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Wealth and Generosity in Rural Colombia

"What is the relationship between wealth and generosity within the rural Colombian context?"

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Inhoud

Abstract

The relationship between wealth and generosity has been studied in the past, but has resulted in mixed result and competing theories. Meanwhile most research has been done within a WEIRD-context (Western, Educated, Industrial, Rich, and Democratic). The goal of this thesis was to find out what the relationship is between wealth and generosity within a non-WEIRD context, specifically Rural Colombia. The dataset used was collected by Redhead and colleagues. It contains data from four different villages. Generosity was measured with the RICH economic allocation game, a method that yields data embedded within the community itself. The variables sex, age, kinship and friendship were including for a more in depth analysis. Results were mostly inconclusive and a network analysis is recommended for future research.

Introduction

In the last decades wealth inequality has grown to new extreme proportions. Today, there are more billionaires on earth than ever before in human history (NOS, 2024). Levels of wealth inequality are in some countries on the same level as they were before the first world war (Piketty, 2017). For example, in the Netherlands the income and wealth inequality has grown a lot over the last decennia and there are large differences between generations (Afman, 2020). In some countries, like Colombia, inequality is even bigger, with 10% earing around 40% of the income within the country (Colombian Reports, 2023). Wealth inequality has been a topic of interest within sociology since the very beginning. One of the first authors who wrote about wealth inequality is Karl Marx (Moham, 2022). Marxian theory see the root of economic inequality in the distribution of capital and labour. His critique stats that although workers offer the labour that actually produces value, most profits go to the owners of capital. The debate around wealth and wealth inequality has continued ever since, but the mechanisms at play are still not completely understood.

Research about the relationship between wealth and generosity shows mixed results. Some findings suggest a positive relationship (Cardenas, 2003; Piff et al., 2010) , were others find a negative one (Gintis et al., 2001) . Generosity is a type of pro-social behaviour were individuals share or give away resources without direct reciprocity from the other party (Klapwijk & Van Lange, 2009; Smith & Davidson, 2014) . When it comes to material wealth, someone can be seen as generous when they share or give away a significant part of their wealth. Here we bump in to some subjectivity, because what is seen as generous is often decided by other people and less so by an objective measurement. What is seen as generous depends on the environment and culture this behaviour is seen. For example, sharing food with someone you do not know, might be seen as generous by some cultures, but may be a norm within other cultures.

A lot of research has been done about the relationship between wealth and generosity. However, like in many cases, most research has been done within a WEIRD context (Henrich et al., 2010). WEIRD is an acronym meaning: Western, Educated, Industrial, Rich and Democratic. Individuals from a WEIRD society are often more easy to reach. They are well connected, often close to the researchers themselves, and most of the time are more willing to participate. However, this is a problem in the case of generalizability of findings within social sciences. One example is the research done by Haidt (2012) about moral psychology. Haidt found that WEIRD individuals are far more liberal then people in general and where more likely to accept so called harmless taboos.

It would be easy to imagine that different social mechanism are dominate within a non-WEIRD context compared to a WEIRD context, especially within a poorer population sample compared to a richer one. Taking a closer look at these non-WEIRD individuals will give us a deeper understanding the variation of human behaviour in relation to the societal context they live in. It can show us which social mechanism are at play when looking at the relationship between wealth and generosity within a non-WEIRD context.

The aim of this thesis is to examine the relationship is between wealth and generosity within the context of rural Colombia. By focusing on the rural Colombian context, a better understanding can be gained of the mechanisms at play within this cultural context. Rural Colombia is an unique non-WEIRD context (Redhead et al., 2023; Redhead et al., 2024). Colombia is not a cultural western country and ethnically diverse. Individuals in rural Colombia are less educated, but more importantly less wealthy and less industrialized. Rural Colombian communities are not only less wealthy in comparison to the western world, they are also less wealthy in comparison to urban Colombian communities (Colombian Reports, 2023). Although some areas have some level of industrialization or market integration, other parts still live of small scale agriculture, fishing, horticulture and hunting. The four communities who were studied for the data I used within the thesis fit the characteristics stated above. I plan to test if there is a positive of negative relationship between wealth and generosity within these communities. I will use the data collected by Redhead and colleagues, with 467 respondents across four different villages. Moreover, I will look at what role sex, age, friendship and kinship play within this relationship and try to look at the differences between these villages. In sum, this leads us to the following research question:

"What is the relationship between wealth and generosity within the rural Colombian context?"

