

Supplemental Materials

A General Benevolence Dimension That Links Neural, Psychological, Economic, and Life-Span Data on Altruistic Tendencies

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Methods

Statistical Power

This is the first attempt to examine the common variance across personality, behavioral economic, and neural measures of altruism and adult age using structural equation modeling. Therefore, *a priori* effect size estimates were available only for a subset of the individual interrelations our model is based on. We evaluated the power of our design for each of the available pairwise relationships involving the constructs/variables in our model (prosocial disposition, giving choices, neural utility, and age). We a-priori determined the sample size for power of .8 and a one-tailed $\alpha = .05$ (as all relationships are expected to be positive). Power analyses were performed using G*Power (Faul, Erdfelder, Buchner, & Lang, 2009).

Previous work from our own lab (Harbaugh et al., 2007) indicates an effect size of $r = .52$ for the neural-utility/giving-choices, which would require a sample size of 20. We are also adequately powered to detect relationships between prosocial disposition and giving choices, requiring a sample size of approximately 40 ($r = .24$ to $.53$; Penner, 2002, see also Feldman, Hall, Dalglish, Evans, & Mobbs, 2015). A sample size of 24 is sufficient for age/giving-choices relationship ($r = .48$; based on Freund & Blanchard-Fields, 2014, Study 3). For the age-agreeableness relationship, a meta-analysis (Roberts, Walton, & Viechtbauer, 2006) and an analysis of two large national panels (Donnellan & Lucas, 2008) suggest correlations between .2 and .3. A power analysis indicates that

sample sizes of 67 to 153 are needed to detect such effect sizes with a power of .8. Because those effect sizes come from observed variables and we were analyzing latent variables that control for measurement error, we believe that a sample on the smaller side of this range can be adequately powered. For the remaining relationships (i.e., neural utility/age, neural utility/prosocial disposition), no effect size estimates were available, but we expected them to be in the same range as the established relationships. Our sample size of 80 participants was determined *a priori* both on the basis of power considerations and financial constraints associated with running an incentive-compatible, fMRI study. While preliminary analyses were conducted with 40 subjects and reported at smaller meetings, these led to no adjustments of the sample size.

Table S1. List of charities and the mission statement presented during the passive view and choice phases of the experiment.

Charity Name	Mission
American Red Cross	Dedicated to preventing and relieving human suffering in all forms
Center for Excellence in Education	Dedicated to careers in science and technology for promising students
Food for Lane County	Dedicated to eliminating hunger locally by creating access to food
Big Brothers Big Sisters of America	Dedicated to helping children through relationships with mentors
Prevent Child Abuse America	Dedicated to valuing children and strengthening families
United Way	Dedicated to improving lives by mobilizing the power of communities
Make-A-Wish Foundation	Dedicated to creating hope for children with life-threatening illnesses
Childrens Hope International Foundation	Dedicated to giving physical, medical and humanitarian help to orphans
International AIDS Vaccine Initiative	Dedicated to developing safe, effective, accessible HIV vaccines
Hospice Foundation of America	Dedicated to providing leadership in hospice and its philosophy of care
Special Olympics	Dedicated to empowering people with disabilities to physical fitness
I Have a Dream Foundation	Dedicated to helping low-income children reach their life goals
Meals on Wheels of America	Dedicated to the nutritional and economic betterment of Americans
HELP International	Provides health, education and literacy programs worldwide
International Medical Corps	Dedicated to providing health care training and relief programs
Child Find of America	Dedicated to the prevention and resolution of child abduction
Candlelighters Childhood Cancer Foundation	Provides support for children with cancer and their families
Childrens Hospice International	Provides support for children with life-threatening illnesses
Educational Advancement Fund International	Provides students from rural China with experiences that build character
Book Aid International	Dedicated to promoting literacy in developing countries
Hellen Keller International	Dedicated to combating the causes of blindness and malnutrition
Teach for America	Dedicated to eliminating educational inequality in America
Unicef	Dedicated to establishing childrens rights and strong principles
Interplast	Provides free surgery for those with clefts and disabling burns

Tasks and Stimuli

Prior to entering the scanner, participants read a booklet containing information from each of the 24 charities used in the experiment (Table S1) and were endowed with \$100. Then, each participant went through two separate tasks in the scanner, the passive-viewing task to assess the neural, “pure-altruism” signal (captured in the Neural Utility factor), and the active-choice task, which we only used to assess behavioral giving choices for this report (captured in the Giving Choices factor).

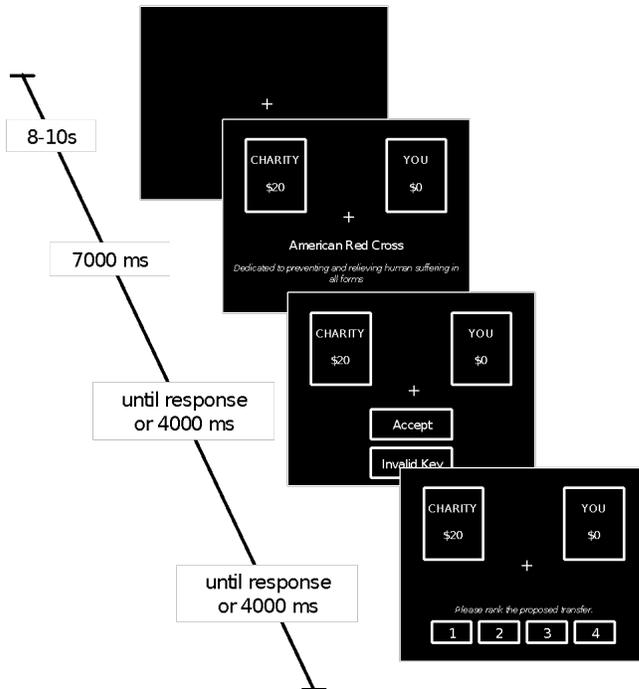


Figure S1. Stimulus sequence used for trials in the passive viewing phase.

