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Choosing for You: Diminished Self–Other Discrepancies in Financial Decisions Under Risk in the Elderly

Narun Pornpattananangkul, Bing Cai Kok, Jingwen Chai, Yi Huang, Lei Feng, and Rongjun Yu
National University of Singapore

Many older adults hold powerful positions in governments and corporate boards throughout the world. Accordingly, older adults often have to make important financial decisions on behalf of others under risk. Although it is common to observe younger adults taking more risks when making financial decisions for others, it is unclear if older adults exhibit the same self–other discrepancies. Here, we conducted 2 studies (88 and 124 participants, respectively) to examine self–other discrepancies in financial decision making under risk in older adults. We focused on 3 aspects of financial decision making: loss aversion (a tendency to weight potential losses more strongly than potential gains), risk-aversion asymmetry (a tendency to be risk-averse for potential gains and risk-seeking for potential losses), and risk preferences separately in gain and loss domains. Using computational modeling and behavioral economics tasks, we found weaker self–other discrepancies in older adults (compared with younger adults) across all 3 aspects. We also replicated the age differences in self–other discrepancies in loss aversion across 2 largely nonoverlapping cohorts. Thus, it appears that when making financial decisions on behalf of others, older adults, relative to younger adults, have a stronger disposition to regard others' financial outcomes as important as their own.

Keywords: loss aversion, risk aversion, decision making, aging, self–other discrepancies

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> Regard your neighbor's gain as your own gain and your neighbor's loss as your own loss.
>
> —Laozi (c. 500 BC)

In 2015, the average age of government leaders was 59.82 years old ($SD = 10.09$), and there were 62 countries whose government leaders were 65 years old or older. Accordingly, citizens in approximately one third of the countries around the world rely heavily on the decisions made by older adults. Thus, it is an important issue to understand not only how older adults make decisions for themselves, but also how they make decisions on behalf of others. This is especially true for financial decision making under risk in which the outcome of decisions can lead to significant gains (e.g., enhancing GDP) or losses (e.g., increasing job losses) for citizens in a country.

Preference in Financial Decisions Under Risk

Financial decisions under risk is not a unified construct: They comprise multiple facets. As such, researchers commonly break down financial decisions under risk into different choice properties (Rabin & Thaler, 2001), which often include domains (gains or losses), probabilities (the likelihood of gaining and/or losing), and magnitudes (the amount of potential gains and/or losses). Researchers then use several approaches to quantify preferences in financial decision making because of these choice properties. First, in the separate-domain approach, researchers examine preferences in financial decisions separately for gain and loss domains. For instance, researchers may compute an expected value (EV), or the multiplication of the probability and magnitude of a choice in a given domain, which reflects the average outcome of a choice in the long run (Von Neumann & Morgenstern, 1944). They then infer risk-preference from people's decisions toward risky choices at different EVs in both loss and gain domains, and express this preference along a risk-seeking/risk-averse continuum. For instance, when choosing between (a) a sure choice of gaining (los-

Narun Pornpattananangkul, Bing Cai Kok, and Jingwen Chai, Department of Psychology, National University of Singapore; Yi Huang, Graduate School for Integrative Sciences and Engineering, National University of Singapore; Lei Feng, Department of Psychological Medicine, National University of Singapore; Rongjun Yu, Department of Psychology and Graduate School for Integrative Sciences & Engineering, National University of Singapore.

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Correspondence concerning this article should be addressed to Rongjun Yu, Department of Psychology, National University of Singapore, AS4, 02-17, 9 Arts Link, Singapore or to Narun Pornpattananangkul, Department of Psychology, National University of Singapore, 9 Arts Link, Singapore. E-mail: psyyr@nus.edu.sg or narunzhang@gmail.com

ing) $50 and (b) a risky choice of having a 50% chance to gain (lose) $100, people are considered more risk-seeking (and less risk-averse) if they choose (b), and vice versa. Alternatively, instead of calculating the EV, researchers can also infer preferences in each domain from the changes in decisions as a function of probability while magnitude is held constant, and vice versa. For instance, risk-seeking individuals, relative to those who are risk-averse, are more likely to choose risky choices when (a) the probability/magnitude of a possible gain is low in the gain domain as well as (b) the probability/magnitude of losing is high in the loss domain.

Second, as opposed to examining financial decision making using the separate-domain approach, researchers have also investigated preferences in financial decisions under risk when choices involve both potential gains and losses in the so-called mixed domain approach. One example is a mixed gamble in which people choose between (a) a sure choice of not gaining or losing anything and (b) a risky choice of having a 50% chance to gain a certain amount and a 50% chance to lose a certain amount. When making decisions in situations similar to this mixed gamble, people usually (1) weight potential losses stronger than potential gains—a phenomenon called *loss-aversion*—and (2) become risk-averse for potential gains and risk-seeking for potential losses, a phenomenon called *risk-aversion asymmetry* (Booij, van Praag, & van de Kuilen, 2009; Kahneman & Tversky, 1979; Tversky & Kahneman, 1991).

Self–Other Discrepancies in Financial Decisions Under Risk

Research conducted in younger participants seems to suggest an asymmetry in (a) how younger adults judge the personality of unfamiliar others versus (b) how younger adults make financial decisions under risk on behalf of unfamiliar others. On the one hand, when meeting with strangers, younger adults tend to perceive the personality of the strangers to be similar to theirs (Beer & Watson, 2008a, 2008b). Beer and Watson (2008b), for instance, showed that younger adults rated unfamiliar others as similar to them in many personality traits, such as neuroticism, agreeableness, and conscientiousness. On the other hand, when having to make financial decisions under risk on behalf of unfamiliar others, younger adults usually show a self–other discrepancy. In a seminal article by Hsee and Weber (1997), undergraduate students were more risk-seeking when making financial decisions for an unfamiliar person (i.e., another person in the United States and another person on campus) than for themselves in the gain domain. Since then, several studies using the separate-domain approach have shown a similar self–other discrepancy effect in which younger adults are often more risk-seeking/less risk-averse when deciding on behalf of others in both gain and loss domains (Beisswanger, Stone, Hupp, & Allgaier, 2003; Garcia-Retamero, Okan, & Maldonado, 2015; Jung, Sul, & Kim, 2013; Stone, Yates, & Caruthers, 2002; Sun, Liu, Zhang, & Lu, 2016).

Similar to these changes in risk preferences in both gain and loss domains, recent studies using the mixed domain approach have also shown a reduction in loss aversion in younger adults when they make decisions on behalf of someone else (Andersson, Holm, Tyran, & Wengström, 2014; Mengarelli, Moretti, Faralla, Vindras, & Sirigu, 2014; Polman, 2012). For example, using a mixed gamble, Mengarelli and colleagues (2014) demonstrated that younger adults were more likely to choose risky choices for others compared with for themselves, even when those risky choices involved high potential losses, suggesting that younger adults do not weight losses as high when other people are the recipients of their decisions. Additionally, Sokol-Hessner and colleagues (2009) demonstrated that simple changes in cognitive strategies can alter risk-taking behavior among younger adults. In their study, the experimenters asked younger adults to think as if they were a stock trader while making decisions in a mixed-gamble task, using the following phrase: "Imagine that this is your job and that the money at stake is not yours—it is someone else's." The use of this intentional cognitive regulation strategy reduced loss aversion among these individuals.

Financial Decisions Under Risk and Social Decision Making in the Elderly

Several studies have examined changes in financial decisions under risk in older adults when they make decisions for themselves (Lim & Yu, 2015; Samanez-Larkin & Knutson, 2015; Sparrow & Spaniol, 2016). A meta-analysis of 17 studies, however, shows mixed, inconclusive results of the changes in older adults' preferences, especially after controlling for a learning feature of financial decision-making tasks (Mata, Josef, Samanez-Larkin, & Hertwig, 2011). Nonetheless, the lack of systematic age-differences in financial decision making under risk for oneself does not necessarily mean that such differences are absent when making decisions on the behalf of others. We argue that, given the alteration in social decision making in older adults (Sze, Gyurak, Goodkind, & Levenson, 2012), the self–other discrepancies in financial decisions commonly seen in younger adults may change with increasing age.

When making decisions in the social domain, older adults often show a stronger sense of generosity and prosociality (Bekkers, 2010; McAdams, St. Aubin, & Logan, 1993). In laboratory settings, older adults usually decide to distribute more money to another stranger in an economic game, known as the dictator game, compared with younger adults (Engel, 2011; Matsumoto, Yamagishi, Li, & Kiyonari, 2016). Older adults also donate more money to charities (Freund & Blanchard-Fields, 2014; Midlarsky & Hannah, 1989; Sze et al., 2012) and express a stronger level of positive emotion after making donations (Bjälkebring, Västfjäll, Dickert, & Slovic, 2016). Older adults also have a stronger reaction upon seeing others in need, as reflected by their heart-rate reactivity and self-reported empathy (Sze et al., 2012). Neuroimaging research reveals that older adults' reward-related brain areas react more strongly when anticipating social rewards (Rademacher, Salama, Gründer, & Spreckelmeyer, 2014) and when donating money to a charity (Hubbard, Harbaugh, Srivastava, Degras, & Mayr, 2016). Outside of laboratories, older adults are inclined to volunteer more frequently (Cornwell, Schumm, & Laumann, 2008). Thus, evidence suggests that in the presence of risk, financial decisions made by older adults on the behalf of others may mirror those made for themselves.

Current Research

On the basis of heightened prosociality in older adults, we expect a diminishment of self–other discrepancies in financial decisions under risk in older adults as compared with younger adults. We tested this hypothesis using both the mixed-domain and separate-domain approaches in two studies. In the first study, we used the mixed-domain approach using Tom's mixed-gamble task (Tom, Fox, Trepel, & Poldrack, 2007). Specifically, this task allowed us to examine loss aversion (or the extent to which participants weighted losses compared with gains) when participants made decisions for others compared with for themselves. Following previous work (e.g., Mengarelli et al., 2014), we predict that younger participants will exhibit stronger loss aversion (i.e., weight losses much more than gains) when making decisions for themselves compared with for others. In the case of our study, we expected this self–other discrepancy in loss aversion to be weaker in older participants as compared with younger participants. In the same study, we also had another experiment to assess risk preferences in gain and loss domains separately using the modified cups task (Levin & Hart, 2003). Here we tested if participants became more risk-seeking when they made decisions for others, compared with for themselves, in both gain and loss domains. Following previous work (e.g., Hsee & Weber, 1997), we expected younger participants to be more risk-seeking for both gains and losses when making decisions for others, as compared with choosing for themselves. Similar to loss aversion, we expected this self–other discrepancy in risk-preferences for both gain and loss domains to be weaker in older participants as compared with younger participants. In the second study, we aimed to replicate the findings in the first study using largely nonoverlapping participants and to extend our investigation to self–other discrepancies in risk-aversion asymmetry (or a tendency to be risk-averse for potential gains and risk-seeking for potential losses). Specifically, we used a modified version of the Sokol-Hessner's mixed-gamble task (Sokol-Hessner et al., 2009) to model both loss aversion and risk-aversion asymmetry. In the second study, we expected to find diminished self–other discrepancy in both loss aversion and risk-aversion asymmetry among the older participants in a similar manner with loss-aversion in the first study.

Study 1

Participants

Participants were 49 older adults (28 women; age $M = 70.41$ years, $SD = 4.01$; education $M = 8.36$ years, $SD = 3.19$) and 39 younger adults (25 women; age $M = 22.79$ years, $SD = 2.54$; education $M = 15.35$ years, $SD = 2.02$) residing in Singapore.[1] We determined the sample size on the basis of the mean of the effect size (Cohen's $d = .54$) from 20 experiments reported in seven articles that examined self–other discrepancies in financial decision making under risk and uncertainty (Beisswanger et al., 2003; Hsee & Weber, 1997; Mengarelli et al., 2014; Polman, 2012; Pronin, Olivola, & Kennedy, 2008; Stone & Allgaier, 2008; Stone et al., 2002). Using G*Power 3.1 (Faul, Erdfelder, Buchner, & Lang, 2009; Faul, Erdfelder, Lang, & Buchner, 2007), we set the value α at .05 and 1-β at .80. Because we examined the self–other discrepancies using repeated measures following these seven articles, we computed the required sample size on the basis of t tests of two dependent means. This resulted in the sample size necessary to achieve a given level of power (.80) at 28 people. Given that our sample size in each age group exceeded 28, our study should have sufficient power to detect self–other discrepancies in both age groups, if there exist self–other discrepancies among participants in that group.

