the other ages. This finding was not hypothesized and would benefit from future replications. When the risky option was disadvantageous, participants from all ages were not more likely to switch from originally preferred safe option to receive risky options, or the other way around. This indicates that the prosocial motive was as strong in this scenario to motive behavioral change as in the previous two, where it clearly motivated individuals from certain ages to relinquish their preferred safe options.

D. Effect of observation on risky choice and peer effects

In addition to the choices varying over experimental conditions, we also had a manipulation of whether active observation by peers (real-time monitoring of performance over zoom) moderated the reported peer effects. We ran two preliminary analyses to explore potential impact observation had on the odds of relinquishing one's preferred options on trials with conflicting self- and friend-preference. A GAM model with a factor smooth interaction for age and categorical variable observation while controlling the probability and amount of money on each trial revealed no main effect of observation (Mean proportion of total choices relinquished when observed vs. unobserved: .302 vs. .294, B=0.04, SE=0.08, Z=0.52, p=.604) or age-related difference. A second GAM model with age as the only smoothed term and observation as a categorical predictor of interest, controlling for the probability and amount of money on each trial also revealed no main effect of observation (Mean proportion of total choices relinquished when observed vs. unobserved: .302 vs. .294, B=0.05, SE=0.08, Z=-0.70, p=.483) or age effect (edf=1.53, $chisq$=1.36, p=0.52). Although previous research has demonstrated that adolescents engage in greater risk seeking under the active observation of peers (Gardner & Steinberg, 2005; Powers et al., 2022) no such effects emerged in the present study. We discuss this further in Chen et al., (under review).

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