Theory

Generosity is closely related to cooperation. Cooperation an individual helps others by investing time or paying another cost. This can be as small as doing the dishes together and as big as combating climate change. Cooperation is not only a human activity, in fact all social animals cooperate in variating degrees (Waal, 2020). Great apes, like chimpanzees and bonobo's, cooperate in ways which are very similar to us humans. They share food, take care of each other's children, make friends and even make alliances within the group to gain influence. Behavioural biologist believe cooperation is rooted within our evolution (Jaeggi & Gurven, 2013; Nowak, 2006). Cooperation increases the survival changes of individual and the group.

Although cooperation in most cases lead to a better outcome, it is often unsuccessful. This may happen due to failed attempts, but in many cases individuals choice actively not to cooperate. The best way to understand this is with the theoretical framework known as the prisoners dilemma (Van Vugt & Van Lange, 2006; De Graaf & Wiertz, 2019). The prisoners dilemma is a specific situation in game theory. Game theory is a theoretical framework used in economics, psychology and sociology. Game theory looks at the choices individuals or players make in situations, which are named games. Game theory states that players make choices based on the pay-off they will receive. Important to note is that these choices are conditional, the pay-off is dependent on the choice other players make. The most used version of game theory is the so called prisoners dilemma. Here, two individuals or players face a social dilemma where they have the option to either cooperate or defect. Their options are shown in in table 1 below. The hypothetical pay-off value for each action is reported. It is important to note that these choices are conditional, meaning the pay-off depends on the choices both players make. If both cooperate, the pay-off value is 2 per player and 4 in total. However, because the pay-off is conditional, defecting when the other person cooperates has a greater pay-off of 3. If the other player defects, it is also better to defect, because a pay-off of 1 is still higher than 0. This means the best option on the individual level is always to defect, but the best option for all is actually to cooperate.

		Player 2 (alter)			
		Cooperate (C)		Defect (D)	
Player 1 (ego)	Cooperate (C)	2, 2	C, C	0, 3	C, D
	Defect (D)	3, 0	D, C	1, 1	D, D

Table 1: Example of a prisoner's dilemma, pay-off value for each strategy is reported in each cell

In theory the dominate strategy is to always defect, which explains why cooperation doesn't always happen. Cooperation requires trust in the other individual, trust in the fact the other one will cooperate as well. In most cases cooperation happens more than ones. Every time cooperation is successful, trust is reinforced. The opposite is true as well, defecting reinforces distrust.

Like cooperation, generosity is a type of pro-social behaviour, meaning it increases social relationships in a positive way (Klapwijk & Van Lange, 2009; Smith & Davidson, 2014). There are some differences however. Cooperation is based on reciprocation, both individuals can work towards a better pay-off for both parties. This can happen simultaneously or with social favours. Generosity differs in that the reciprocity is not automatically implied. Doing something generous implies doing or giving something without automatically being reciprocated. Often generous giving is believed by the recipient to go further than socially necessary. In terms of game theory, this means choices are not conditional. A player who is generous choices to cooperate, regardless of the choice other players make.

Costly signalling

Generosity might however not immediately be reciprocated, it might still be benefitable to the generous sender. Being perceived as generous can have a positive effect on the reputation of an individual (Gintis et al., 2001; Nowak, 2006). Reputation is a mechanism that shows others what kind of person you might be. It is a collective idea within the community of an individual, which is spread by gossip. By being generous, others may perceive you as a generous person, which may give you a reputation of a generous or trustworthy individual. Of course it might built trust with the individual who received a generous gift, the effect be more defuse as well. Reputation can be a stand in for trust when direct knowledges of an individual is missing. Someone might not personally know if someone is trustworthy, but a positive reputation of someone within the community might pursue someone to trust them anyway.