We also measured the subjective social status (SSS) from 44 older participants and all younger participants using the social ladder task (Adler, Epel, Castellazzo, & Ickovics, 2000). In this social ladder task, we showed the participants with a picture of a ladder with 10 rungs. We told them that the ladder represented the Singapore society and asked them to report which rung they were at compared with others in the society. Higher rungs indicated higher SSS. There was no significant difference between the older participants ($M = 5.61$, $SD = 1.7$) and younger participants ($M = 5.95$, $SD = 1.37$) in SSS, $t(81) = -.99$, $p = .32$.

We recruited participants via a website and phone calls. We mainly called older participants who lived in the community near our testing site in Singapore and have participated in other unrelated studies with separate groups of researchers at this site in the past. We informed participants that other participants in the current study may come from different age groups—some of whom were in the same age range as them, whereas others were not. The older participants were screened for their eligibility to participate in the experiment by trained nurses as part of a larger longitudinal study. Experimenters also tested older participants' understanding of the task before starting the experiment. All participants provided informed consent prior to the experiment and were given $S15[2] for showing-up in addition to a monetary bonus based on their performance in the tasks (see the following text). All participants provided informed consent and completed the session on the basis of a protocol that was approved by the National University of Singapore Institutional Review Board (ID: A-15–091).

Procedure

Participants completed a battery of computerized decision-making tests, including Tom's mixed-gamble task (Tom et al., 2007) and the cups task (Weller, Levin, Shiv, & Bechara, 2007). We decided to include both tasks to capture different aspects of financial decision making. Specifically, Tom's mixed-gamble task allowed us to examine risky decision making in the mixed-domain setting, whereas the cups task enabled us to study financial decision making under risk for gains and losses separately. Participants completed both tasks within a single session that lasted approximately 2 hr. Because we presented the outcome of each gamble in the cups task, but not in the mixed-gamble task, we asked participants to complete the mixed-gamble task first, followed by the cups task. This is so that outcomes from the cups task did not influence participants' choices in the mixed-gamble task. Participants were given monetary bonus based on their performance in the two tasks at the end of the experiment session.

Tom's mixed-gamble task. To examine self–other discrepancies in loss aversion, we modified the mixed-gamble task used in earlier fMRI and patient studies (Brown et al., 2013; De Martino, Camerer, & Adolphs, 2010; Tom et al., 2007; see Figure 1 for the schematic representation of the task). In each trial, participants had to decide whether to accept or reject a gamble. If participants

[1] Two older adults did not report their years of education.

[2] S$ 1 SGD is around $.73 USD. Thus, a showing-up fee of S$15 SGD is around $11 USD. Hereafter we refer to SGD as S$.

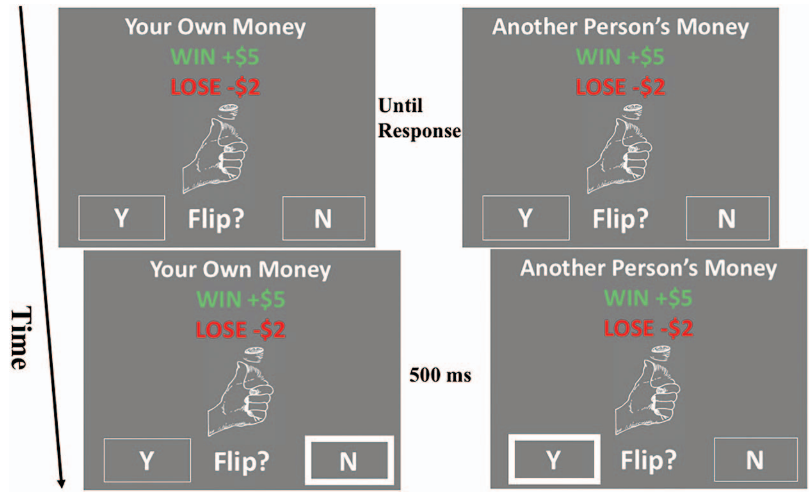

Figure 1. Schematic representation of the Tom's mixed-gamble task in Study 1. In each trial, we presented participants with a risky option and a sure option. If participants chose the risky option (i.e., deciding to flip a coin), there would be a 50% chance of gaining the amount specified in green following the word *WIN* and a 50% chance of losing the amount specified in red following the word *LOSE*. Participants either made decisions for themselves or for another person, as indicated on the screen. After making their choice, the participants' choice was highlighted for 500 ms. In this task, there was no feedback indicating the amount they gained/lost. For every trial, the aforementioned sequence was preceded by an intertrial interval (ITI) interval (a blank screen) of 1,000 ms. See the online article for the color version of this figure.

accepted the gamble, they would have a 50% chance to gain a specified amount (ranging from $S2 to $S9 in $S1 increments) and a 50% chance to lose a specified amount (ranging from $S1 to $S4.5 in $S.5 increments). If participants decided to reject the gamble, then they would not gain or lose any amount for that trial. To manipulate the self–other conditions, we first randomly picked three IDs of other participants and asked the participants to choose one ID (i.e., another participant) whom they would like to make decisions for. In the self condition, the outcomes of participants' selections would go to the participants themselves. In the other condition, the outcomes of participants' choices would go to the person whose ID was picked. We did not explicitly inform participants about the demographics of the other person for whom they made decisions. We told participants that this person was another participant who decided to participate in the study, just like themselves. Trials were presented in blocks of self trials and blocks of other trials (the participant or another person will be the recipient of his or her choice).

We presented self and other trials as separated blocks of 16 trials, isolated by breaks of participant-determined length. In total, there were 64 self trials and 64 other trials, covering all of the unique combinations of gain (eight possibilities) and loss (eight possibilities) amounts. We counterbalanced the order of self-trial and other-trial blocks across participants. Within the self-trial and other-trial blocks, we fully randomized the order of gain and loss combinations. Following previous research (Tom et al., 2007), we did not present the outcome of each gamble. We told participants to treat every decision as equally important, given that we would randomly pick one trial at the end of the experiment for reimbursement.

To improve participants' understanding, we presented the gamble as a coin flipping game (see Figure 1). Furthermore, to make things concrete, we used a physical coin to explain the task and had participants practice the task using the physical coin before the formal experiment. Probing questions such as "If you chose to flip a coin, and it turns out to be a gain, who will get the money?" were asked to ensure that participants fully understood the task. Participants were endowed with an initial fund of $S5 that was separated from that of the cups task. They were encouraged to earn as much as possible and to lose as little as possible in the task.

Computational modeling of choice data: Tom's mixed-gamble task. In addition to excluding data from one participant due to technical difficulty, we also excluded data from four older participants because they expressed confusion during the practice session. To ensure that every participant took both gain and loss information into consideration when deciding whether to gamble, we implemented similar exclusion procedures used previously (Brown et al., 2013). First, for each participant, we fit his or her trial-by-trial choices to a logistic regression model with magnitudes of the potential gain and loss on that trial as regressors. This was performed using a "nlmefit" command in MATLAB (Mathworks, 2011). We did this separately for the self and other trials. We then excluded participants whose regression coefficient for either the self or other conditions was not significantly different from zero. This left 34 older participants (19 women) and 37 younger participants (24 women), which is consistent with previous research (Brown et al., 2013; Sokol-Hessner, Camerer, & Phelps, 2013).

After exclusion, we fit trial-by-trial choices of all participants to a prospect theory-inspired (Tversky & Kahneman, 1992) model used earlier (Brown et al., 2013; De Martino et al., 2010; Tom et al., 2007). Briefly, the model consists of two main parts. The first part is concerned with the mechanisms behind the value-to-utility transformation. Specifically, the model posits that people process objective monetary value (e.g., \$5) by converting into a participant-specific subjective value, also known as its *utility*. The utilities of each individual objective monetary value are then combined to form the utility of the gamble and the utility of the sure choice. In the second part, the model seeks to describe how each participant make choices based on the utilities. Concretely, participants are thought to make their decisions on the basis of the utility of the gamble relative to that of the sure choice. That is, when the relative difference in utilities favors the gamble, participants are more likely to choose the gamble over the sure choice. On the basis of this model, the behavior of these participants can be succinctly described in terms of two subject-specific free parameters, each corresponding to the two parts of the model. The first of them, lambda (λ), governs the transformation of objective values into subjective utilities. The latter, tau (τ), describes the extent to which participants make use of subjective utilities to make their decision on any given trial. When considered together, this model provides a parsimonious description of choice behavior in the mixed-gamble task.

This model assumes a linear value function and is considered appropriate when all of the trials are mixed gambles (Sokol-Hessner et al., 2013).

$$u(x) = \begin{cases} |x| & \text{if } x \geq 0 \\ -\lambda \times |x| & \text{if } x < 0 \end{cases} \tag{1}$$

u is the utility of the objective monetary amounts, x is the objective value (i.e., the amount shown on the screen) of the potential outcome, and λ (i.e., the loss-aversion parameter) is a relative multiplicative weighting of loss to gain amounts. As a participant-specific free parameter, the lambda value reflects individual differences in loss aversion: 1 = loss/gain-neutral, <1 = gain-seeking, >1 = loss-averse. We then calculated the expected utility of each choice (accepting vs. rejecting a gamble) by additionally assuming that our participants linearly combined utilities and probabilities (Mosteller & Nogee, 1951):

$$eu_c = \sum\nolimits_i p_i \times u(x_i) \tag{2}$$

eu_c is the expected utility of each choice, c is a member of the set of choices, p_i is the probability of obtaining an outcome x_i. In our experiment, the set of choices consists of (1) accepting and (2) rejecting the gamble. Therefore, the expected utility for each possible choice (i.e., accept or reject) can be computed as follows:

$$eu_{accepting} = p_{gain} \times u(x_{gain}) + p_{loss} \times u(x_{loss}) \tag{3}$$

$$eu_{rejecting} = p_{sure} \times u(x_{sure}) = 1 \times 0 = 0 \tag{4}$$

We then calculated the overall expected utility (EU) for a particular trial as follows:

$$\begin{aligned} EU = eu_{accepting} - \ eu_{rejecting} &= p_{gain} \times u(x_{gain}) + p_{loss} \times u(x_{loss}) - 0 \\ &= .5 \times u(x_{gain}) + \ .5 \times u(x_{loss}) \end{aligned} \tag{5}$$

Thus, a more positive value of EU indicates a higher utility to accept, than to reject, the gamble in that trial. To capture how individuals transformed EU into actual choices, we then entered the EU calculated by both models to a softmax function (Luce, 1959). This function predicts a probability (P) of accepting the gamble based on EU as follows:

$$P(accept) = (1 + \ e^{-\tau \times EU})^{-1} \tag{6}$$

The softmax function has another participant-specific free-parameter, the inverse temperature (τ) that reflects individual differences in behavioral consistency. Higher values represent greater consistency across trials.

To fit the model, we used the hierarchical Bayesian analysis (HBA) approach (Gelman, 2013; Kruschke, 2014). There are three different components that make up this Bayesian modeling approach. The first component is the prior distribution. It is chosen by the researcher to reflect one's initial beliefs in the distribution of free parameters. For example, if one has strong initial beliefs that there is no loss-aversion (i.e., λ = 1), one could specify a normal distribution with a small variance that is centered at one as the prior distribution. On the other hand, if the researcher has no strong initial beliefs on the presence of loss-aversion, he or she could use a weakly informative prior, such as a normal distribution with a large variance. In accordance with previous recommendations (Ahn, Haines, & Zhang, 2017), we used weakly informative priors in all our analyses.

The second component of interest is the likelihood. Specifically, the likelihood refers to the probability distribution of our data, conditional on the free parameters. In the context of this study, the likelihood is the joint probability distribution of all choices made by the participants. For instance, if we consider only a single participant, the joint probability is given by $\prod_{i=1}^{n} P(choice_i)$, where the choice probabilities follow from Equation 6. That is, the likelihood is derived from the behavioral model under investigation. Furthermore, if we were to expand Equation 6 using the preceding five equations, we can see that the likelihood is a function of the free parameters in the model. More concretely, if we have specific values of the free parameters (e.g., λ = 1.2, τ = 0.8), we can substitute these values into the likelihood to compute the probability of the observed data occurring under the given behavioral model. The question is then this: What are the values that the free parameters can take such that it they are consistent with the observed data?

