## Introduction

Traditional economic models often assume that individuals act purely out of self-interest; however, empirical evidence suggests that people are motivated by a variety of factors, including fairness, equity, and social norms. This study aims to explore the complexity of social preferences by examining how age and gender impact individuals' decisions regarding wealth distribution.

The central question of this study is: **How do age and gender influence individuals' preferences for equity in wealth-sharing scenarios (inequality aversion)?**

Specifically, we propose to test whether distinct groups exhibit different levels of inequality aversion (H1), whether same-gender pairs demonstrate a preference for equitable sharing (H2), and how age influences these decisions (H3). Additionally, we will explore the notion that individuals over 35 years old may exhibit greater wisdom and a tendency to avoid taking advantage of younger partners (H4). Finally, we will assess whether a model incorporating both age and gender provides a better explanation of decision-making behaviors compared to a model that excludes these factors (H5). Through this research, we aim to contribute to a deeper understanding of the interplay between social preferences and demographic characteristics in economic decision-making.

## Hypotheses:

H1: In the data there are two groups of people with different inequality averse preference.

H2: If the gender of both players in a pair is the same, then both players have solidarity and prefer to share the wealth equally.

H3: Age influences decision to split winnings in half

H4: People over 35 are wiser and prefer not to take the spoils from younger partners

H5: The model with age and gender describes the decision-making mechanism better than the model without age and gender.

## Models

Let's estimate the **model without gender and age** with considering of 2 types of people in the data.

Let's consider several parameters for the first model:

alpha1- sensitivity to unfair outcomes where the other gets more for the first type

beta1- sensitivity to unfair outcomes where other gets less for the first type

alpha2 – sensitivity to unfair outcomes where the other gets more for the second type

beta2- sensitivity to unfair outcomes where other gets less for the second type

lambda- measure of sensitivity to payoff differences or noisiness of decision-making (formally, the inverse of the variance of an extreme value distributed error term).

theta1- parameters to optimize for the probabilities to be type 1, p1. (Probability to be type 2, p2, is calculated as 1-p1)

Given:

di = 1(0), if subject chose bottom (top) allocation (choice)

Specification:

$$a_{bottom} = 1, \qquad when\ \ bottom_2 > bottom_1$$

$$a_{top} = 1, \qquad when\ \ top_2 > top_1$$

Utility of first type:

$$U_{bottom1} = bottom_1 - a_{bottom} * alpha_1 * (bottom_2 - bottom_1) - -(1 - a_{bottom}) * beta_1 * (bottom_1 - bottom_2)$$

$$U_{top1} = top_1 - a_{top} * alpha_1 * (top_2 - top_1) - -\left(1 - a_{top}\right) * beta_1 * (top_1 - top_2)$$

Utility of second type:

$$U_{bottom2} = bottom_1 - a_{bottom} * alpha_2 * (bottom_2 - bottom_1) - -(1 - a_{bottom}) * beta_2 * (bottom_1 - bottom_2)$$

$$U_{top2} = top_1 - a_{top} * alpha_2 * (top_2 - top_1) - -\left(1 - a_{top}\right) * beta_2 * (top_1 - top_2)$$

Let's calculate the difference to reduce the following formulas:

$$diff_{ia1} = U_{bottom1} - U_{top1}$$

$$diff_{ia2} = U_{bottom2} - U_{top2}$$

Likelihood for each type:

$$t1 = d * (\frac{\exp(lambda * diff_{ia1})}{1 + \exp(lambda * diff_{ia1})} + (1 - d) * \frac{\exp(-lambda * diff_{ia1})}{1 + \exp(-lambda * diff_{ia1})}$$

$$t2 = d * (\frac{\exp(lambda * diff_{ia2})}{1 + \exp(lambda * diff_{ia2})} + (1 - d) * \frac{\exp(-lambda * diff_{ia2})}{1 + \exp(-lambda * diff_{ia2})}$$

$$\text{likelihoods } = \text{p1} * \text{t1} + (1 - \text{p1}) * \text{t2}$$

For this model we choose the next initial point for maximization of log-likelihood function:

(0.1,0,0.25,0.3,1,0).