Giving generously could be used to signal to others you are a trustworthy individual. This mechanism is described as costly signalling (Gintis et al., 2001; Bird et al., 2001). The signal is costly due to the high cost of generous giving, it takes a lot of money or resources to show others if you are a good quality partner to cooperate with. Due to this high cost, it likely that wealthier individuals are more able to signal. This leads me to my first hypotheses:

H1a: Wealthier individuals are more likely to show generous behaviour.

Interdependence

Cooperation is not always necessary. In some situation, individuals are able to reach goals without help from others. Cooperation can be a risky strategy, because it is not always clear if cooperation is reciprocated. However in some situations cooperation can be the only option to survive. If cooperation is necessary depends on the individual context and access to alternatives (Piff et al., 2010; Cardenas, 2003; Keltner et al., 2003). Wealth is one way to avoid cooperation, someone can simply buy their way out of a social dilemma. For poorer individuals this is often not an option, so cooperation is a greater necessity. Due to this, poorer individuals are often more interdependent on each other for help and other resources. If individuals are more dependent on each other to survive, it might be beneficial to be generous when sharing. If you are seen as more generous, you are more likely to be trusted by other. This leads me to my second hypothesis, which is opposite to the first one:

H1b: Wealthier individuals are less likely to show generous behaviour.

Relationship influences

Cooperation is easier when individuals know and trust each other. Two types of relationship are most likely to play some role when it comes to the relationship between wealth and generosity. First off, individuals are more likely to be generous toward family members (Nowak, 2006; Jaeggi & Gurven, 2013). Families are often the closed individuals to us and family members are in many cases trusted. Evolutionarily it also makes sense to be generous to family members due to shared genes. If someone helps out family members, they are in a way helping out part of a shared gene pool which increases the survival rate for those genes. Friendship is the second type of relationship. Friendship can mean a lot of different things for different people, but in general people like to spend time with their friends (Redhead et al., 2023). Generosity toward friends helps to reinforce friendship and makes reciprocated pro-social behaviour even more likely.

Kinship or family is often a source of wealth, because wealth is often shared within families and households. Therefore I believe kinship has a spurious effect on the relationship between wealth and generosity. Friendship might be partially influenced by wealth, either because wealth might attract more friends, or because similar levels of wealth might make friendship easier due to a shared social class identity (Keltner et al., 2003). My hypotheses for these variables are:

H2: Part of the effect of wealth on generosity can be explained by a spurious effect of kinship

H3: Part of the effect of wealth on generosity can be explained by a mediation effect of friendship

Control variables

Age and sex may have some effect on wealth and generosity. Wealth is often accumulated within a lifetime, which means older individuals are more likely to own more material wealth (Kapteyn et al., 2005). Older individuals are also more likely to be generous due to less immediate need for resources. Teenagers and young adults often are in a developmental phase where they place themselves before others (Siegler et al., 2014).

The gender wage gap is worldwide still a significant issue. Women are paid less then men on average, so it is likely that men accumulate more wealth as well (Blau & Kahn, 2017). The relationship between sex and cooperation is often different between situations. These are often triggered by network structure differences and associated gender identities (Sell & Kuipers, 2009).

Community differences

Finally I believe there will be some differences between the four communities. There is a lot of variation between these communities, because of different subsistence practices, geographic isolation and internal displacement due to violence (Redhead et al., 2023; Redhead et al., 2024). Unlike friendship and kinship, these factors are difficult to quantify, but can absolutely play a role. These factors may lead to a shared identity, shared values or increased interdependence (Kadushin, 2012). It is difficult to say how these factors influence the relationship between wealth and generosity, but I do believe there is some influence. This leads met to my last hypothesis:

H4: The effect of Wealth on Generosity differs between the four communities.