The procedure for the passive viewing task is depicted in Figure S1. On each trial, a particular money transfer affecting the participant’s or the charity’s endowment was presented within two boxes representing the participant (“YOU”) and the charity (“CHARITY”). The positions of the boxes were randomized and remained on the screen for the duration of the trial. The name of the current charity along with a one-sentence description of its mission was displayed at the bottom of the screen (Table S1; e.g., “American Red Cross: Dedicated to preventing and relieving human suffering in all forms”). After 7 s, the charity name and description were replaced with two boxes, one with the word “Accept” and the other “Invalid Key”. The position of the “Accept” option was randomized on each trial. Participants were instructed to acknowledge the transfer by pressing the key corresponding to the location of the “Accept” option. They were also instructed that the transfer would occur even when selecting “Invalid Key” or making no

response after 4 seconds and that the money for transfers to either the participant or the charity came out of the experimenters' account. After the response, another prompt asked participants to rate their satisfaction with the transaction on a 1-4 scale, and they selected the appropriate box using the keys on their left hand (using their pinky, ring, middle, or index finger). These options remained for a maximum of 3 s, followed by a jittered intertrial interval of either 8, 9, or 10 s with a fixation cross in the center. Twelve of the charities were chosen at random, and each one was presented under 4 conditions: money-to-oneself (\$20 to participant, \$0 to charity), money-to-charity (\$0 to participant, \$20 to charity), loss-to-oneself (\$20 from participant, \$0 to charity), and baseline (\$0 to participant, \$0 to charity) for a total of 48 trials. All trials were presented during a single functional run of fMRI. Following previous work, we only used the money-to-oneself and the money-to-charity conditions in the main paper (Harbaugh et al., 2007), but present details regarding the remaining conditions below, in the section *Relationships with component neural measures*.

The active-choice phase was a variant of the dictator game (Forsythe et al., 1994). Figure S2 shows the trial structure. First, participants were informed for each trial whether the choice was private or observed ($p=.5$) in the form of an image and text presented for 4 seconds. Before entering the fMRI scanner, a female and male observer in white lab coats had been introduced to the participant as “observers” whose task was to “record and evaluate” participants' responses. On observed (i.e., public) trials, a monitor in the control room mirrored the display seen by the participant, including their highlighted choices, whereas on private trials the screen remained blank. Participants also received an extensive demonstration of this overall setup and were instructed about

the ethical standards of not misleading participants in economic experiments. Second, each transaction now involved a variable amount of money (either \$10, \$20, or \$40) that was always taken from the participant's endowment and donated to the named charity. Finally, participants had the option to "Accept" or "Reject" the transfer. Participants completed two functional runs of the choice phase, with 36 trials each. All 24 charities were used in the choice phase, with each one repeated 3 times (once for each unique donation amount).

The private/public manipulation was originally included in order to experimentally vary the relevance of prestige/signaling motives. The rate of giving did increase significantly in the public condition, suggesting that such impure motives were in fact induced by this condition. However, a reliable individual differences factor could not be established from this condition (which would have indicated that some subjects reacted to the manipulation more strongly than others), nor did this manipulation interact with age. Therefore, we ignored the private/public factor within the main manuscript, but provide additional information under the *Public versus Private Giving* section below.

Participants were instructed that one transaction from the passive phase and two transactions from the choice phase would be chosen at random and could change their payoff and the money the charity received. Participants were carefully instructed that aside from the public condition, all of their responses and brain imaging results would be strictly anonymous and that out of principle, researchers conducting economics experiments cannot mislead participants in any manner.

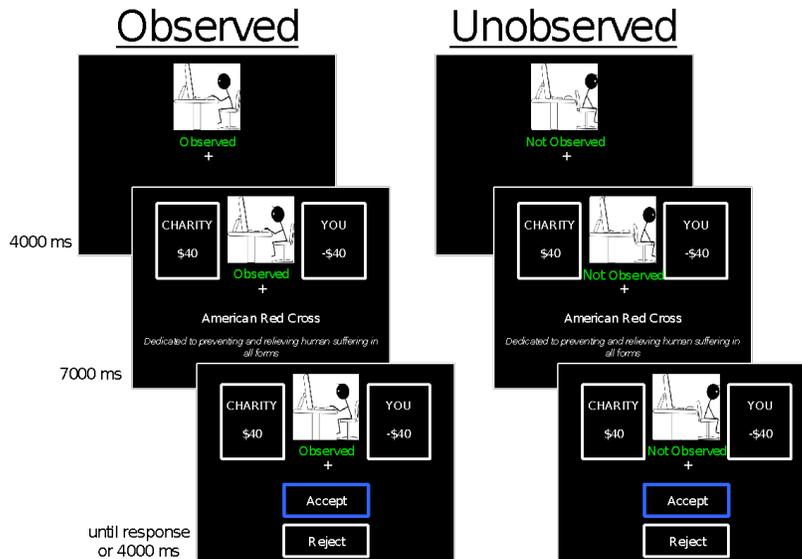


Figure S2. Depiction of the private/public manipulation used in the choice phase. The private/public cue was presented for 4s and remained on screen for the duration of the trial. Besides the central cue, the trial proceeded in the same manner as in the passive viewing phase.

fMRI Scanning Parameters

All participants were scanned using a Siemens Allegra 3.0 Tesla head-only scanner at the Lewis Center for Neuroimaging at the University of Oregon. Functional blood oxygen dependent (BOLD) images were obtained using gradient echo-planar imaging (32 axial slices, 4mm thick, FOV=200; Voxel size= 3.125 x 3.125 x 4 mm; TR=2000 ms, TE=30 ms, Flip Angle = 90 degrees). Structural images were obtained using an MPRAGE T1-weighted sequence (FOV=256, 160 slices 1mm thick, Matrix=192 x 256, 1mm x 1mm x 1mm resolution, TR=2500ms, TE=4.38ms, TI=1100, flip angle=8 degrees).