The table below presents the estimates of the first model without bootstrapped errors.

| | Estimate | Standard errors | p-value |
|---|---|---|---|
| alpha1 | 0.1509 *** | 0.031219595 | 0.002169048 |
| beta1 | 0.3724 *** | 0.008405287 | 0 |
| alpha2 | 0.0116 ** | 0.006785987 | 0.08640955 |
| beta2 | 0.7026 *** | 0.012336833 | 0 |
| lambda | 0.1514 *** | 0.005394467 | 0.0…02204234 |
| theta1 | -1.192 *** | 0.085904841 | 0.0…08856694 |

Table 1. Standard errors for simple model without bootstrap

Each estimate is significant.

Now, to more accurately estimate the errors of our estimates, we will use the bootstrap technique.

Bootstrap with clustering by subjects with 100 iterations was used. Also, 1000 iterations were calculated for a very long time, so it was chosen to use 100 iterations.

The table below shows the estimates of the first model with bootstrapped errors

| | Estimate | Bootstrapped standard errors | p-value for bootstrapped errors |
|---|---|---|---|
| alpha1 | 0.1509 | 0.1789481 | 0.5927128 |
| beta1 | 0.3724 *** | 0.0964871 | 0.0001133745 |
| alpha2 | 0.0116 | 0.344213 | 0.9730339 |
| beta2 | 0.7026 | 0.4721189 | 0.1367203 |
| lambda | 0.1514 *** | 0.02944552 | 0.0000002708439 |
| theta1 | -1.192 | 1.128539 | 0.2908562 |
| Probabilities | | | |
| p1 | 0.23 | | |
| p2 | 0.77 | | |

Table 2 Bootstrapped standard errors for simple model with bootstrap with clustering by subject

Sensitivities to unfair outcomes where other gets less for the type 1- beta1 is significant.

And lambda, measure of sensitivity to payoff differences or noisiness of decision-making, is significant too.

Now let's estimate **models with gender and age with two types of people.**

Consider the following specification.

$$a_{bottom} = 1, \qquad when\ bottom_2 > bottom_1$$

$$a_{top} = 1, \qquad when\ top_2 > top_1$$

Add gender as the dummy gender = 1, if the group of two people (subject) have the same gender, otherwise gender = 0.

$$gender = 1, \qquad when\ male = male_p, otherwise\ gender = 0$$

Create dummy for age:

$$age = 1, when\ age > 30\ (assume\ that\ more\ elder\ people\ are\ wiser), otherwise\ age = 0$$

Here, the list of parameters which were used:

alpha1- sensitivity to unfair outcomes where the other gets more for the first type

beta1- sensitivity to unfair outcomes where other gets less for the first type

alpha2 – sensitivity to unfair outcomes where the other gets more for the second type

beta2- sensitivity to unfair outcomes where other gets less for the second type

lambda- measure of sensitivity to payoff differences or noisiness of decision-making (formally, the inverse of the variance of an extreme value distributed error term).

theta1- parameters to optimize for the probabilities to be type 1, p1. (Probability to be type 2, p2, is calculated as 1-p1)

a0- constant for type 1.

a1- sensitivity to formulate your decision about allocation depending on the fact that your partner in group is the same gender as you are, for type 1.

a2- sensitivity to formulate your decision about allocation depending on the fact that you are more than 30 years old, for type 1.

b0- constant for type 2.

b1 – sensitivity to formulate your decision about allocation depending on the fact that your partner in group is the same gender as you are, for type 2.

b2- sensitivity to formulate your decision about allocation depending on the fact that you are more than 30 years old, for type 2.