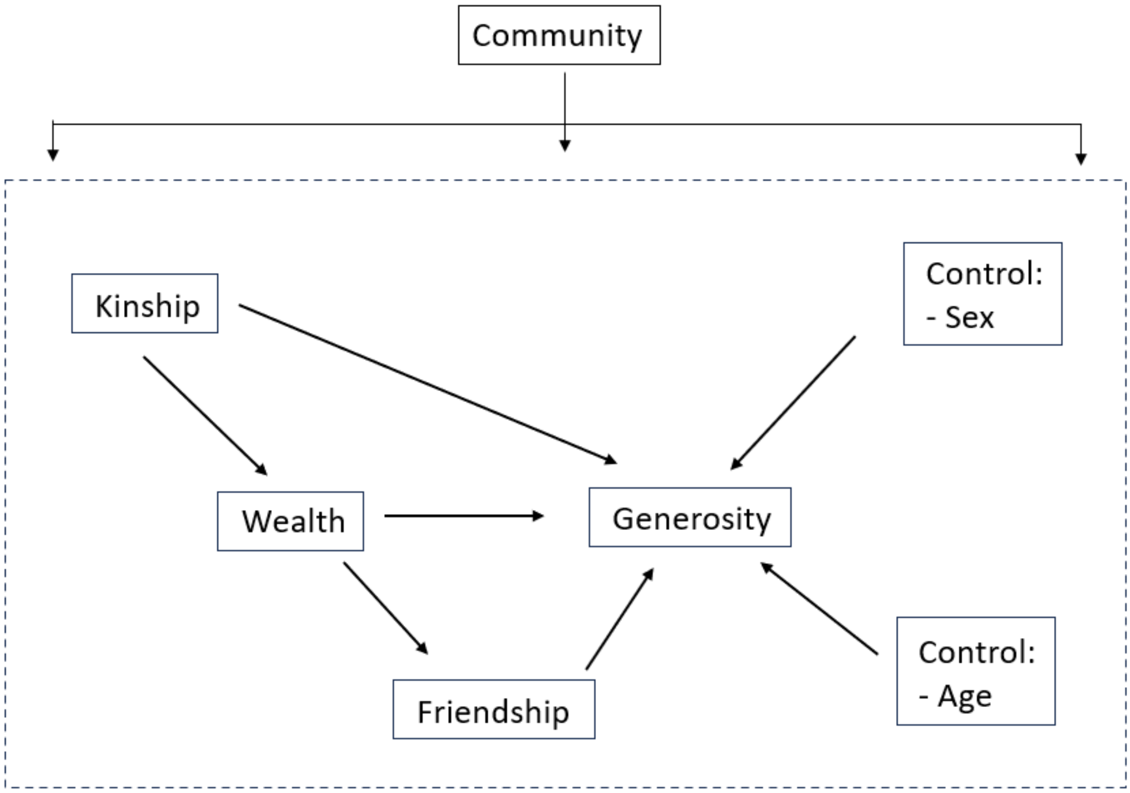

Figure 1: Graphic visualization of research model

Method

Sample and community characteristics

The dataset used was collected by Redhead and colleagues. The sample contains 467 respondents from four different villages within Colombia (Redhead et al., 2023; Redhead et al., 2024). These communities are:

- A coastal Afrocolombian/ Emberá community (n = 117)
- A lowland Afrocolombian/Emberá community (n = 149)
- A highland Mestizo community (n = 65)
- An Altiplano Mestizo community (n = 136)

Henceforth these communities will be named by their geographic signature: the coastal, lowland, highland and altiplano communities. All adult residents from these communities where asked to participate and the non-response was actually quite low. Almost everyone from the coastal, lowland and highland community participated and three-quarters of the altiplano community participated. Informed consent was obtained for all respondents, although in some cases this was done verbally due to low literary rates. The communities have some differences when it comes to ethnic composition, geographic isolation, subsistence and labour practices and internal displacement due to violence.

Coastal

The coastal community is the most isolated of the four communities. They require a long-distance boat or air trip to reach. 53% of the respondents identified as woman, the average age is 39,8 years (*SD* = 15,6), median household wealth is 5880, and 68% identified as Afro-Colombian, 24% as Emberá, 7% as Mestizo, and one individual as Afro-Emberá.