This in turn brings us to the last component of the Bayesian modeling approach—the posterior distribution. The posterior distribution is the probability distribution of the free parameters, conditional on the observed data. Put simply, the posterior distribution reflects our updated beliefs of the parameters (e.g., loss aversion parameter λ) after observing the data. That is, given a prior and likelihood, we are interested in obtaining the associated posterior distribution. Another way to understand the posterior is that it describes the probability of each possible value of λ and τ after observing the data. Intuitively, we can then use the posterior distribution to perform hypothesis testing on the free parameters with methods such as the highest density interval (HDI; see the following text). However, there are usually no explicit formulas to represent the posterior distribution. Thus, we have to use numerical methods such as Monte Carlo Markov Chain (MCMC) to approximate the posterior distribution. Thereafter, we can use the posterior distribution for statistical inference.

To model the effect of the self–other condition, we took a Bayesian parameter estimation approach (Kruschke, 2011) used in previous research on loss aversion (Sokol-Hessner, Raio, Gottesman, Lackovic, & Phelps, 2016):

$$\lambda_{participant,condition} = e^{\lambda_{participant} + SelfOther_{condition} \times \Delta\lambda_{participant}} \tag{7}$$

$$\tau_{participant,condition} = e^{\tau_{participant} + SelfOther_{condition} \times \Delta\tau_{participant}} \quad (8)$$

Specifically, we implemented $SelfOther_{condition}$ as a binary indicator for the self (0) and other (1) conditions. Because self is coded as 0, $\lambda_{participant}$ and $\tau_{participant}$ are each participant's "baseline" parameters that reflect λ and τ values in the self condition. $\Delta\lambda_{participant}$ and $\Delta\tau_{participant}$ are each participant's "change" parameters that capture the change from the self condition to the other condition. A negative value in $\Delta\lambda_{participant}$, for instance, reflects that λ was smaller when a particular participant made his or her decisions for another person, relative to making decisions for him/herself. Note that the summation between the baseline and change parameters occurred within the exponential to constrain their values to be positive (see the following text).

To estimate the free parameters, we followed the HBA framework used in both the hBayesDM R package (Ahn et al., 2017) and previous research on loss aversion (Sokol-Hessner et al., 2016). HBA allows us to estimate the full posterior distributions of parameter values and also enables group tendencies to inform each participant's parameter values. Several studies have shown that HBA is superior to conventional, nonhierarchical maximum likelihood estimation in parameter recovery (Ahn, Krawitz, Kim, Busmeyer, & Brown, 2011; Katahira, 2016; Lee, 2011). To implement HBA, we used the Hamiltonian Monte Carlo (HMC) algorithm to run MCMC sampling in Stan 2.16 (Carpenter et al., 2017) via R 3.3.3 (R Core Team, 2017). Specifically, each participant's parameters were assumed to be drawn from group-level normal distributions. We used standard normal and half-Cauchy prior distributions for group-level means (μ) and standard deviations (σ), respectively (Gelman, 2006). Following previous recommendation (Sokol-Hessner et al., 2016), we bounded all parameters to be positive using an exponential transformation as follows:

$$\mu_{\lambda'},\ \mu_{\Delta\lambda'},\ \mu_{\tau'},\ \mu_{\Delta\tau'} \sim \text{Normal}(0, 1) \quad (9)$$

$$\sigma_{\lambda'}, \sigma_{\Delta\lambda'}, \sigma_{\tau'}\ \sigma_{\Delta\tau'} \sim \text{half} - \text{Cauchy}(0, 5) \quad (10)$$

$$\lambda' \sim \text{Normal}(\mu_{\lambda'}, \sigma_{\lambda'}) \quad (11)$$

$$\lambda = \text{Exp}(\lambda') \quad (12)$$

$$\Delta\lambda' \sim \text{Normal}(\mu_{\Delta\lambda'}, \sigma_{\Delta\lambda'}) \quad (13)$$

$$\Delta\lambda = \text{Exp}(\Delta\lambda') \quad (14)$$

$$\tau' \sim \text{Normal}(\mu_{\tau'}, \sigma_{\tau'}) \quad (15)$$

$$\tau = \text{Exp}(\tau') \quad (16)$$

$$\Delta\tau' \sim \text{Normal}(\mu_{\Delta\tau'}, \sigma_{\Delta\tau'}) \quad (17)$$

$$\Delta\tau = \text{Exp}(\Delta\tau') \quad (18)$$

We used four MCMC chains. For each chain, we randomized its initial value and drew 40,000 samples in addition to 1,000 burn-in samples. This left a total of 160,000 samples across chains. To evaluate the convergence of the MCMC chains, we visually evaluated the trace plots of the group-level (hyper) parameters, as well as checked $\hat{R}$ statistic computed from the Gelman-Rubin test (Gelman & Rubin, 1992).

Analyses and results: Tom's mixed-gamble task. The trace plots in our data confirmed excellent mixing of MCMC samples. Moreover, all $\hat{R}$ values from all parameters were less than 1.1, suggesting that our MCMC chains converged well. Additionally, the effective sample sizes (ESS) for all parameters were well above 10,000, in line with prevailing standards for the estimation of the HDI (see the following text; Kruschke, 2014). Table 1 summarizes proportion of gambles and group-level (hyper) parameters as a function of self–other conditions and age groups. Notably, our λ values recovered from the self condition among our younger participants (M = 2.06) are close to what was found among younger participants in the previous article (Tom et al., 2007) on which our task was based (Mdn λ = 1.93).

We examined the change in λ and τ values due to the self–other conditions within each age group and between age groups with fully Bayesian approaches (Ahn et al., 2017; Kruschke, 2014; Sokol-Hessner et al., 2016). To begin, we investigated the 95% HDI of the posterior distributions of the group-level (hyper) change parameters, Δλ and Δτ, within each age group. The HDI summarizes the uncertainty of the parameters by providing the most credible span of estimated values (Kruschke, 2014). Accordingly, if the 95% HDI of the Δλ and Δτ parameters within each age group does not include zero, then we can be 95% confident that there is a change in a particular parameter from the baseline (self) within a particular age group. As shown in Figure 2 and Table 1, the 95% HDI of the Δλ parameter among the younger adults contained only negative values (−0.26, −0.03). This means that the younger adults had a higher λ value for themselves (M = 2.06, SD = .15) compared with for others (M = 1.78, SD = .17). Given that a higher λ value indicates more loss-aversion, this suggests that the younger adults were more loss-averse for themselves compared with for others. In contrast, the 95% HDI of the Δλ parameter among the older adults (−0.05, 0.02) contains zero, suggesting a lack of change in their λ values between self and other conditions. As for the Δτ parameter, both the younger (−0.41, 0.16) and older (−0.45, 0.06) adults had their posterior distributions shifted toward the negative side, although the 95% HDIs of the Δτ parameters still contained zero.

As for the effect of age, we first computed the differences of the group-level parameter distributions between the two groups (Kruschke, 2010, 2011) by subtracting the older adults' posterior distributions from those of the younger adults. We then investigated the 95% HDI of these differences. Similar to the effect within each group, if the 95% HDI of these differences does not include zero, then we can be 95% confident that the change

Table 1
Proportion of Gamble and Group-Level (Hyper) Parameters in Tom's Mixed-Gamble Task in Study 1 as a Function of Self–Other Conditions and Age Groups

Proportion of gamble and group-level parameters	Younger adults		Older adults	
	M	SD	M	SD
Self				
Proportion of gamble	.48	.21	.55	.17
λ	2.06	.15	1.76	.12
τ	2.71	.34	2.41	.42
Δ				
Δλ	−.15	.06	−.02	.02
Δτ	−.13	.15	−.19	.13
Other				
Proportion of gamble	.54	.21	.54	.15
λ	1.78	.17	1.73	.12
τ	2.41	.42	2.20	.39

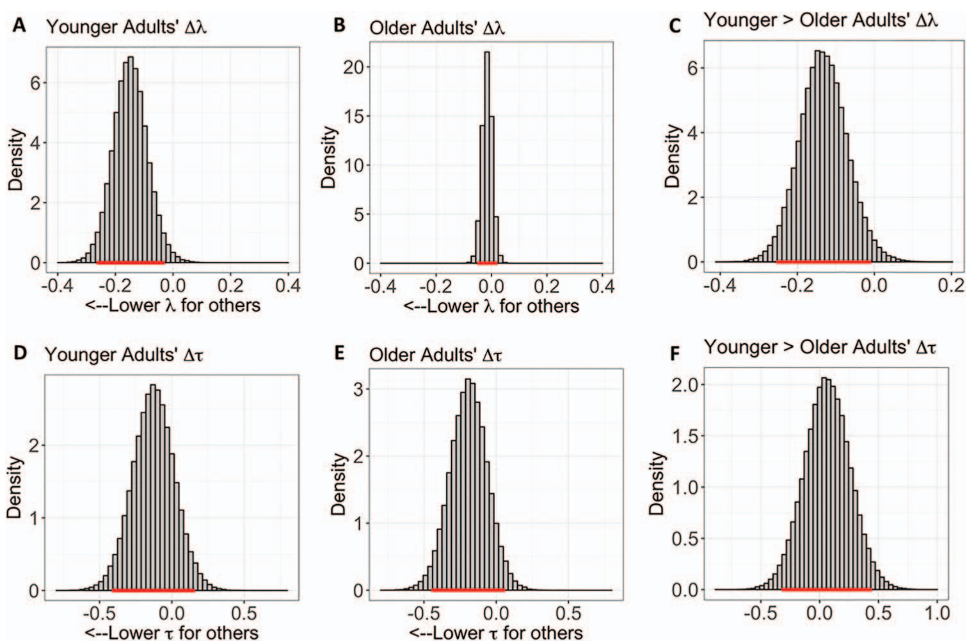

Figure 2. Posterior distributions of the estimated group-level (hyper) parameters: $\Delta\lambda$ (Panels A and B) and $\Delta\tau$ (Panels D and E) from the Tom's mixed-gamble task in Study 1. These distributions indicate the changes in λ (loss-aversion) and τ (consistency) due to the self–other conditions. The red/dark gray bars indicate the 95% highest density interval (HDI). Only the HDI of the posterior distributions of the $\Delta\lambda$ parameter among the younger adults (Panel A) was negative and did not include zero. This suggests that the younger adults had a lower λ value for others compared with that for themselves. We created plots for the differences of the hyper-parameter distributions between age groups for both the $\Delta\lambda$ (Panel C) and $\Delta\tau$ (Panel F) parameters, by subtracting the older adults' posterior distributions from those of the younger adults. Only the HDI of the difference of the group-level parameter distributions of the $\Delta\lambda$ (Panel C), but not $\Delta\tau$ (Panel F), parameter did not include zero. This suggests that there was a difference in the change in the λ (but not in τ) value between the age groups. See the online article for the color version of this figure.

parameters varied between age groups. On the basis of the 95% HDIs shown in Figure 2, only the difference of the group-level parameter distributions of the $\Delta\lambda$ (-0.25, -0.01), but not $\Delta\tau$ (-0.32, 0.44), parameter did not include zero. This suggests that there was a difference between the two age groups in the self–other discrepancy in loss aversion (λ), but not in behavioral consistency (τ). That is, the younger adults had more negative $\Delta\lambda$, as compared with the older adults.

Cups task. To examine self–other discrepancies in preferences in financial decision making in the separate domain approach, we adapted an established computerized risky decision making task called the cups task (Levin & Hart, 2003). Designed to be easily comprehensible, the cups task has been used with older adults (Weller, Levin, & Denburg, 2011), children as young as 5 years old (Levin & Hart, 2003; Levin, Weller, Pederson, & Harshman, 2007) and patients with brain lesions. See Figure 3 for a schematic representation of the task.

For our adapted version of the cups task, we varied four different features of the choices over trials: self–other (the participant or another person will be the recipient of his or her choice), domain (gain or loss), probability (.20, .33, or .5), and magnitude (two, three, or five 50-cent coins). We presented each unique combination of self–other, domain, probability, and magnitude three times, for a total of 108 trials. To manipulate the self–other conditions, we used the same procedure with that in Tom's mixed-gamble task. Particularly, we first randomly picked three IDs of other participants and asked the participants to choose one ID (i.e., another participant) whom they would like to make decisions for. This is a separate randomization from Tom's mixed-gamble task. As in the previous task, in the self condition, the outcomes of participants' choices would go to the participants themselves, whereas in the other condition, the outcomes of participants' choices would go to the person whose ID was picked.