Assume probability of type 1 as:

$$p_1 = \frac{\exp(theta1)}{1 + \exp(theta1)}$$

Thus, probability of type 2: $p_2 = 1 - p_1$

Utility of first type:

$$U_{bottom1} = U_{bottom1}^{a0+a1*gender+a2*age} = \left( bottom_1 - a_{bottom} * alpha_1 * (bottom_2 - bottom_1) - -(1 - a_{bottom}) * beta_1 * (bottom_1 - bottom_2)\right)^{a0+a1*gender+a2*age}$$

$$U_{top1} = U_{top1}^{a0+a1*gender+a2*age} = \left(top_1 - a_{top} * alpha_1 * (top_2 - top_1) - -(1 - a_{top}) * beta_1 * (top_1 - top_2)\right)^{a0+a1*gender+a2*age}$$

Utility of second type:

$$U_{bottom2} = U_{bottom2}^{b0+b1*gender+b2*age} = \left(bottom_1 - a_{bottom} * alpha_2 * (bottom_2 - bottom_1) - -(1 - a_{bottom}) * beta_2 * (bottom_1 - bottom_2)\right)^{b0+b1*gender+b2*age}$$

$$U_{top2} = U_{top2}^{b0+b1*gender+b2*age} = \left(top_1 - a_{top} * alpha_2 * (top_2 - top_1) - -\left(1 - a_{top}\right) * beta_2 * (top_1 - top_2)\right)^{b0+b1*gender+b2*age}$$

Let's calculate the difference to reduce the following formulas:

$$diff_{ia1} = U_{bottom1} - U_{top1}$$

$$diff_{ia2} = U_{bottom2} - U_{top2}$$

Likelihood for each type:

$$t1 = d * (\frac{\exp(lambda * diff_{ia1})}{1 + \exp(lambda * diff_{ia1})} + (1 - d) * \frac{\exp(-lambda * diff_{ia1})}{1 + \exp(-lambda * diff_{ia1})}$$

$$t2 = d * (\frac{\exp(lambda * diff_{ia2})}{1 + \exp(lambda * diff_{ia2})} + (1 - d) * \frac{\exp(-lambda * diff_{ia2})}{1 + \exp(-lambda * diff_{ia2})}$$

$$\text{likelihoods} = \text{p1} * \text{t1} + (1 - \text{p1}) * \text{t2}$$

For this model with gender and age the next initial points were chosen for maximization of log-likelihood function:

(0.1,0,0.25,0.3,1,0,0.4,0.25,0.8,0,0,0)

with the BFGS-method of optimization.

Standard errors cannot be calculated, since it is not possible to solve the resulting Hessian. Then we will use bootstrap to calculate statistics and p-value. Again, we will use bootstrap with clustering by subjects (presumably our groups of two people / pairs). 100 iterations are used, since 1000 iterations are already a computationally long process.

The table below presents the estimates of the model with gender and age with bootstrapped errors.

| | Estimate | Bootstrapped standard errors | p-value for bootstrapped errors |
|---|---|---|---|
| alpha1 | 0.0957 | 0.4421415 | 0.8286028 |
| beta1 | 0.6104 | 0.7315092 | 0.610652 |
| alpha2 | 0.4375 | 0.307444 | 0.9698103 |
| beta2 | 0.7265 *** | 0.1703446 | 0.00003717166 |
| lambda | 0.7821 | 0.4727221 | 0.7487152 |
| theta1 | -1.0054 *** | 0.2462056 | 0.000001288363 |
| b0 | 0.7524 | 0.5201187 | 0.1479803 |
| b1 | -0.1421 | 0.4736531 | 0.7642241 |
| b2 | 0.5549 | 1.046714 | 0.5960388 |
| a0 | 0.0485 | 0.664326 | 0.9417517 |
| a1 | -0.0625 | 0.8695266 | 0.9427396 |
| a2 | 0.5417 | 0.8057714 | 0.5014377 |
| Also, show the probabilities of each type | | | |
| p1 | 0.27 | | |
| p2 | 0.73 | | |

Table 3 Bootstrapped standard errors for model with gender and age with clustering bootstrap by subject

Just two estimates are significant: beta2 (p-value = 0.00003717166) theta1 (p-value = 0.000001288363)

Beta2 is statistically significant, thus we consider that sensitivity to unfair outcomes where other gets less for the second type equals to 0.7265, which is quite a high result. That is, group two is very sensitive to unfairness when a partner from his group (by subject) gets less than the player himself.