Lowland

The lowland community is still relatively isolated, but can be reached by bus within three to four hours. The community is located in the rainforest in the west of Colombia. It is relatively close to the highland community, only a 40 minutes bus ride. 61% of the respondents identified as woman, the average age is 46,3 (*SD* = 18,4), the median household wealth is the lowest of all four communities with 4350, and 78% identified as Afro-Colombian, 14% as Emberá and 12% as Mestizo.

Highland

As mentioned before, the highland community is relatively close to the lowland community, and therefore also relatively isolated. 55% of the respondents identified as woman, the average age is 37,0% (*SD* = 17,4), the median household wealth is 5455, and 94% identified as Mestizo, 4,6% as Afro-Colombian, and one individual as Emberá.

Altiplano

The Altiplano community is the least isolated of the four communities. It is only a 1,5 hour bus ride away from the capital Bogotá. 60% of the respondents identified as woman, the average age is 39,1 (*SD* = 16,6), and all respondents identified as Mestizo. The median household wealth was by far the highest with 10630, but compared to the urban area this is still relatively low.

Subsistence and labour

Fishing and local wage labour are the primary subsistence and labour practices within the community. To a lesser extent, there is some hunting, horticulture and animal husbandry as well. By selling some fish, there is a limited amount of market integration. The lowland community lives of a mixture of horticulture, local wage labour, hunting, animal husbandry. Artisanal gold panning, a small scale form of mining by filtering gold from rivers, is also practiced. In both communities, market integration is limited and mostly focuses on self-reliance.

The highland and Altiplano community are more market integrated. The highland community is based on small-scale agricultural production of coffee and sugarcane. The altiplano community is lives primarily on wage labour, mostly within large-scale flower cultivation.

Internal displacement due to violence

The coastal and lowland communities have been greatly affected by the internal conflicts within Colombia over the years. Due to this, a lot of individuals are internally displaced. The highland community lays on the border of former guerilla territory. The altiplano community meanwhile lays distant from these conflict zones. Together with the other differences a clear association can be seen between these factors. The coastal and lowland communities are geographically isolated, are mostly self-reliant and are the most affected by internal violence. Meanwhile, the altiplano community and to a lesser extend the highland community, are better connected, more market integrated and less affected by internal violence. It is also imported to note that the ethnic composition is really different between the mostly Afro-Colombian and Emberá communities, and the Mestizo communities. Furthermore, the relative distance from the violence in the Altiplano community might also explain the somewhat higher levels of household wealth. It is simply easier to accumulated wealth when the living environment is more stable. Lastly, it should be noted again that while there are some differences between these communities, all of them experience some levels of poverty in comparison with the urban areas in Colombia.

Data collection and procedure

The field work was done in two waves. First, surveys about different demographic and network data were collected. These took place in 2016-2017 for the coastal and lowland community, and in 2018-2019 for the Highland and Altiplano community. In the second wave the data from the RICH economic games where collected. These took place in 2017-2018 for the coastal and lowland community, and in 2018-2019 for the highland and altiplano community. Due to some emigration the number of respondents was somewhat smaller (n = 393; coastal: n = 93; lowland: n = 135; highland: n = 57; altiplano: n = 109).

Rich economic games

Three RICH economic games where preformed during the second data collection. To measure the concept of generosity embedded within the community, the allocation RICH game was used (Pisor et al., 2020). The allocation RICH game is similar to the economic dictator game, which is a measurement instrument for generosity. In it most basic form a player gets a small amount of money. They then have to distribute the money between themself and a secondary player. The player can keep everything, share some money, or even all of it. The second “player” cannot respond within the dictator game, hence the name of the game, player 1 decides everything like a dictator. This means there is no direct incentive to give any money away, which is ideal when measuring generosity. Giving away money can only be because of generosity.