In each trial, we presented participants with two options: a sure choice and a risky choice. A picture of one cup indicated the sure option, whereas a picture of several cups indicated the risky option. Participants were told that a 50-cent coin was always beneath the sure one-cup option. If they selected this sure option, it would result in gaining a 50-cent coin for sure in the gain-domain trials, and losing one 50-cent coin for sure in the loss-domain trials. For the risky choice, participants were told that there were 50-cent coins (two, three, or five coins, which correspond to different magnitudes) underneath one of the cups (two, three, or five cups, which are equivalent to .50, .33, or .20 probability, respectively). The designated number of coins, which reflected the magnitude of the risky choice, was presented above the picture of the cups. In the gain-domain condition, if participants selected the risky choice, participants would have a chance of obtaining either

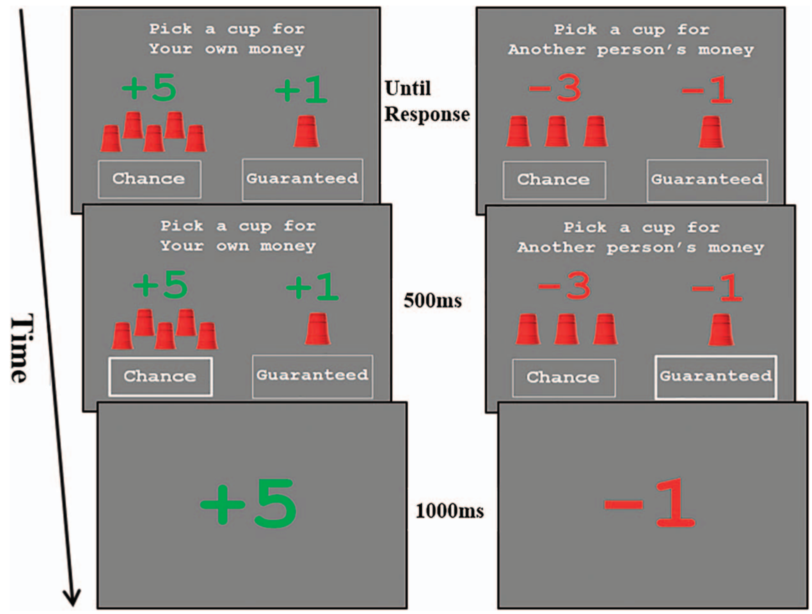

Figure 3. Schematic representation of the cups task in Study 1. In each trial, we presented participants with a risky option and a sure option. The sure option (indicated by the word *Guaranteed*) always led to winning/losing one 50-cent coin. The risky option (indicated by the word *Chance*) featured a variable number of cups and coins. Only one of the several cups contained the stated number of 50-cent coins. Participants either made decisions for themselves or for another person as indicated on the screen. After making their choice, the participants' choice was highlighted for 500 ms. This was followed by a feedback screen indicating the amount they gained/lost. For every trial, the aforementioned sequence was preceded by an intertrial interval (a blank screen) of 1,000 ms. See the online article for the color version of this figure.

a cup with more than one coin (thus earning them more coins than the sure choice) or a cup without any coins. Similarly, in the loss-domain condition, choosing the risky choice meant that they either lost more than one coin or lost nothing at all. The outcome on each trial was shown at the end of the trial. If the risky choice was chosen, the outcome would be determined by a random process with probability equal to one divided by the number of cups.

Participants were endowed with an initial fund of $S5 that was separate from that of the loss-aversion Task. They were encouraged to earn as much as possible and to lose as little as possible in the task. They were told that nine trials of self-gain, self-loss, other-gain, and other-loss combinations would be randomly selected at the end of the task, and that they would be paid the total amount earned/lost in these self-gain and self-loss trials. Self and other trials were presented as separate blocks of 18 trials, isolated by breaks of participant-determined length. Gain and loss trials were embedded as separate blocks of nine trials within self-trial and other-trial blocks. We counterbalanced across participants the order of (1) self-trial and other-trial blocks and (2) gain-trial and loss-trials blocks. Within gain-trial and loss-trial blocks, we fully randomized the order of probability and magnitude combinations. Similar to the Tom's mixed-gamble task, to improve participants' understanding, we used physical cups and coins to explain the task and had participants practice the task using these physical cups before the formal experiment. Probing questions such as "If you chose the risky option and it turns out to be a gain, who will get the money?" were asked to ensure that participants fully understood the task.

First analytic approach: Mixed-design analysis of variance (ANOVA). We used three analytic approaches to derive risk preferences from the cups task. First, on the basis of an established protocol of the cups task (e.g., Jasper, Bhattacharya, Levin, Jones, & Bossard, 2013; Weller et al., 2011; Weller et al., 2007), risk preferences were defined by the proportion of risky choices chosen in three Risk categories. This standard method of analysis allows us to compare the pattern of our results with those in previous studies. These three risk categories were defined based on the differences in EVs (calculated by Magnitude × Probability for the gain domain and by −1 × Magnitude × Probability for the loss domain) between the risky and sure choices. In the risk-advantageous (risk-equal and risk-disadvantage) category, the EV of the risky choice was higher than (equal to and lower than) the EV of the sure choice. Note that, although the EV of the risky choice changed trial-by-trial, the EV of the sure choice for the gain domain always equaled to 1 (Magnitude = 1 coin × Probability = 1), whereas that for the loss domain always equaled to −1 (−1 × Magnitude = 1 coin × Probability = 1). Following a standard procedure for the cups task (e.g., Jasper et al., 2013; Weller et al., 2011; Weller et al., 2007), risk preference in the gain domain was analyzed separately from risk preference in the loss domain. Accordingly, we implemented a three-way mixed designed ANOVA [3 Risk Categories × 2 Self–Other Conditions × 2 Age Groups] on the proportion of risky choices chosen for both the gain and loss domains. When the sphericity assumption was violated, the Greenhouse-Geisser corrected degrees of freedom were used. Multiple comparisons were controlled using the Sidak method.

Similar to previous decision-making research in older adults (Tymula, Rosenberg Belmaker, Ruderman, Glimcher, & Levy, 2013), we set an a priori exclusion criteria to detect and exclude nonsystematic data based on their preference reversal, separately for the gain and loss domains. Specifically, for the gain domain, we excluded subjects who selected the risky choice more when the choice's EV (defined by Magnitude × Probability) was the lowest (Magnitude = 2 coins and Probability = .2 [5 cups]; EV = .4) compared to when the choice's expected value was the highest (Magnitude = 5 coins and Probability = .5 [2 cups]; EV = 2.5). For the loss domain, we defined EV of the risky choice by −1 × Magnitude Probability. Similar to the gain domain, we excluded subjects who selected the risky choice more when the choice's value was the lowest (Magnitude = 5 coins and Probability = .5 [2 cups]; EV = −2.5) compared to when the choice's expected value was the highest (Magnitude = 2 coins and Probability = .2 [5 cups]; EV = −.4). We used these exclusion criteria to ensure that participants' choices reflected their risk preferences. For the gain domain, eight older adults and two younger adults were excluded, leaving 41 older adults (23 women) and 37 younger adults (25 women). Similarly, for the loss domain, eight older adults and two younger adults were excluded, leaving 41 older adults (24 women) and 37 younger adults (24 women).

Overall, the pattern of risk propensity in our participants (see Table 2, Figure 4 for descriptive statistics) is visually similar to that of healthy participants in previous studies (e.g., Jasper et al., 2013; Weller et al., 2007, 2011; Xue et al., 2009). For the gain domain, although the three-way interaction, $F(2, 152) = .63$, $p = .53$, $\eta_p^2 = .008$, and the main effect of age groups, $F(1, 76) = 1.20$, $p = .28$, $\eta_p^2 = .016$, were not significant, all other effects were ($ps < .05$). First, there was the main effect of risk categories, $F(1.8, 127.45) = 225.42$, $p < .001$, $\eta_p^2 = .748$ (Greenhouse-Geisser corrected). The proportion of risky choices chosen was higher during risk-advantage trials than during risk-equal trials ($p < .001$, 95% confidence interval [CI] [.208, .299]) and higher during risk-equal trials than during risk-disadvantage trials ($p < .001$, 95% CI [.270, .379]; Morey, 2008). There was also the main effect of self–other conditions, $F(1, 152) = 12.53$, $p = .001$, $\eta_p^2 = .141$, as reflected in a higher proportion of risky choices chosen when deciding for others (compared with for self), 95% CI [.029, .105]. These main effects were qualified by significant two-way interactions between all three pairs of the factors. First, there was a significant two-way interaction between risk categories and self–other conditions, $F(1.68, 127.45) = 6.57$, $p = .003$, $\eta_p^2 = .080$ (Greenhouse-Geisser corrected). Simple-effect analyses of this interaction revealed that deciding for others (compared with for self) was associated with significantly higher proportion of risky choices chosen during risk-equal ($p = .007$, 95% CI [.022, .131]) and risk-disadvantage ($p < .001$, 95% CI [.056, .184]) trials, but not during risk-advantage ($p = .75$, 95% CI [–.030, .041]) trials. Second, there was a significant two-way interaction between risk categories and age groups, $F(1.80, 127.45) = 5.33$, $p = .008$, $\eta_p^2 = .066$ (Greenhouse-Geisser corrected). Simple-effect analyses of this interaction revealed that older participants (compared with younger participants) had a significantly lower proportion of risky choices chosen during risk-advantage trials ($p = .005$, 95% CI [–.175, −.033]), but not during risk-equal ($p = .11$, 95% CI [–.203, .021]) and risk-disadvantage ($p = .36$, 95% CI, [–.066, .180]) trials. Finally, pertaining to our main hypothesis was the significant two-way interaction between self–other conditions and age groups, $F(1, 152) = 5.53$, $p = .021$, $\eta_p^2 = .068$. Simple-effect analyses of this interaction revealed that deciding for others (compared with for self) was associated with a significantly higher proportion of risky choices chosen in younger participants ($p < .001$, 95% CI [.057, .167]) but not in older participants ($p = .39$, 95% CI [–.03, .075]). To directly test if older adults exhibited a weaker self–other discrepancy in risk-preferences relative to younger adults, we also computed the self–other risky-choice difference score by subtracting the proportion of risky choices chosen in the other condition from that in the self condition. Lower score of this index indicates a stronger risk-preference for the other (compared with self) condition. We found that younger participants ($M = -.1121$, $SD = .1459$) had a significantly lower self–other risky-choice difference score than older participants ($M = -.0226$, $SD = .1853$), $t(76) = -2.35$, $p = .02$, $d = .54$, 95% CI [–.0137, −.1653].

For the loss domain (see Table 2, Figure 4, Panels C and D), whereas the main effect of age groups, $F(1, 76) = 1.51$, $p = .70$, $\eta_p^2 = .002$, and the main effect of self–other conditions, $F(1, 152) = 2.50$, $p = .12$, $\eta_p^2 = .032$, were not significant, all other effects were ($ps < .05$). This includes the three-way interaction, $F(1.77, 134.47) = 4.60$, $p = .015$, $\eta_p^2 = .057$ (Greenhouse-Geisser corrected). Pertaining to our main hypothesis, we followed up the three-way interaction by examining the two-way interaction between risk categories and self–other conditions separately for each age group. We found a signifi-

Table 2
Proportion of Risky Choices Chosen in the Cups Task in Study 1 as a Function of Domains, Self–Other Conditions, Age Groups, and Expected Values (EVs)

	Self		Other	
EV	*M*	*SD*	*M*	*SD*
	Gain			
Younger adults				
Advantage	.92	.14	.95	.08
Equal	.62	.29	.74	.25
Disadvantage	.19	.25	.37	.34
Older adults				
Advantage	.85	.21	.82	.22
Equal	.57	.27	.60	.29
Disadvantage	.31	.29	.37	.34
	Loss			
Younger adults				
Advantage	.88	.19	.86	.17
Equal	.56	.28	.67	.22
Disadvantage	.15	.19	.30	.29
Older adults				
Advantage	.78	.25	.76	.27
Equal	.58	.28	.53	.31
Disadvantage	.34	.32	.32	.34