fMRI Preprocessing and Analysis

Imaging data were processed using a workflow of FSL (Smith et al., 2004) and Freesurfer (Dale, Fischl, & Sereno, 1999) tools implemented in Nipype (Gorgolewski et

al., 2011). Each functional run was realigned to its middle volume, data were high-pass filtered using a cutoff of 100 s, and images were spatially smoothed using an 8mm FWHM Gaussian kernel. The T1-weighted anatomical images were processed using Freesurfer, parceling both the cortical surface and subcortical structures according to the Desikan-Killiany Atlas (Dale et al., 1999). Functional data from each run were then registered to the anatomical volume using rigid body alignment with a boundary-based cost function (Greve & Fischl, 2009). Each anatomical image was normalized into Montreal Neurological Institute (MNI) stereotaxic space using nonlinear symmetric normalization as implemented in Advanced Normalization Tools (ANTS; Avants, Epstein, Grossman, & Gee, 2008). The neural data included in the structural equation model were obtained from the passive view run, specifically at the point at which the transaction amounts were initially presented (Figure S1). More specifically, the fMRI data were analyzed using a general linear model (GLM) that included four regressors indicating the onset of the transaction amounts separately for each condition (money-to-oneseif, loss-to-oneseif, money-to-charity, and baseline) and convolved with a double-gamma hemodynamic response function (HRF). Additionally, the onsets of the response (to acknowledge the transaction) and the rating were included as nuisance regressors, as were the motion parameters obtained from motion correction. The contrast of interest was between the money-to-charity and money-to-oneseif conditions, reflecting the “pure altruism” neural response to other-directed versus self-directed utility. A positive value for this contrast would reflect a greater response to a charity receiving money compared to oneseif, and in previous work has shown to be predictive of greater giving behavior (Harbaugh et al., 2007). Mean parameter estimates (across voxels) were extracted from

regions of interest (ROIs) within this charity-gain/self-gain contrast image in each subject's native functional space.

ROI Selection

The Nucleus Accumbens (NAcc) and caudate were included as anatomical ROIs due to the fact that they have been consistently implicated in representing subjective value relevant for choice (Clithero & Rangel, 2014; Knutson, Adams, Fong, & Hommer, 2001), including charitable giving (Harbaugh et al., 2007; Zaki, López, & Mitchell, 2014). Masks of the NAcc and caudate were created in each subject's native anatomical space according to the Freesurfer subcortical parcellation, and warped into their native functional space. The mean signal was then extracted from each ROI from the charity-gain/self-gain contrast image as discussed above. The ventromedial prefrontal cortex (vmPFC) has also been consistently implicated in representing subjective value across a variety of decision-making scenarios, and this region was included as a functional ROI based on a recent meta-analysis examining value-based decision making (Clithero & Rangel, 2014). We chose the region the authors called the "central vmPFC" because it was most consistently associated with value and subsequent choice across a variety of decision making scenarios. A mask image with a spherical ROI (radius = 6mm) was generated in MNI space, then that image was warped into each individual's native functional space. The mean signal was then extracted from the same charity-gain/self-gain contrast for each subject. Because this ROI was drawn near the midline, data were not extracted separately for each hemisphere. This procedure resulted in a total of 5 indicators for our Neural Utility factor in the structural equation modeling analysis (see Figure S7 to see relations between this ROIs and the other factors in the overall model).

Results

Public versus Private Giving Choices

Originally, an additional goal of this study had been to capture the effect of impure altruistic motives and the individual differences therein. To this end, half of the giving choices were private and the other half were public. Only the latter could induce a prestige or “social desirability” motive. Figure S3 shows the rate of giving for each of these two conditions as a function of age. As evident, participants on average gave more in the public condition ($\beta = .08$, $SE = .02$, $t = 5.4$), a result that suggests that giving can be influenced by impure altruistic motives. More importantly, there was a general main effect of age ($\beta = .01$, $SE = .003$, $t = 4.0$) and if anything the age slope was smaller for the observed than the private condition ($\beta = -.003$, $SE = .001$, $t = -1.89$). This suggests that age differences in giving behavior are *not* due to an age-related increase in prestige/social-pressure motives. As detailed in the section on structural equation modeling, no reliable individual differences variance was associated with the difference in observed versus private giving. Therefore, we do not present the results associated with this factor within the main manuscript. Because of the failure of obtaining a stable, impure-altruism, individual differences factor from the Giving Choices we also did not focus on fMRI results during the active-giving task in this report.

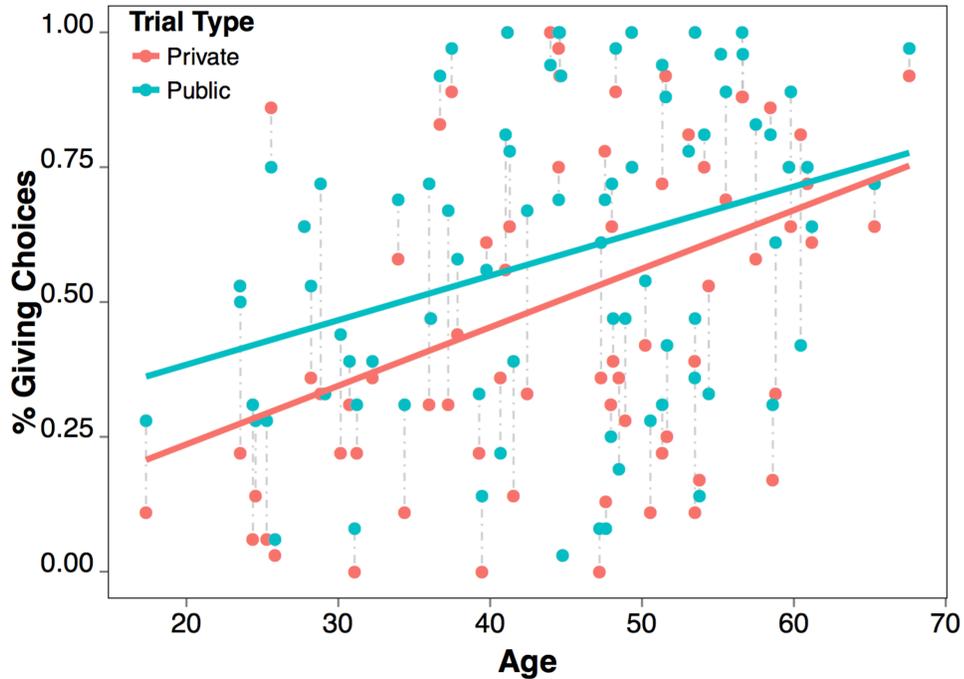


Figure S3. Correlation between percentage of giving choices and age for the two different trial types in the choice phase. This pattern does not support the notion that increased giving with age is due to an increase in impure altruistic motives. Each participant is represented by two points, one for private, the other for public choices. Individuals' age was slightly jittered to avoid overlapping data points. Only the public data point is shown in case of identical public and private scores.