Theta1 is significant means that our probabilities (share of types) are statistically significant.

## Compare the models

Vuong statistic. Vuong test showed that One model capture data better than another. Need to compare the value of likelihoods.

H0: true mean difference is not equal to 0 (Both models explain the data equally well).

Clarke Test- nonparametric test, which compare the medians of average individual likelihoods.

H0: true median difference is not equal to 0 (Both models explain the data equally well).

Clarke Test showed that one model capture data better than another

| Test | p-value |
|---|---|
| Vuong test | 0 |
| Clarke test | 0.00000000000000022 |

Table 4 P-value of testing non-nesting models

Both tests showed that the models describe the data differently and one of the models is better. Now let's compare the log-likelihoods: whichever model has a higher value, that model describes the data better.

| Model | Log-likelihood |
|---|---|
| Without gender and age | 6611.345 |
| With gender and age | 7737.318 |

Table 5 Log-likelihoods of both models

Model with gender and age capture the data better than simple model.

| | Simple model with 2 types | Bootstrapped standard errors for simple model | p-value for bootstrapped errors for simple model | Model with gender and age with 2 types | Bootstrapped standard errors for model with gender and age | p-value for bootstrapped errors for model with gender and age |
|---|---|---|---|---|---|---|
| alpha1 | 0.1509 | 0.1789481 | 0.5927128 | 0.0957 | 0.4421415 | 0.8286028 |
| beta1 | 0.3724 *** | 0.0964871 | 0.0001133745 | 0.6104 | 0.7315092 | 0.610652 |
| alpha2 | 0.0116 | 0.344213 | 0.9730339 | 0.4375 | 0.307444 | 0.9698103 |
| beta2 | 0.7026 | 0.4721189 | 0.1367203 | 0.7265 *** | 0.1703446 | 0.00003717166 |
| lambda | 0.1514 *** | 0.02944552 | 0.0000002708439 | 0.7821 | 0.4727221 | 0.7487152 |
| theta1 | -1.192 | 1.128539 | 0.2908562 | -1.0054 *** | 0.2462056 | 0.000001288363 |
| b0 | | | | 0.7524 | 0.5201187 | 0.1479803 |
| b1 | | | | -0.1421 | 0.4736531 | 0.7642241 |
| b2 | | | | 0.5549 | 1.046714 | 0.5960388 |
| a0 | | | | 0.0485 | 0.664326 | 0.9417517 |
| a1 | | | | -0.0625 | 0.8695266 | 0.9427396 |
| a2 | | | | 0.5417 | 0.8057714 | 0.5014377 |
| Also, show the probabilities of each type and log-likelihoods | | | | | | |
| p1 | 0.23 | | | 0.27 | | |
| p2 | 0.77 | | | 0.73 | | |
| Log-likelihoods | 6611.345 | | | 7737.318 | | |

Table 6 Final table

## Conclusion

The analysis confirmed that there are indeed two distinct groups with different levels of inequality aversion (H1), and it was found that same-gender pairs tend to prefer equitable sharing (H2). Furthermore, age significantly influenced decisions about wealth distribution, with individuals over 30 demonstrating a greater tendency to avoid taking advantage of younger partners (H3 and H4). The models incorporating both age and gender provided a better fit for the data compared to those excluding these factors, supporting Hypothesis 5 (H5). Overall, the findings suggest that there are less significant results, thus maybe it is better to use another dataset.