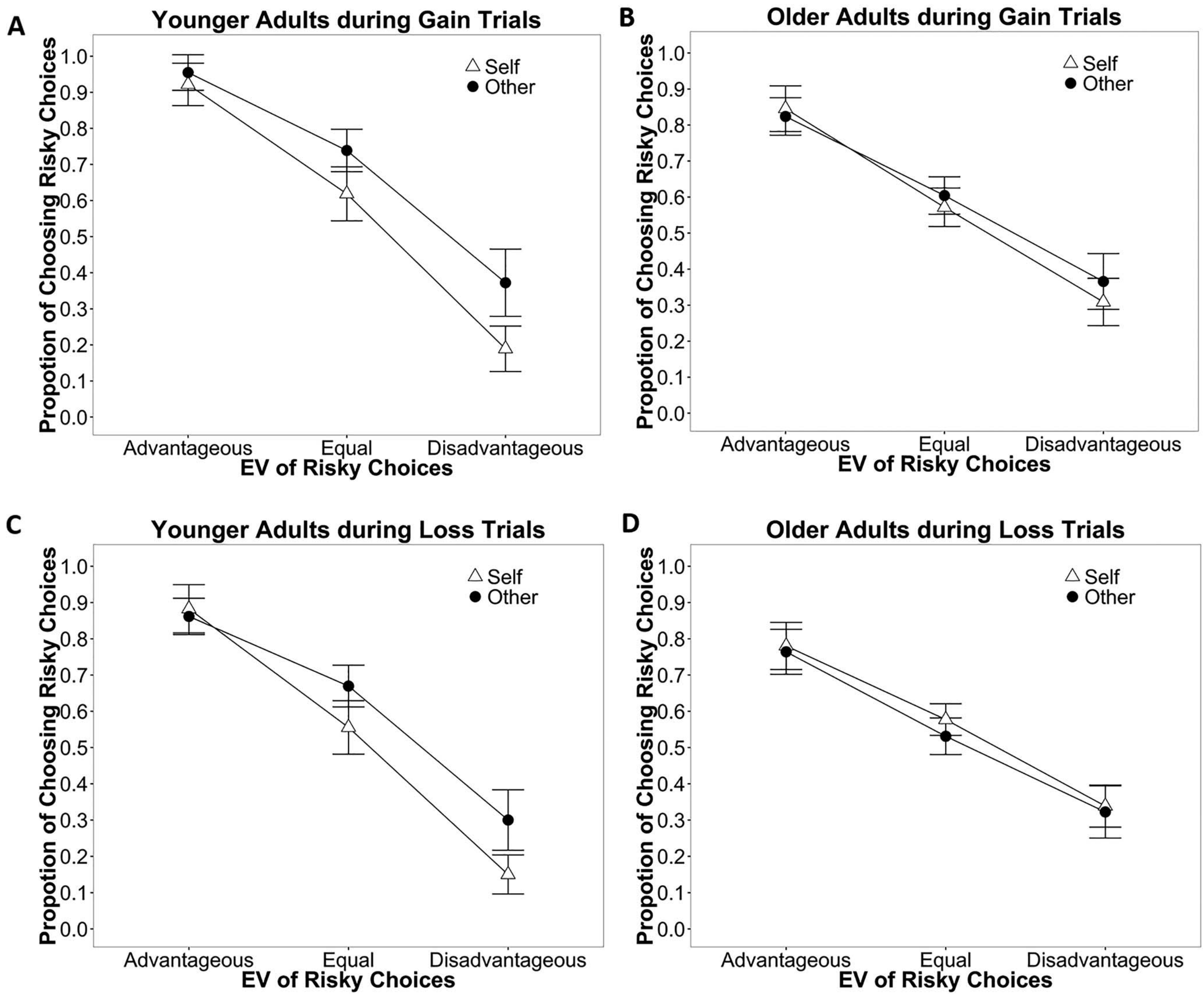

Figure 4. Proportion of risky choices chosen during gain trials (Panels A and B) and loss trials (Panels C and D) as a function of risk categories (based on expected value [EV] of risky choices), self–other conditions and age groups from the cups task in Study 1. Error bars represent repeated-measure 95% CI.

cant two-way interaction between risk categories and self–other conditions in younger participants, $F(1.45, 52.33) = 6.45$, $p = .007$, $\eta_p^2 = .152$ (Greenhouse-Geisser corrected) but not in older participants, $F(2, 80) = .36$, $p = .70$, $\eta_p^2 = .009$. Simple-effect analyses of this interaction in younger participants revealed that deciding for others (compared with for self) was associated with a significantly higher proportion of risky choices chosen during risk-equal ($p = .027$, 95% CI [.014, .215]) and risk-disadvantage ($p = .001$, 95% CI [.064, .236]) trials, but not during risk-advantage ($p = .44$, 95% CI [–.076, .034]) trials. Additionally, the effect of self–other conditions was only significant in younger participants, $F(1, 72) = 8.04$, $p = .007$, $\eta_p^2 = .183$, but not in older participants, $F(1, 80) = 1.63$, $p = .21$, $\eta_p^2 = .009$. Specifically, younger participants had a higher proportion of risky choices chosen when deciding for others compared with self (95% CI [.023, .130]). Similar to the gain domain, we also computed the self–other risky-choice difference score by subtracting the proportion of risky choices chosen in the other condition from that in the self condition. We found that younger participants ($M = -.0811$, $SD = .1739$) had a significantly lower self–other risky-choice difference score than older participants ($M = .0262$, $SD = .1315$), $t(76) = -3.091$, $p = .003$, $d = .71$, 95% CI [–.0381, $-.1764$]. This suggests that younger participants had higher proportion of risky choices chosen when deciding for others compared with self, than older participants. Lastly, the main effect of risk categories was significant in both younger participants, $F(2, 72) = 157.88$, $p < .001$, $\eta_p^2 = .814$, and older participants, $F(1.48, 1.35) = 68.59$, $p < .001$, $\eta_p^2 = .632$. That is, the proportion of risky choices chosen was higher during risk-advantage than risk-equal trials in both younger participants ($p < .001$, 95% CI [.179, .340]) and older participants ($p <$

.001, 95% CI [.144, .293]). Similarly, the proportion of risky choices chosen was higher during risk-equal than risk-disadvantage trials in both younger participants ($p < .001$, 95% CI [.303, .472]) and older participants ($p < .001$, 95% CI [.141, .307]).

Second analytic approach: Generalized linear mixed-effects regression. For the second analytic approach, we used the generalized linear mixed-effects regression (GLMER; Barr, Levy, Scheepers, & Tily, 2013; Bates, Mächler, Bolker, & Walker, 2015) and regressed a chosen choice in each trial on five predictors: magnitude, probability, domain, self–other, and age groups. Unlike the first approach, we did not categorize trials into three risk categories based on EVs to compute the proportion of risky choices in each of these categories. This analytic approach has several benefits. First, it does not assume that people treat different choices within the same risk category as the same, regardless of the probability and magnitude of the potential outcomes. The first analytic approach, for instance, implies that in the risk-equal trials, people treat a choice of two coins under two cups and the same with a choice five coins under five cups. Modern economic theories have long criticized such an assumption (Von Neumann & Morgenstern, 1944). Second, separating EVs into probability and magnitude may give us better indicators of risk preferences because probability and magnitude, when considered by themselves, are less confounded by rationality. For instance, one may view that choosing lower EV choices is less rational than choosing higher EV choices (as opposed to more risk-seeking). However, it is more difficult to conclude that choosing the low probability choices (regardless of magnitude) is due purely to rationality given that low probability choices can be more or less rational choices depending on the magnitude of the choices. Third, using the maximum GLMER approach (Barr et al., 2013), we can examine the effects of interest while statistically controlling for other variables. For instance, we can examine the interaction between the self–other conditions and age groups while controlling for magnitude, probability, and domain. Accordingly, the statistical outputs from this approach are more easily interpreted than the outputs from using the self–other risky-choice difference score as in the first analytic approach. Fourth, averaging a binary outcome variable, such as the choice chosen, into a proportion and analyzing it with ANOVA can sometimes yield spurious results (Jaeger, 2008). GLMER with a logit model is viewed as a more appropriate treatment for binary choice data (Jaeger, 2008).

For the sake of brevity, we defer the full details of the GLMER approach to the supplementary and report only the effects of interest. Three main findings emerged from the GLMER approach. First, consistent with the first ANOVA analytic approach, we found that when controlling for probability and magnitude, the younger but not the older participants are more likely to choose a risky choice for others regardless of domain. Second, as is shown in Figure 5, we found that the modulation of self–other on the effect of magnitude (controlling for probability) depends on the age group to which participants belonged. More specifically, when the magnitude of a possible gain was low or a possible loss was high, the younger participants were more likely to choose a risky choice for others, more so than for themselves. In contrast, this pattern was weaker in the older participants. Similarly, we also found that the extent to which self–other modulated the effect of probability on the tendency to choose a risky choice depends on age. This can be seen in Figure 6. Concretely, when the probability of a possible gain was low or a possible loss was high, the younger participants were more likely to choose a risky choice

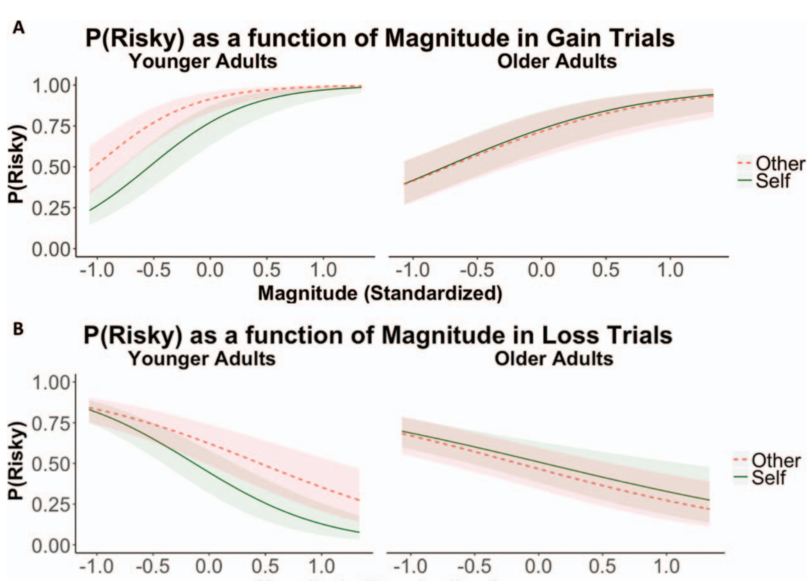

Figure 5. Probability of choosing a risky choice (P[Risky]) during gain [Panel A] and loss [Panel B] as a function of magnitude, self–other conditions and age groups from the cups task in Study 1. Shaded areas represent 95% CI. See the online article for the color version of this figure.

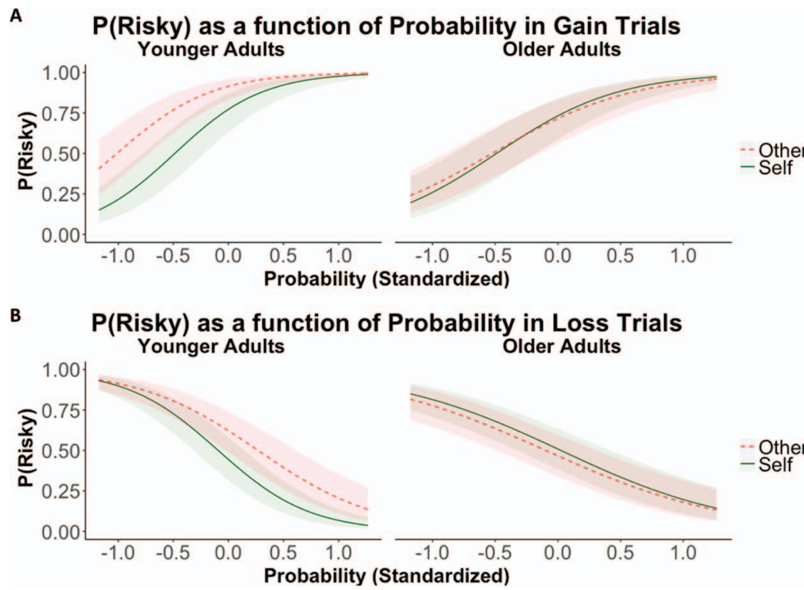

Figure 6. Probability of choosing a risky choice (P(Risky)) during gain (Panel A) and loss (Panel B) trials as a function of probability, self–other conditions and age groups in Study 1. Shaded areas represent 95% CI. See the online article for the color version of this figure.

for others, more so than for themselves. Once again, this pattern was not observed among the older adults.