Structural Equation Modeling

Specifying the Measurement Model

Table S2, shows the intercorrelations between all indicators the model is based on, including age. Table S3 reports the descriptive statistics for all indicators, as well as reliability estimates (Cronbach alpha) for those variables that were based on scales.

Table S2. Intercorrelations between all indicators.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1 Age															
2 Agreeableness	0.26*														
3 Empathic Concern	0.27*	0.50***													
4 Perspective Taking	0.18	0.49***	0.47***												
5 Altruistic Traits	0.26*	0.57***	0.56***	0.39***											
6 UGiving1	0.33**	0.33**	0.19	0.09	0.22										
7 UGiving2	0.33**	0.40***	0.30**	0.15	0.27*	0.82***									
8 UGiving3	0.38***	0.40***	0.35**	0.19	0.28*	0.67***	0.84***								
9 OGiving1	0.29**	0.40***	0.12	0.09	0.18	0.69***	0.81***	0.71***							
10 OGiving2	0.39***	0.45***	0.31**	0.23*	0.31**	0.74***	0.77***	0.77***	0.71***						
11 OGiving3	0.24*	0.41***	0.23*	0.18	0.21	0.76***	0.61***	0.71***	0.80***	0.78***					
12 vmPFC	0.38***	0.34**	0.22	0.10	0.11	0.35**	0.36**	0.41***	0.34**	0.48***	0.33**				
13 L NAcc	0.38***	0.34**	0.22	0.18	0.14	0.28*	0.29**	0.37***	0.27*	0.39***	0.24*	0.68***			
14 R NAcc	0.37***	0.32**	0.17	0.16	0.18	0.26*	0.26*	0.33**	0.23*	0.30**	0.16	0.65***	0.84***		
15 L Caudate	0.23*	0.32**	0.15	0.13	0.10	0.24*	0.2	0.28*	0.23*	0.28*	0.18	0.55***	0.62***	0.52***	
16 R Caudate	0.20	0.27*	0.18	0.10	0.05	0.21	0.17	0.27*	0.16	0.23*	0.11	0.54***	0.58***	0.56***	0.92***

* p < .05; ** p < .01; *** p < .001

Table S3. Descriptive Statistics for all indicators

Descriptive Statistics for Variables used in SEM model

Variable	<i>M</i>	<i>SD</i>	skewness	kurtosis	Chronbach's α
Age	44.20	11.52	-0.25	-0.88	-
Agreeableness	1.14	0.53	-0.61	0.57	0.73
Empathic Concern	2.04	0.64	-0.34	-0.41	0.77
Perspective Taking	2.04	0.57	-0.49	-0.26	0.77
Altruistic Traits	1.20	0.57	-0.46	0.19	0.75
UGiving1	0.48	0.33	0.15	-1.28	0.85
UGiving2	0.51	0.34	0.03	-1.44	0.86
UGiving3	0.47	0.31	0.21	-1.19	0.83
OGiving1	0.59	0.30	-0.20	-1.19	0.85
OGiving2	0.59	0.29	-0.32	-0.76	0.83
OGiving3	0.54	0.33	-0.10	-1.26	0.86
vmPFC	1.51	17.22	0.17	0.09	-
L NAcc	1.81	17.06	0.18	0.06	-
R NAcc	0.38	15.49	0.03	1.60	-
L Caudate	1.00	15.84	0.12	1.60	-
R Caudate	-0.44	18.71	0.19	0.18	-

As discussed in the main text, the “Prosocial Disposition” factor was constructed on the basis of the four self-report indicators agreeableness, empathic concern, perspective taking, and altruistic traits.

The “Giving Choices” factor was constructed from the behavioral responses in the active choice phase of the experiment, that is the proportion of trials that participants chose “Accept” and donate to the named charity. In order to represent giving choices as a latent variable, we partitioned the 24 unique charities into six groups of 4 charities each, then averaged responses within each partition (see Little, Cunningham, Shahar, Widaman, 2002). Three of these partitions represented private choices and three represented public choices.

As mentioned above, there was a highly reliable increase in rate of giving for public compared to private choices. However, our attempts to represent the public, giving choices through an additional latent construct within the structural equation model failed, because no reliable individual differences variance was associated with the difference between observed and private giving. Consequently, in all subsequent analyses both the observed and unobserved giving indicators were pooled together into a single “Giving Choices” factor.

Indicators for the Neural Utility factor consisted of mean parameter estimates from the charity-gain/self-gain contrast from the passive view phase, taken from the five *a priori* ROIs described above: the vmPFC, the left NAcc, right NAcc, left caudate, and right caudate. Based on observation of the modification indices, the homologous structures in the left and right hemispheres (both NAcc and both caudate regions) were allowed to correlate in the final model. Fit indices indicate that the model fitted the data very well ($\chi^2(97) = 112.72, p > .13$; SRMR = .056, CFI = .983, RMSEA = .045; see Figure 1A).

Caveats Regarding the SEM Analyses

An important limitation of this work is that our conclusions rely on a sample that, even though reasonably large for a neuroimaging study, is small for a correlational study using structural equation modeling. Therefore, these results need to be replicated with a larger sample and ideally using a longitudinal design. However, despite this caveat we have several reasons to believe that our results are robust.

First, subjects were carefully sampled to represent a homogeneous selection from a population with similar work/life experiences (i.e., all were University of Oregon, non-

teaching staff). This not only helps to reduce error variance, but is particularly important for reducing the influence of potential age confounds that might affect life-span comparisons within convenience samples.

Second, sample size planning for structural equation models depends on a number of different factors, and broad “rules of thumb” are difficult to apply. Models with complex causal paths often require larger samples; simpler models with high factor loadings (as was the case here) can be adequately studied with smaller samples (Wolf, Harrington, Clark, & Miller, 2013). Moreover, this approach allowed us to use the entire set of a-priori relevant variables in a unified model, rather than focusing on bivariate correlations between specific brain areas and behavioral measures—as is commonly done in studies looking at brain-behavior relationships.

Third, many of the individual, construct-to-construct relationships that provide the basis of our model have strong a-priori grounding in previous work (e.g., the neural-giving link, Harbaugh et al., 2007; the age-giving link, Freund & Blanchard-Fields, 2014; the age-disposition link, Roberts et al, 2006, or the disposition-giving link, Penner, 2002; see Supplemental Material). The novel contribution here is the integration of these individual results within a common construct and measurement space, as well as the fact that the neural measures allow tying General Benevolence to pure altruistic tendencies. The overall pattern of results also survived a number of robustness checks. In the main paper we present results based on analyses using unit-weighted aggregates. In the next sections we also show that our results are robust when using a simplified model with fewer indicators, and when partialling out age. We also provide evidence of divergent

validity with regard to the neural measures.

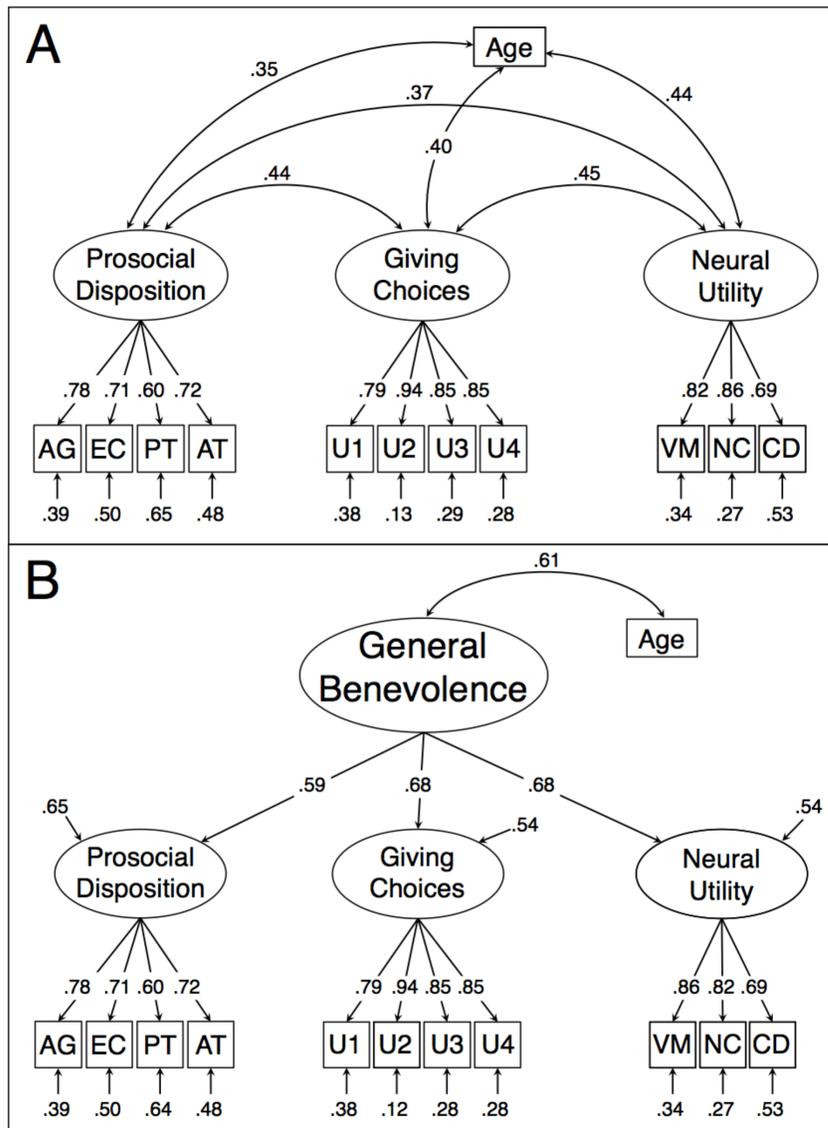


Figure S4. Simplified structural equation models. These models are the same as those depicted in Figure 1, except the brain regions from both hemispheres are averaged together, and only unobserved giving trials are included. NC = nucleus accumbens, CD = caudate.

Simplified Model

As an attempt to reduce the number of parameters in our model to counteract any potential sample size issues, we ran another analysis using a simplified version of our *a priori* SEM model. For the Neural Utility factor, we averaged across hemispheres for the

NAcc and caudate, which reduced the number of indicators and negated the need for the correlated error terms. For the Giving Choices factor, we reduced the number of indicators by 2 by focusing on the unobserved giving trials only ($n = 36$), but partitioning them into 4 groups instead of 3. This was repeated for both the measurement model (Figure S4A) and the General Benevolence model (Figure S4B). Both models produced an excellent fit ($\chi^2(49) = 39.96, p > .81, SRMR = .050$ for the measurement model, $\chi^2(51) = 40.38, p > .85; SRMR = .051$ for the General Benevolence model) and importantly, showed the same pattern observed in the *a priori* model reported in the main text.

Partiallying out age.

The relatively strong relationships between age and the different aspects of altruistic tendencies raise the question to what degree the latent structure portrayed in Figures 1A and 1B is dependent on shared age variance. To examine this issue, we estimated an alternative model specification in which the variance of each indicator was explained both by the corresponding latent construct and age. Here, the influence of age is no longer present in the factor loadings and the relationship between latent constructs (Figure 3). We replicated the two-level structure from Figure 1B, with an excellent fit ($\chi^2(85) = 103.79, p = .08; SRMR = .051, CFI = .980, RMSEA = .053$). Also, all loadings of the first-order constructs and the paths connecting first-order and second-order constructs were significant. Thus, the finding of a strong General Benevolence factor is not simply an epiphenomenon of the age variance being shared across measures.