Third analytic approach: Indifference-point risk-premium index. For the third analytic approach, we used a risk-premium index (Stanton et al., 2011) to quantify risk preferences as done in recent aging research (Kurnianingsih, Sim, Chee, & Mullette-Gillman, 2015). In this approach, as opposed to categorizing trials into three risk categories, we ranked trials on the basis of the ratio of the EV (rEV) of the risky choice to the EV of the sure choice. We then constructed a choice function based on the proportion of risky choices chosen at each ranked rEV for each self–other condition. The risk-premium index was the first point where the projected choice function crossed the 50% mark, reflecting the indifference between choosing risky and sure choices. One benefit of this method is the interpretation of the risk-premium index is closely related to the concept of risk-sensitivity in economics. Yet, it still implies that people treat trials with the same EVs but different probability and magnitude as the same in the risk-equal trials (see the online supplemental material for the results of this approach). Briefly, consistent with the first and second approaches, analyses based on risk-premium for both gain and loss domains revealed significantly higher risk preferences when deciding for others (compared with for self) in younger but not in older participants.

Clinical Screening Status

Before the decision-making test session, older participants completed a battery of questionnaires to assess their neuropsychological status, including the Geriatric Depression Scale (Yesavage et al., 1982), Geriatric Anxiety Inventory (Pachana et al., 2007), Mini Mental State Examination (Feng, Chong, Lim, & Ng, 2012; Folstein, Folstein, & McHugh, 1975), Montreal Cognitive Assessment (Liew, Feng, Gao, Ng, & Yap, 2015; Nasreddine et al., 2005) and Repeated Battery for the Assessment of Neuropsychological Status (Collinson, Fang, Lim, Feng, & Ng, 2014; Randolph, 1998). Correlations of assessment scores with each participant's $\Delta\lambda$ parameter and self–other risky-choice difference score were not significant (all $ps > .05$), confirming that cognitive abilities were not a cause in explaining the diminished self–other discrepancies.

Self–Other Discrepancies Between Tasks

We next examined if the self–other discrepancies found in Tom's mixed-gamble task and the cups task were related to each other. We used each participant's $\Delta\lambda$ parameter and self–other risky-choice difference score as indices for self–other discrepancies in the loss-aversion and cups tasks, respectively. More specifically, to obtain each participant's $\Delta\lambda$ parameter, we took the mean of his or her posterior distribution of the estimated individual-level $\Delta\lambda$ parameter. Because the normality assumption is violated (as revealed by Kolmogorov–Smirnov tests), we used Spearman's correlation (ρ). The $\Delta\lambda$ parameter was significantly correlated with the self–other risky-choice difference scores in both the gain, $\rho(63) = .28$, $p = .02$, and loss, $\rho(62) = .25$, $p = .04$, domains as well as with the averaged self–other risky-choice difference score across domains, $\rho(57) = .35$ $p = .006$ (see Figure 7). Note that the degree of freedom in each correlation was different because we only analyzed the data from participants who passed the exclusion criteria in each pair. Overall, these positive correlations indicate that those who were less loss-aversive for others in the loss-aversion task had a higher propensity to choose a risky choice when making a decision for others in the cups task.

We then tested if age group modulated the relationship between the two tasks using a rank-transformed regression (Conover & Iman, 1981). We first ranked, centered and standardized both the

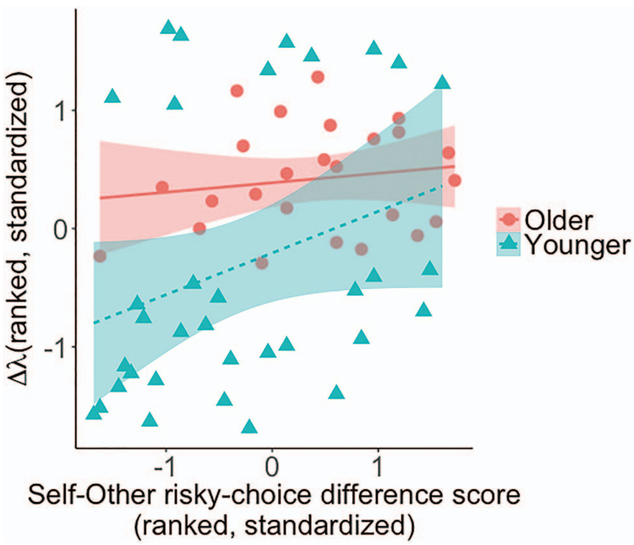

Figure 7. Scatterplot between the Δλ from the Tom's mixed-gamble task and averaged self–other risky-choice difference score across domains from the cups task in Study 1. The data points were ranked and standardized. Shaded areas represent 95% CI around the regression line of each age groups. See the online article for the color version of this figure.

Δλ parameter and averaged self–other risky-choice difference score. After these transformations, we entered the Δλ parameter as a criterion and the averaged self–other risky-choice difference score as a predictor in our first model. In our second model, we added an interaction term (Age × Averaged Self–Other Risky-Choice Difference Score) to the first model. However, the second model did not provide a significant improvement from the first model, $F(56, 1) = 0.41$, $p = .52$, suggesting that the relationship between the two tasks did not significantly vary as a function of age groups (see Figure 7).

Study 2

We designed the second Study (a) to replicate the main findings of Study 1 on self–other discrepancies in financial decisions under risk and (b) to extend our examination of preferences in financial decisions in the mixed domain to risk-aversion asymmetry (or a tendency to be risk-averse for potential gains and risk-seeking for potential losses). Here, we implemented a modified version of the Sokol-Hessner's mixed-gamble task (Sokol-Hessner et al., 2009) that enabled us to computationally model both loss aversion and risk-aversion asymmetry.

Participants

We used the same protocol to recruit participants in Study 2 as in Study 1. Sixty-four older and 60 younger adults residing in Singapore participated in the study. We excluded two older participants who were younger than 60 years old, and six older participants who expressed confusion during the session. We then implemented similar exclusion procedures used in Tom's mixed-gamble task used in Study 1 based on regression coefficients (Brown et al., 2013). The final pool of participants included 44 older participants (26 women; age $M = 69.20$ years, $SD = 4.23$; education $M = 9.86$ years, $SD = 3.03$, Mini Mental State Examination $M = 29.77$, $SD = .48$) and 59 younger participants (36 women; age $M = 22.07$ years, $SD = 2.10$; education $M = 14.58$ years, $SD = 1.33$). Similar to Study 1, there was no significant difference between the older ($M = 5.68$, $SD = 1.62$) and younger ($M = 6.10$, $SD = 1.40$) participants in the SSS (Adler et al., 2000), $t(101) = 1.98$, $p = .16$. Note that we started recruiting participants for Study 2 around 1 year after Study 1. Unbeknown to us at the time of data collection, 13 out of 44 final older participants in Study 2 also participated in Study 1. Excluding these 13 participants did not change the pattern of the data (see Table 2 and Figure 3 in the online supplemental material for the results). We used the same payment scheme as in Study 1, and participants provided informed consent before beginning the experiment.

Procedure

Sokol-Hessner's mixed-gamble task. The experimental procedure in Study 2 was very similar to that in Study 1. Participants completed a battery of computerized decision-making tests in a 2-hr session. They completed Sokol-Hessner's mixed-gamble task as the first task. This task (see Figure 8 for the schematic representation of the task) is very similar to Tom's mixed-gamble task used in Study 1, except for three main characteristics. First, there were both gain–loss and gain-only trials in this task. The gain–loss trials were the same with the trials in Tom's mixed-gamble task. The gain-only trials, on the other hand, consisted of a risky option that has equal chances of gaining some amount and gaining nothing and a sure option of gaining another smaller amount for certain. As argued previously (Sokol-Hessner et al., 2016), including both types of trials in the task allowed the separation of λ (loss-aversion), ρ (risk-aversion asymmetry), and τ (behavioral consistency) parameters. Second, the developers of this task selected the magnitude of gains and losses in each trial on the basis of a parameter recovery study (Sokol-Hessner et al., 2009). Essentially, specific magnitudes were chosen to ensure the effective recovery of all three parameters. Accordingly, this task should be more appropriate for modeling these parameters. As such, we used the same set of choices with their study (see the full list in the online supplemental material of Sokol-Hessner et al., 2013). However, to make the monetary values comparable to those in Study 1, we converted the amounts used in the original list (Sokol-Hessner et al., 2013) to points in which one point equaled to $S0.10. Third, unlike Tom's mixed-gamble task, Sokol-Hessner's mixed-gamble task provided feedback for every gamble made. Because descriptive-based decision making may be altered by the presentation of the outcomes (Hertwig, Barron, Weber, & Erev, 2004), using Sokol-Hessner's mixed-gamble task allowed us to generalize our findings to financial decision-making situations with or without immediate outcomes. We used the same procedure to manipulate the self–other condition as in Study 1 (i.e., randomly picked three IDs of other participants), with the exception of one crucial difference. To ensure that participants did not believe they were making decisions for someone from the same age group as them, we explicitly told participants that the recipient could be anyone in Singapore who responded to the recruitment advertisement, with ages ranging from 18 to 80 years old.

Similar to Study 1, we presented self and other trials as separate blocks of 16 trials, isolated by breaks of participant-determined

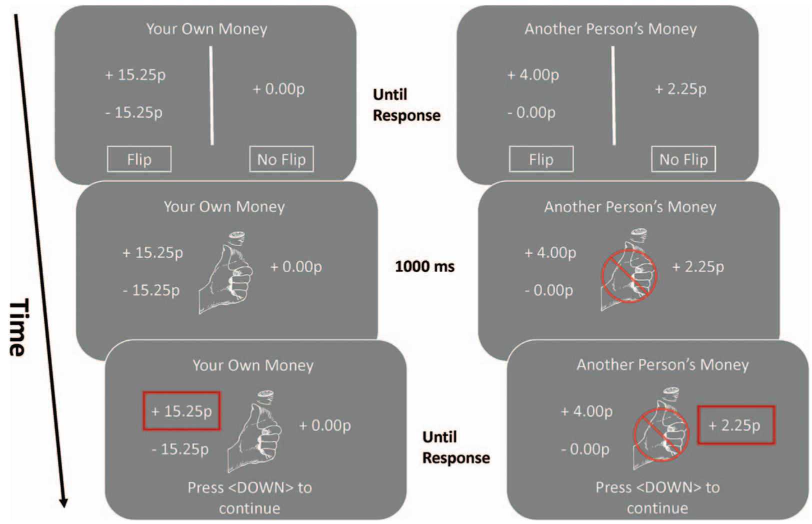

Figure 8. Schematic representation of the Sokol-Hessner's mixed-gamble task in Study 2. In each trial, we presented participants with a risky (i.e., left) option and a sure (i.e., right) option. If participants chose the risky option, there would be a 50% chance of one of the two values on the left side of the screen. Participants either made decisions for themselves or for another person as indicated on the screen. After making their choice, participants' choice was highlighted for 1,000 ms. Subsequently, participants saw a feedback screen indicating the amount they gained/lost. They have to press a key to move on to the next trial. For every trial, the above sequence was preceded by an intertrial interval (a blank screen) of 500 ms. See the online article for the color version of this figure.

length. In total, there were 160 self trials and 160 other trials. Within each self and other condition, there were 120 gain–loss trials, 30 gain-only trials, and 10 fillers. We used the same counterbalance and randomization strategy with Study 1. Participants were endowed with an initial fund of $S3 before the experiment.

Computational modeling of choice data: Sokol-Hessner's mixed-gamble task. As opposed to using the linear value function as done in Study 1, the current task enabled us to estimate the curvilinear value function (Sokol-Hessner et al., 2009, 2013; 2016):

$$u(x) = \begin{cases} |x|^{\rho} & \text{if } x \geq 0 \\ -\lambda \times |x|^{\rho} & \text{if } x < 0 \end{cases} \tag{19}$$

That is, this "curvilinear-value" model adds another participant-specific rho (ρ) parameter to the linear-value model (see Equation 1). Rho captures the curvature of the utility function across gain and loss amounts, and its value reflects individual differences in risk-aversion asymmetry between gain and loss domains: 1 = risk-neutral, <1 = risk-averse for gains and risk-seeking for losses, >1 = risk-seeking for gains and risk-averse for losses. This is different from the lambda parameter, which is a relative multiplicative weighting of loss to gain amounts reflecting loss aversion. See Figure 9 for a graphical representation of the model.