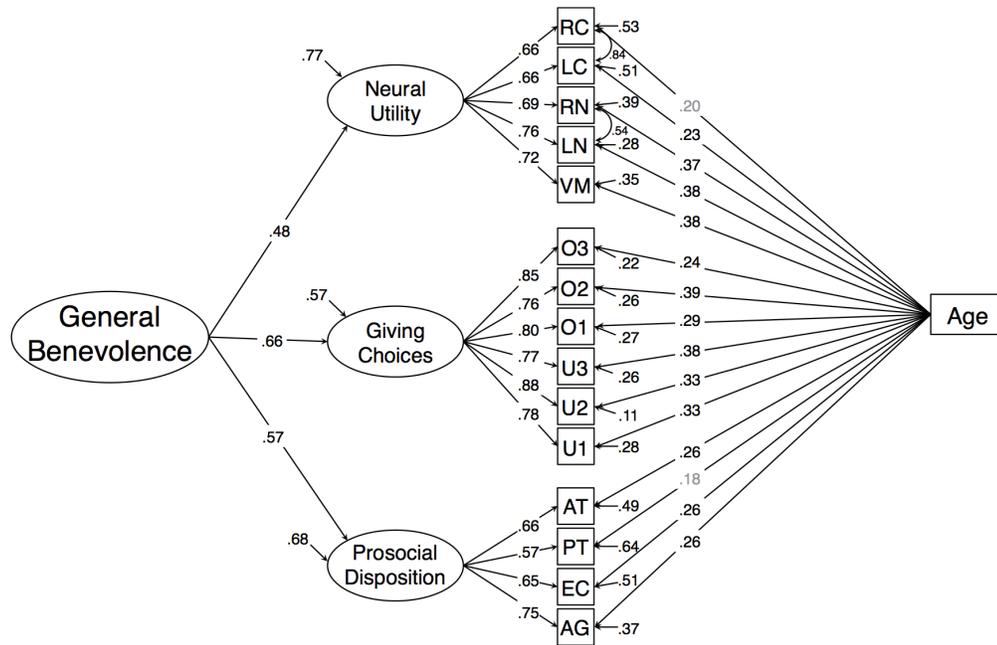


Figure S5. Second-order model with age controlled on the level of indicators. Gray coefficients were not statistically significant.

Convergent and divergent validity of the Neural Utility factor.

This is the first attempt in the literature to capture the common variance in neural activity across different, but related neural areas, through a latent factor. The results indicate a high degree of convergent validity across areas, but leave open the question of divergent validity, that is, how specific the pattern of relationships is to the a-priori targeted areas. In principle it is possible that individuals expressing high prosocial tendencies are characterized by a nonspecific, increased neural response to a charity gaining money. To address this question, we attempted to select a set of brain regions that a) are expected to be engaged to some extent in the passive viewing task b) are functionally related to each other and thus expected to be co-activated and c) most importantly, do not have a primary role in valuation, like our Neural Utility regions.

As the passive viewing task involves the consideration of a transfer and an appropriate response to stimuli (albeit a forced one), it would be expected to involve some activity in executive control regions. Rather than hand-picking a set of regions from different sources in the literature, we instead turned to previous work examining functional brain networks, which, by definition, should exhibit coherent activity. We chose a set of 8 regions that were functionally-defined as the “fronto-parietal task control” network, using meta-analytic and graph theoretical techniques (Power et al., 2011), and subsequently examined in executive control specifically (Cole et al., 2013).

We expected that these indicators would form a reliable factor, however given that they should not be involved in valuation *per se* they should show no significant relationships with the altruism-related latent constructs, or age. The regions correspond roughly (since they were functionally rather than anatomically defined) to the superior frontal gyrus, precentral gyrus, inferior frontal gyrus (IFG), supramarginal gyrus, middle frontal gyrus, inferior temporal, lateral orbitofrontal cortex (OFC), and the OFC/frontal pole. Spherical ROIs were created in MNI space and warped into each participant’s native functional space and brain data were extracted in the same manner as with the Neural Utility ROIs. Then a Neural Control factor was constructed with these indicators and used in place of the Neural Utility factor in both models in Figure 1. As we did not want to hand-pick regions within this network, we initially included all 8 indicators in the model. However, two of the regions which reside in the OFC did not load significantly on the Neural Control factor and were excluded. Notably, the OFC has been implicated in the evaluation of rewards, but in a manner that can be independent of the options being weighed (c.f. Kringelbach, 2005; Hare, O’Doherty, Camerer, Schultz, & Rangel, 2008).

For this reason, it was not included as part of the Neural Utility factor, but is probably more closely related to the valuation regions than the task control regions.

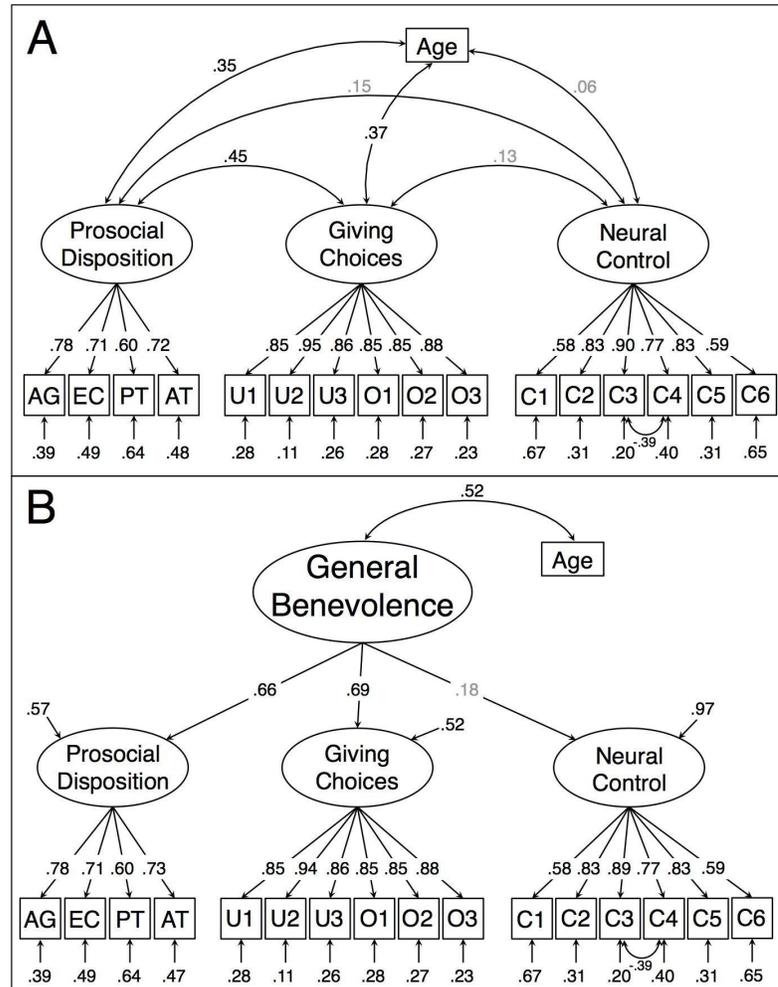


Figure S6. Neural Control model used to test divergent validity. The models are the same as in Figure 1, except the Neural Utility factor is replaced by a Neural Control factor consisting of six ROIs from the frontoparietal network (Power, Cohen, Nelson, Wig, Barnes, Church, Vogel, Laumann, Miezin, Schlaggar, & Petersen, 2011b). Loadings in gray are non-significant.