We then calculated the same expected utility of each choice using Equation 2 (Mosteller & Nogee, 1951). Yet, unlike Study 1 where an outcome for rejecting the gamble always equaled to zero, here we needed to adjust how to calculate the expected utility of rejecting the gamble (i.e., Equation 4) to

$$eu_{rejecting} = p_{sure} \times u(x_{sure}) = 1 \times u(x_{sure}) = u(x_{sure}) \tag{20}$$

We then calculated the overall expected utility (eu) for a particular trial as follows:

$$\begin{aligned} EU &= eu_{accepting} - eu_{rejecting} \\ &= p_{gain} \times u(x_{gain}) + p_{loss} \times u(x_{loss}) - u(x_{sure}) \\ &= .5 \times u(x_{gain}) + .5 \times u(x_{loss}) - u(x_{sure}) \end{aligned} \tag{21}$$

We then used the same softmax function (Luce, 1959; Equation 6). As before, this function requires us to estimate the inverse temperature τ (behavioral consistency).

To model the effect of the self–other condition, we used the same method as in Study 1. That is, we used Equations 7 and 8 for the λ and τ parameters and added another equation for the ρ parameter (Sokol-Hessner et al., 2016):

$$\rho_{participant,condition} = e^{\rho_{participant} + SelfOther_{condition} \times \Delta\rho_{participant}} \tag{22}$$

Accordingly, we computed three change parameters: $\Delta\lambda_{participant}$, $\Delta\rho_{participant}$, and $\Delta\tau_{participant}$.

As with Study 1, we used the HBA framework to estimate free parameters (Ahn et al., 2017; Sokol-Hessner et al., 2016). However, we encountered numerical problems when implementing the model using Stan. Thus, instead of using the HMC algorithm, we used the Gibbs sampling algorithm to run MCMC sampling in JAGS 4.3 (Plummer, 2003) via runjags 2.0.4.2 (Denwood, 2016) and R 3.3.3 (R Core Team, 2017). We used the same prior distributions for the λ and τ parameters with Study 1 and added similar prior distributions for the ρ parameters as follows:

$$\mu_{\rho'} \sim \text{Normal}(0, 1) \tag{23}$$

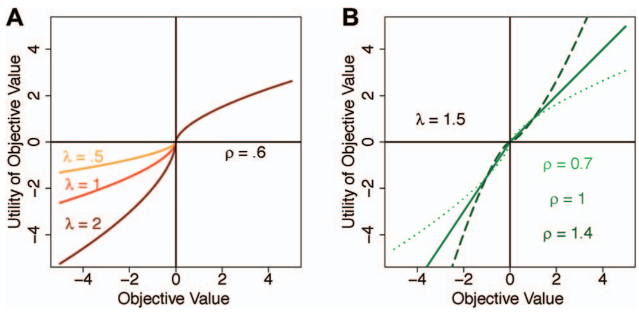

Figure 9. Graphical representations of the utility function based on the curvilinear-value model used in Sokol-Hessner's mixed-gamble task. Panel A represents individual differences in loss-aversion, which is captured by the λ (lambda) parameter, whereas Panel B represents individual differences in risk-aversion asymmetry, which is captured by the ρ (rho) parameter. On the *x*-axis is objective value (i.e., the amount of the potential outcome). Positive objective values reflect potential gains while negative objective values reflect potential losses. On the *y*-axis is the utility of the objective value (or subjective value). Panel A fixes ρ at .6 and shows the changes in the utility of potential losses as a function of λ. Changes in the value of λ correspond to changes in the utility of potential losses, but not the utility of potential gains. Panel A also shows that people who have larger λ would translate the same potential loss into lower utility (i.e., more negative utility) than people who have smaller λ. Thus, people with larger λ are considered to be more loss averse. On the other hand, Panel B fixes λ at 1.5 and shows the changes in the utility of objective values as a function of ρ. As shown here, ρ captures the curvature of the utility function across both potential gains and losses. For people with smaller ρ, the increase (decrease) in utility for a unit change of the objective value diminishes as the magnitude of potential gains (losses) increases. Because the utility of potential gains is diminishing, they are less likely to take a risk for potential gains compared with people with larger ρ. Thus, people with small ρ can be seen as being risk-averse in the gain domain. Likewise, since the utility of potential losses is also diminishing, a prospect of obtaining a loss is less impactful. Therefore, these same people (i.e., people with small ρ) would be more risk-seeking in the loss domain. Thus, the value of ρ can be taken to reflect the risk-aversion asymmetry (being risk-averse for potential gains but risk-seeking for potential losses). See the online article for the color version of this figure.

$$\sigma_{\rho'} \sim \text{half} - \text{Cauchy}\ (0, 5) \tag{24}$$

$$\rho' \sim \text{Normal}\ (\mu_{\rho'}, \sigma_{\rho'}) \tag{25}$$

$$\rho = \text{Exp}(\rho') \tag{26}$$

Similar to Study 1, we used four MCMC chains. For each chain, we randomized its initial value and drew 71,000 samples in addition to 3000 burn-in samples. This left a total of 284,000 samples across chains.

Analyses and results: Sokol-Hessner's mixed-gamble task. The trace plots in our data confirmed excellent mixing of MCMC samples. Moreover, all $\hat{R}$ values from all parameters were less than 1.1, suggesting that our MCMC chains converged well. Additionally, the ESS for the change parameters were acceptable (M = 5,802.33, range = 2,950–12,248). Table 3 summarizes proportion of gambles and group-level (hyper) parameters as a function of self–other conditions and age groups. Notably, our λ and ρ values recovered from the self condition among our younger participants (λ_M = 1.29; ρ_M = .89) are close to what was found in among younger participants in the original article (Sokol-Hessner et al., 2009) on which our task was based (λ_M = 1.31; ρ_M = .88).

As shown in Table 3 and Figure 10, we found a similar pattern for the Δλ parameter between Study 1 and 2. In particular, similar to Study 1, the 95% HDI of the Δλ parameter among the younger adults contained only negative values (−0.29, −0.12) in Study 2. This means that younger adults had higher λ values for themselves (M = 1.29, SD = .09), compared with for others (M = 1.06, SD = .09). Given that a higher λ value indicates more loss-averse, this suggests that the younger adults were more loss-averse for themselves compared with for others. In contrast, the 95% HDI of the Δλ parameter among the older adults contained zero (−0.08, 0.02), suggesting their lack of change in loss aversion between self and other conditions. When we formally compared the effect of age on the Δλ parameter using the subtracted parameter distributions between the two groups, we found that the younger adults had more negative Δλ as compared with the older adults. This is reflected in the 95% HDI (−0.27, −0.08).

Moreover, we found a similar pattern for the Δρ parameter. The 95% HDI of the Δρ parameter among the younger adults contained only positive values (0.05, 0.15). This means that younger adults had lower ρ values for themselves (M = .89, SD = .04) compared with for others (M = .98, SD = .05). A lower ρ value indicates (1) more risk-averse for gains and (2) more risk-seeking for losses. Accordingly, this suggests that, when making decisions for themselves (compared with for others), the younger adults were more risk-averse for potential gains and more risk-seeking for potential losses. In contrast, the 95% HDI of the Δρ parameter among the older adults contained zero (−0.04, 0.05), suggesting their lack of change in risk-aversion asymmetry between self and other conditions. Furthermore, the younger adults had more positive Δρ values than the older adults, as reflected by the 95% HDI of the subtracted parameter distributions (0.03, 0.16). Last, for the Δτ parameter, similar to Study 1, both the younger and older adults had the posterior distribution of the Δτ parameter shifted toward negative side. Yet, now the 95% HDI of both the younger (−0.83, −0.31) and older (−0.47, −0.02) adults did not include

Table 3
Proportion of Gamble and Group-Level (Hyper) Parameters in the Sokol-Hessner's Mixed-Gamble Task in Study 2 as a Function of Self–Other Conditions and Age Groups

Proportion of gamble and group-level parameters	Younger adults		Older adults	
	M	*SD*	*M*	*SD*
Self				
Proportion of gamble	.40	.17	.48	.21
λ	1.29	.09	.99	.11
ρ	.89	.04	.85	.06
τ	1.38	.19	1.33	.20
Δ				
Δλ	−.20	.04	−.03	.02
Δρ	.10	.02	.01	.02
Δτ	−.57	.13	−.25	.12
Other				
Proportion of gamble	.50	.20	.49	.20
λ	1.06	.09	.96	.11
ρ	.98	.05	.85	.06
τ	.79	.14	1.04	.19

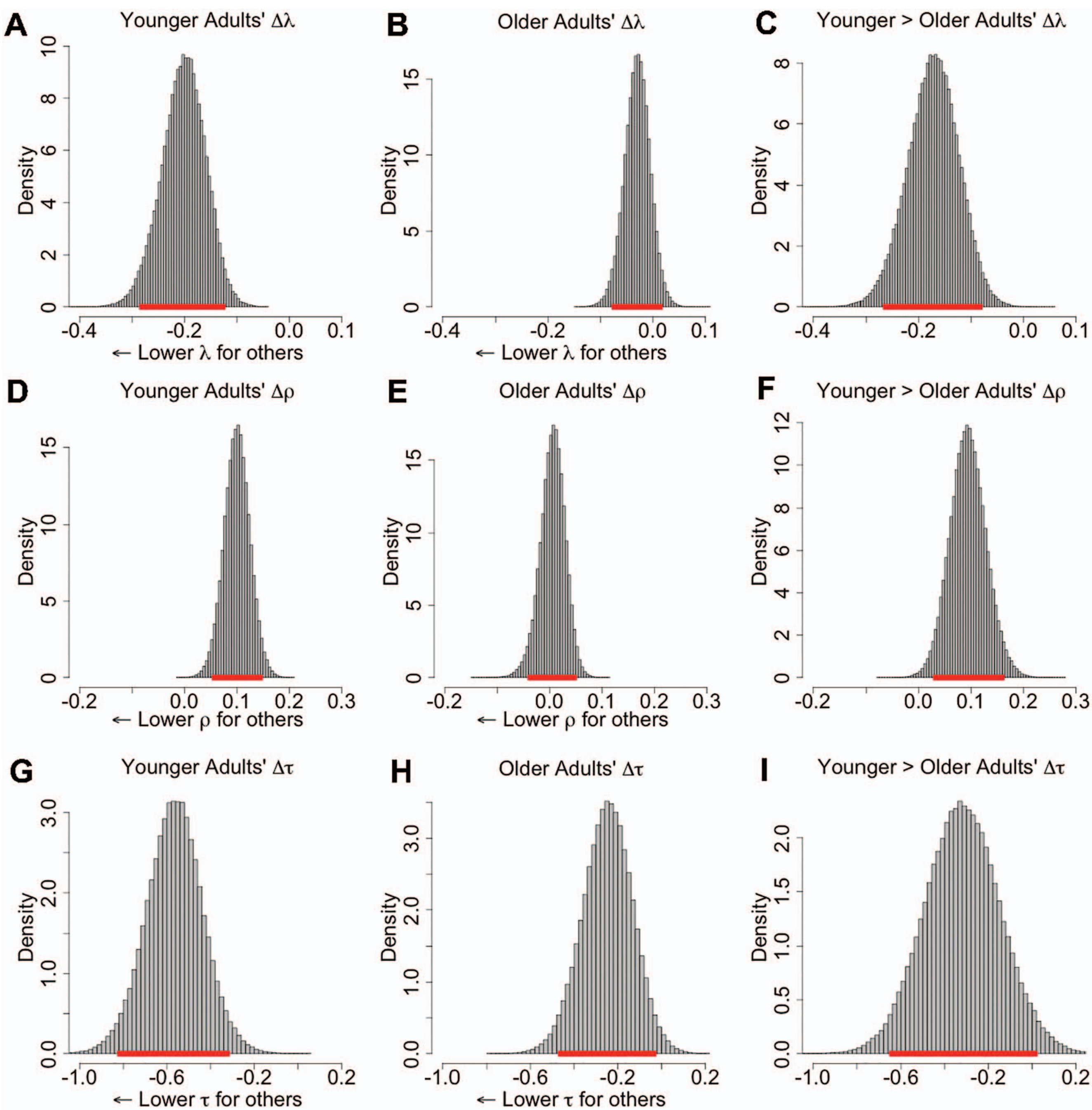

Figure 10. Posterior distributions of the estimated group-level (hyper) parameters: Δλ (Panels A and B), Δρ (Panels D and E) and Δτ (Panels G and H) from the Sokol-Hessner's mixed-gamble task in Study 2. These distributions indicate the changes in λ (loss-aversion), ρ (risk-aversion asymmetry) and τ (consistency) due to the self–other conditions. The red/dark gray bars indicate the 95% highest density Interval (HDI). Among the younger adults, the HDIs of the posterior distributions of their Δλ parameter (Panel A) and Δτ parameter (Panel G) were negative and did not include zero while that of their Δρ parameter (Panel D) was positive and did not include zero. This suggests that the younger adults had lower λ and τ values and a higher ρ value for others compared with for themselves. Among the older adults, only their Δτ parameter (Panel G) was negative and did not include zero. We created plots for the differences of the hyper-parameter distributions between age groups for both the Δλ (Panel C), Δρ (Panel F), and Δτ (Panel I) parameters, by subtracting the older adults' posterior distributions from those of the younger adults. The HDIs of the difference of the group-level parameter distributions of the Δλ (Panel C) and Δρ (Panel F), but not Δτ (Panel I), parameter did not include zero. This suggests that there was a difference in the change in the λ and ρ (but not in τ) value between the age groups. See the online article for the color version of this figure.

zero, suggesting that both groups behave less consistently toward others. The difference between the two groups in the $\Delta\tau$ parameter still included zero (−0.65, 0.03).