Despite the fact that the remaining indicators had highly reliable factor loadings (indicating shared variance and reliable individual differences), all correlations between the Neural Control factor and the remaining factors were weak and non-significant

(Figure S6A) and also did not contribute significantly to the General Benevolence factor (Figure S6B). This analysis rules out the possibility that individuals expressing high prosocial tendencies may show some type of generalized neural response to a charity gaining money. Rather, the observed relationships with our neural utility factors seemed specific to our a-priori defined “value/utility areas”.

Relationships with component neural measures.

Our Neural Utility factor was constructed in an a-priori manner (based on Harbaugh et al., 2007) on the difference between the money-to-self and money-to-charity conditions. However, it is also of interest to examine the independent relationships that each condition may have with the General Benevolence factor. Specifically, one would expect that General Benevolence is negatively correlated with the activity in the self-gain and positively correlated with the charity-gain condition. We ran two additional models in which we replaced the neural utility factor with either the neural self-gain or the neural charity-gain condition, each after subtracting out the baseline condition. We found adequate fit in each of these cases and as predicted, a negative relationship between self-gain and General Benevolence ($b = -.39, p = .004$) and a positive relationship between charity-gain and General Benevolence ($b = .31, p = .05$). We had also included a self-loss condition, because it was also part of the design of the Harbaugh et al. (2007) precursor study, where it had shown no consistent relationships with charitable giving. When using this condition instead of our neural utility indicator, we again found no reliable relationship with General Benevolence ($b = -.16, p = .35$). Overall these more detailed relationships were either consistent with the decision-utility framework or with previous results.

Given the increase in General Benevolence across the lifespan, we also expected that the self-gain and charity-gain conditions would have similar, opposing relationships with age. We tested this more focused prediction using multiple regression and unit-weighted neural self-gain and charity-gain aggregates instead of latent factors. Consistent with our prediction and the model above, we found that the neural activation to the self-gain condition was negatively related ($\beta = -4.50, p < .01$) and the charity-gain condition was positively related ($\beta = 3.60, p < .05$) with age.

Whole-Brain Representation of Prosocial Tendencies

Figure 3 depicts our attempt to establish the distinct and overlapping areas associated with the different aspects of altruistic tendencies in a descriptive and whole-brain manner. In order to create these images, we first extracted the factor scores corresponding to our Prosocial Disposition and Giving Choices factors in our structural equation model. For each factor, the factor score (1 number per participant) was used as a covariate in a separate group-level model of the fMRI analysis, focusing on the charity-gain/self-gain contrast. The same procedure was performed using age as a covariate. The resulting images show the regions in which the degree of activation to a charity gaining money (above oneself gaining money) correlates with one's Prosocial Disposition, Giving Choices, and age. Obviously, the fact that these factors are "projected" onto our charity-gain/self-gain contrast precludes us from projecting the Neural Utility factor onto the brain in the same fashion (as this would be completely circular).

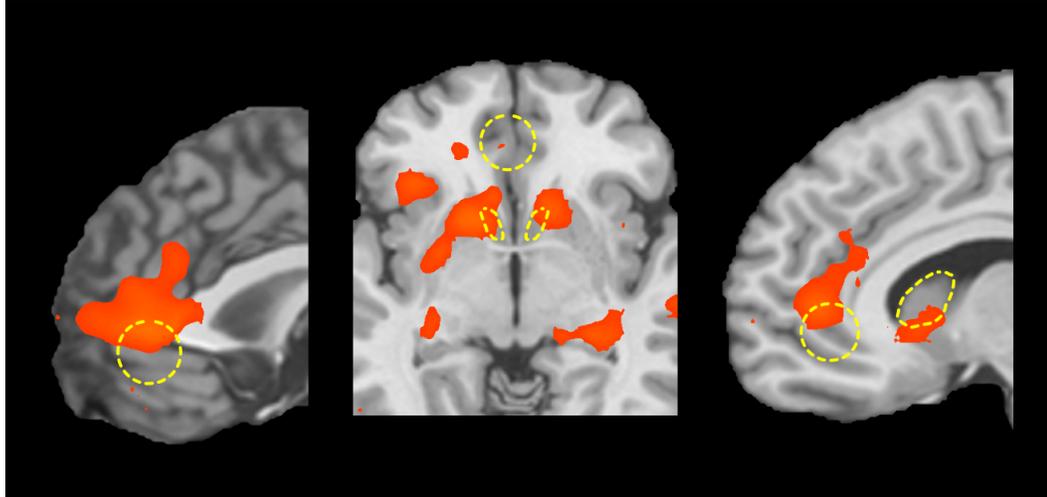


Figure S7. Convergence of a priori ROIs used in the calculation of neural utility (depicted by yellow dotted lines) and correlations in brain activity associated with our first-order Prosocial Disposition and Giving Choices factors established in the structural equation model (the union of these areas are depicted in red).

To check how our a-priori defined ROIs for the Neural, Pure Altruism factor fared in the context of whole-brain analyses, we projected the Prosocial Disposition and Giving Choices onto the brain in our charity-gain/self-gain contrast as in Figure 3, and overlaid our a-priori selected Neural Utility ROIs on the resulting image. The results are presented in Figure S7. For ease of presentation, only the union of Prosocial Disposition and Giving Choices is presented in red (see Figure 3 for the regions unique to each factor) and the ROIs for the Neural Utility factor are depicted by dotted lines. As evident, regions in which increased activation in money-to-charity trials correlates with Prosocial Disposition and/or Giving Choices show substantial overlap with our a-priori ROIs (Clithero & Rangel, 2014; Harbaugh et al., 2007; Knutson et al., 2001; D. J. Levy & Glimcher, 2012; I. Levy, Lazzaro, Rutledge, & Glimcher, 2011; Zaki et al., 2014). This

provides complementary evidence (along with the structural equation model itself) that the neural "pure-altruism" factor does indeed share variance with the other two factors.