General Discussion

We hypothesized a diminishment of self–other discrepancies in financial decisions under risk in older adults as compared with younger adults. To this end, we used two different approaches to study different aspects of financial decision making under risk. The first approach involves financial decision making in gain-only or loss-only situations (i.e., separate domain), thus allowing us to examine risk sensitivities independent of domain effects. In the second approach, decisions were made in the presence of both gains and losses (i.e., mixed domain), an approach that provides insight into the phenomena of loss aversion and risk-aversion asymmetry. We found converging evidence of the diminishment of self–other discrepancies in older adults across measures of preferences in financial decision making under risk. Moreover, this diminishment was replicated across two studies. More specifically, in the mixed domain, we implemented two separate tasks: Tom's and Sokol-Hessner's mixed-gamble tasks. Consistent with previous studies (Andersson et al., 2014; Mengarelli et al., 2014; Polman, 2012), our younger participants were (1) more loss averse, (2) more risk-averse for gains, and (3) more risk-seeking for losses when making decisions for themselves than for others. The (1) tendency is reflected by the $\Delta\lambda$ loss-aversion parameter, whereas the (2) and (3) tendencies are reflected by the $\Delta\rho$ risk-aversion asymmetry parameter. Crucially, these self–other discrepancies were much weaker in older adults. Furthermore, we were able to replicate the differences between age groups in loss aversion across two studies. Thus, these findings suggest that when making financial decisions in the mixed domain, older participants had weaker self–other discrepancies, in direct contrast with the pattern of results in the younger participants.

Similarly, we implemented the cups task (Levin & Hart, 2003) to examine financial decision making in gain-only or loss-only situations. This task allowed us to test if age dependent self–other discrepancies differ between gain and loss domains. We analyzed data from this task using three different approaches (i.e., mixed designed ANOVA, generalized linear mixed-effects regression and indifference-point risk-premium index), and across the three approaches we found that younger participants were more risk-seeking for both gain and loss domains when making decisions for others compared with for themselves. This self–other discrepancy in younger participants is in line with previous research (Beisswanger et al., 2003; Garcia-Retamero et al., 2015; Hsee & Weber, 1997; Jung et al., 2013; Stone et al., 2002; Sun et al., 2016). Consistent with the pattern in the mixed domain, older participants had a weaker self–other discrepancy in risk-preferences than younger participants in both gain and loss domains in the cups task. More importantly, there was a significant relationship between the self–other discrepancies in Tom's mixed-gamble task and those in the cups task. This suggests that the self–other discrepancies in both mixed and separate domains may reflect a similar construct. Altogether, we found a consistent pattern of the diminishment of self–other discrepancies in older adults across measures of preferences in financial decisions under risk: risk preferences in gain and loss domains, loss aversion, and risk-aversion asymmetry. This seems to suggest that the diminishment of self–other discrepancies among the older adults reflects a generalizable phenomenon across many financial decision-making contexts.

Although the age differences in self–other discrepancies were consistent across different measures, it is important to discuss whether the diminished self–other discrepancies among the older participants reflect the changes in their preferences in financial decision making or, rather, the decline in their rationality. To address this issue, we used two different definitions of rationality: (1) the degree to which choices are internally consistent (Samuelson, 1938) and (2) the degree to which choices are made according to EVs (Von Neumann & Morgenstern, 1944). For the first definition, results from Tom's and Sokol-Hessner's mixed-gamble tasks may address this. In the case where rationality is defined as the extent to which decisions are internally consistent (Samuelson, 1938), the $\Delta\tau$ parameter is more closely related to rationality than the $\Delta\lambda$ and $\Delta\rho$ parameters. That is, the $\Delta\tau$ parameter reflects the changes in how consistent people are in making the decisions based on the expected utility whereas the $\Delta\lambda$ and $\Delta\rho$ parameters reflect the changes in loss aversion and risk-aversion asymmetry, respectively. Sokol-Hessner and colleagues (2009) used simulations to show that these three parameters can be separately identified with similar computational modeling techniques used in the current article. Thus, we should be able to infer the changes in the preferences in financial decision making when interpreting the $\Delta\lambda$ and $\Delta\rho$ parameters, given that rationality was separately modeled as the $\Delta\tau$ parameter. Note that although rationality is not the focus of our study, we found interesting patterns in the $\Delta\tau$ parameter that are consistent across Tom's and Sokol-Hessner's mixed-gamble tasks. Both young and older adults generally behave less consistently toward others compared with themselves, as reflected by having the distribution of their $\Delta\tau$ parameter negatively shifted. This pattern exhibited by the $\Delta\tau$ parameter is different from that of the $\Delta\lambda$ and $\Delta\rho$ parameters.

As for the second definition in which rational choices are those made following the EV (Von Neumann & Morgenstern, 1944), we used the second analytic GLMER approach in the cups task to address this. There is an inherent problem confounding risk preferences with rationality when defining risk categories based on EVs as in our first analytic ANOVA approach, which is the standard strategy for the cups task (Jasper et al., 2013; Weller et al., 2007, 2011). For instance, choosing a risky choice when its EV is low can be viewed as either risk-seeking or irrational. However, separating EVs into probability and magnitude in our second analytic GLMER approach (which allows us to examine the influence of probability while controlling for magnitude and vice versa) may give us better indicators of risk preferences. This is because it is more difficult to conclude that choosing the low probability choices (regardless of magnitude) is due purely to rationality given that low probability choices can be more or less rational choices depending on the magnitude of the choices. Strongly risk-seeking individuals would be more likely to choose risky choices when (a) the probability (magnitude) of a possible gain was low in the gain domain as well as (b) the probability (magnitude) of losing was high in the loss domain. On the basis of the second analytic GLMER approach, we found that these risk-seeking patterns were more pronounced when younger participants chose choices for others than for themselves. However, this self–other discrepancy was not significant in the older participants. Thus, the self–other discrepancies in the cups task more likely reflect the changes in preferences, rather than rationality as defined by the second definition (Von Neumann & Morgenstern, 1944).

Numerous studies have demonstrated that older adults exhibit enhanced generosity and prosociality (Bekkers, 2010; Bjälkebring et al., 2016; Cornwell et al., 2008; Engel, 2011; Freund & Blanchard-Fields, 2014; Hubbard et al., 2016; Matsumoto et al., 2016; McAdams, St. Aubin, & Logan, 1993; Midlarsky & Hannah, 1989; Rademacher et al., 2014; Sze et al., 2012). In line with this, the diminished self–other discrepancies in financial decisions under risk found in the current study may be another instance of these changes in social decision making among older adults. Future research is needed to elucidate the underlying mechanisms of the diminished self–other discrepancies. The dominant theory used to explain the self–other discrepancies is the risk-as-feelings account (Hsee & Weber, 1997; Loewenstein, Weber, Hsee, & Welch, 2001) for both mixed and separate domains of financial decision making (Garcia-Retamero et al., 2015; Kobbeltvedt & Wolff, 2009; Mengarelli et al., 2014). This account suggests that people rely on their feelings toward risky options (e.g., dread) when making decisions under risk. Consequently, the difficulty in experiencing the feelings of others usually results in stronger risk-seeking tendencies when making decisions for others (Hsee & Weber, 1997). In line with this reasoning, a recent study also demonstrated a lower level of self–other discrepancies among people with high prosociality (Jung et al., 2013). Although this emotional disconnect between the self and others appears to be particularly pronounced in younger adults (Andersson et al., 2014; Beisswanger et al., 2003; Garcia-Retamero et al., 2015; Hsee & Weber, 1997; Jung et al., 2013; Polman, 2012; Stone et al., 2002; Sun et al., 2016), it may, however, be weakened or even absent among older adults. Thus, older adults may experience similar feelings when evaluating risky choices for others and for themselves, resulting in a diminishment of self–other discrepancies in their risk preferences as shown in our study.

Our study is, however, not without limitations. First, our participants were collectivists residing in a Southeast Asian country (Singapore). Self–other discrepancies are thought to be weaker among collectivists when compared with individualists (e.g., Westerners; Markus & Kitayama, 1991) although, to our knowledge, no formal cross-cultural study has been conducted in the financial domain yet. However, given that we compared two age groups within the same culture, our study should not be confounded by culture. Moreover, being more risk-seeking when making risky decisions for others is found not only in younger Westerners (e.g., Hsee & Weber, 1997), but also in younger Asians including Koreans (Jung et al., 2013) and Chinese (Sun et al., 2016). Thus, the pattern found in our Singaporean participants is consistent with research done in both collectivistic and individualistic cultures. Nevertheless, future studies may examine the effect of age on self–other discrepancies in other cultures to establish the generalizability of our findings. It is also possible that globalization may cause our young participants to be more Westernized than our older participants, and thus the age effect here may be due, in part, to the globalization. Accordingly, future studies should also examine self–other discrepancies in relation to cultural values as reflected in psychometric scales, such as the self-construal scale (Singelis, 1994). We did not include this scale in the current study because we were not aware of a cultural- and age-appropriate version of this scale that is validated among Singaporean older adults.

Second, the cohort effect may affect our results since our older Singaporean participants moved to Singapore before its formal establishment in 1965. Thus, older Singaporeans, in contrast to their younger counterparts, had limited access to formal education and may have a different lifestyle. Nonetheless, we aimed to be ecologically valid in the context of Singapore by randomly selecting older and younger participants and not forcing the two groups to be similar in education and lifestyle. It is important to note that there was no significant difference between the older and younger participants in their SSS (Adler et al., 2000). Thus, it appears that we succeeded in controlling for social demographics between the two age groups. Yet, future research in a country where the older and younger cohorts do not differ much is still needed. Finally, we did not have a middle-age group in the current study, making it difficult to draw conclusion beyond the younger and older adults. Having the middle-age group would allow us to examine a linear or curvilinear age effect in the self–other discrepancies. This would be an important extension for future studies.

Making financial decisions under risk on others' behalves is ubiquitous. For the first time, our study demonstrated that when making financial decisions on behalf of others, older adults have a stronger disposition to regard others' decisions as important as their own when compared with younger adults. In two separate studies, we found this diminishment of self–other discrepancies in older adults across various measures: loss aversion, risk-aversion asymmetry and risk preferences in both gain and loss domains. This finding has profound implications for policy-making in a world where older adults often hold positions of great power.

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Correction to Seaman et al. (2016)

In the article "Adult Age Differences in Decision Making Across Domains: Increased Discounting of Social and Health-Related Rewards," by Kendra L. Seaman, Marissa A. Gorlick, Kruti M. Vekaria, Ming Hsu, David H. Zald, and Gregory R. Samanez-Larkin (*Psychology and Aging*, 2016, Vol. 31, No. 7, pp. 737–746, http://dx.doi.org/10.1037/pag0000131), the levels for the effort task were mischaracterized; levels from an earlier pilot version of the task were accidentally reported. This error does not affect any of the results because the data for the modeling and analyses used the correct levels. The only necessary correction is to the text description of the task. In the first paragraph of the Effort Expenditure for Rewards Tasks (EEfRT) section, the text "The effort required for the smaller reward was set as 20%, 40%, or 60% (of each participant's maximum press rate), while the effort required for the larger reward was set as 20%, 40%, or 60% higher than the smaller reward" should read "The effort required for the smaller reward was set as 35%, 55%, or 75% (of each participant's maximum press rate), while the effort required for the larger reward was set as 20% or 40% higher than the smaller reward with no effort >95% required."

http://dx.doi.org/10.1037/pag0000290