References

- Avants, B. B., Epstein, C. L., Grossman, M., & Gee, J. C. (2008). Symmetric diffeomorphic image registration with cross-correlation: evaluating automated labeling of elderly and neurodegenerative brain. *Medical Image Analysis, 12*, 26–41.
- Clithero, J. A., & Rangel, A. (2014). Informatic parcellation of the network involved in the computation of subjective value. *Social cognitive and affective neuroscience, 9*, 1289-1302. <http://doi.org/10.1093/scan/nst106>
- Cole, M. W., Reynolds, J. R., Power, J. D., Repovs, G., Anticevic, A., & Braver, T. S. (2013). Multi-task connectivity reveals flexible hubs for adaptive task control. *Nature Publishing Group, 16*, 1348–1355. <http://doi.org/10.1038/nn.3470>
- Dale, A. M., Fischl, B., & Sereno, M. I. (1999). Cortical surface-based analysis: I. Segmentation and surface reconstruction. *NeuroImage, 9*, 179–194.
- Donnellan, M. B., & Lucas, R. E. (2008). Age differences in the Big Five across the life span: Evidence from two national samples. *Psychology and Aging, 23*, 558-566.
- Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*, 1149–1160. <http://doi.org/10.3758/BRM.41.4.1149>
- FeldmanHall, O., Dalgleish, T., Evans, D., & Mobbs, D. (2015). Empathic concern drives costly altruism. *NeuroImage, 105*, 347–356.
<http://doi.org/10.1016/j.neuroimage.2014.10.043>
- Forsythe, R., Horowitz, J. L., Savin, N. E., & Sefton, M. (1994). Fairness in Simple Bargaining Experiments. *Games and Economic Behavior, 6*, 347–369.
<http://doi.org/10.1006/game.1994.1021>

- Freund, A. M., & Blanchard-Fields, F. (2014). Age-related differences in altruism across adulthood: Making personal financial gain versus contributing to the public good. *Developmental Psychology, 50*, 1125–1136. <http://doi.org/10.1037/a0034491>
- Gorgolewski, K., Burns, C. D., Madison, C., Clark, D., Halchenko, Y. O., Waskom, M. L., & Ghosh, S. S. (2011). Nipype: a flexible, lightweight and extensible neuroimaging data processing framework in python. *Frontiers in Neuroinformatics, 5*.
- Greve, D. N., & Fischl, B. (2009). Accurate and robust brain image alignment using boundary-based registration. *NeuroImage, 48*, 63–72.
- Harbaugh, W. T., Mayr, U., & Burghart, D. R. (2007). Neural responses to taxation and voluntary giving reveal motives for charitable donations. *Science, 316*, 1622–1625. <http://doi.org/10.1126/science.1140738>
- Knutson, B., Adams, C. M., Fong, G. W., & Hommer, D. (2001). Anticipation of increasing monetary reward selectively recruits nucleus accumbens. *The Journal of Neuroscience, 21*, RC159.
- Levy, D. J., & Glimcher, P. W. (2012). The root of all value: a neural common currency for choice. *Current Opinion in Neurobiology, 22*, 1027–1038. <http://doi.org/10.1016/j.conb.2012.06.001>
- Levy, I., Lazzaro, S. C., Rutledge, R. B., & Glimcher, P. W. (2011). Choice from non-choice: predicting consumer preferences from blood oxygenation level-dependent signals obtained during passive viewing. *Journal of Neuroscience, 31*, 118–125. <http://doi.org/10.1523/JNEUROSCI.3214-10.2011>
- Little TD, Cunningham WA, Shahar G, Widaman KF (2002) To Parcel or Not to Parcel:

Exploring the Question, Weighing the Merits. *Structural Equation Modeling: A Multidisciplinary Journal* 92, 151–173.

Midlarsky, E., & Hannah, M. E. (1989). The generous elderly: Naturalistic studies of donations across the life span. *Psychology and Aging*, 4, 346–351.

<http://doi.org/10.1037//0882-7974.4.3.346>

Moll, J., Krueger, F., Zahn, R., Pardini, M., de Oliveira-Souza, R., & Grafman, J. (2006). Human fronto–mesolimbic networks guide decisions about charitable donation. *Proceedings of the National Academy of Sciences*, 103, 15623–15628.

<http://doi.org/10.1073/pnas.0604475103>

Penner, L. A. (2002). Dispositional and organizational influences on sustained volunteerism: An interactionist perspective. *Journal of Social Issues*, 58, 447–467.

Power, J. D., Cohen, A. L., Nelson, S. M., Wig, G. S., Barnes, K. A., Church, J. A., Vogel, A. C., Laumann, T. O., Miezin, F. M., Schlaggar, B. L., & Petersen, S. E. (2011). Functional Network Organization of the Human Brain. *Neuron*, 72, 665–678.

<http://doi.org/10.1016/j.neuron.2011.09.006>

Roberts, B. W., Walton, K. E., & Viechtbauer, W. (2006). Patterns of Mean-Level Change in Personality Traits Across the Life Course: A Meta-Analysis of Longitudinal Studies. *Psychological Bulletin*, 132, 1–25. <http://doi.org/10.1037/0033-2909.132.1.1>

Smith, S. M., Jenkinson, M., Woolrich, M. W., Beckmann, C. F., Behrens, T. E., Johansen-Berg, H., et al. (2004). Advances in functional and structural MR image analysis and implementation as FSL. *NeuroImage*, 23, S208–S219.

Zaki, J., López, G., & Mitchell, J. P. (2014). Activity in ventromedial prefrontal cortex

co-varies with revealed social preferences: evidence for person-invariant value.

Social Cognitive and Affective Neuroscience, 9, 464–469.

<http://doi.org/10.1093/scan/nst005>