The allocation game is a bit different from the dictator game. Just like in the dictator game, players where given a small amount of money, they could keep or share, without input from others. The differences is that player could now share their money with other members from the community. This was done by placing money on the photos of individuals within the community, see figure 2 below. If they wanted to share, they could do this with multiple individuals. Furthermore, this means generous giving is now embedded within the community, because money is shared with people they actually know. In the end a network of this data can be constructed that shows who gave who what and how much.

(a)

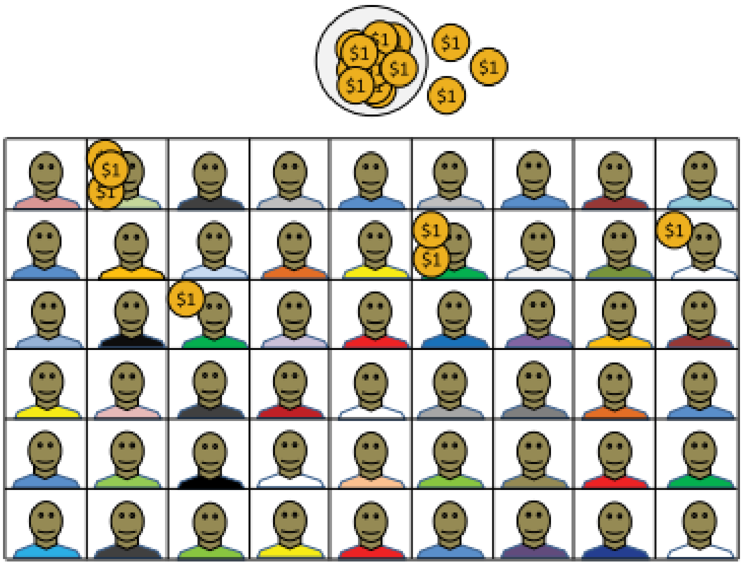

Figure 2: research design for the RICH economic allocation game. Individuals where given a small amount of money they could either keep or share with community members by placing the money on the picture (Pisor et al., 2020).

Variables

The control variables sex and age were measured with a socio-demographic survey. Participants gave their self-reported age and gender identity. Age is measured in years, including months. Sex coded with M for men and F for woman. These have been recoded to: 0 = men and 1 = women.

The kinship network was constructed by asking respondents to name all their parents, children, and siblings. These where given the relatedness value of 0,5. For lower values the degree of separation was used, so if A is the child of B, and B the child of C, it makes A the grandchild of C and has a relatedness value of 0,25. To create the variable for close kinship the network was dichotomized with all values equal or greater then 0,25 recoded to 1 and all other values recoded to 0. Next, the degree centrality for each node were calculated. These values showed the number of close family member each respondent has within the community, the higher the value, the more close family members each individual has.

The friendship network was measured with the question: "Name whom you spent the most time socializing with" in the month prior to the interview. This created a binary network with: 1 = friendship and 0 = no friendship. It is important to note that the friendship network is not symmetrical, which means not all friendship ties where reciprocated. To construct the friendship variable, the outdegree centrality values where used. The outdegree values were chosen, because for the analysis it matters whether the respondents themselves thought an alter was a friend, and less so if alter agrees with ego or not. The outdegree centrality value is the sum of friendship nominations by alter, or in other words: the count of how many friends the participants thinks they have. Both the variables for kinship and friendship were recoded with the UciNET software.

The variable wealth was measured by giving an estimate monetary value of material items in the participants household, for example: vehicles, computers, refrigerators, livestock, and more. This estimate is the sum of these material items in the local currency. The variable was transformed by taking the logistic function of wealth. The transformation makes the variable a bit more difficult to interrupt, but it does mean there is now a linear relationship between (log)wealth and generosity. If the value of log wealth is one step higher, this means the real wealth increase is a factor ten.

Generosity was measured with the RICH allocation game. Participants were given 10.000 (Highland and Altiplano), 15.000 (Coastal), or 20.000 (Lowland) Colombian peso's. They could allocate this money between different individuals within their community by placing it on photos of the other, keep everything for themselves, or a mix of the two. Money could be allocated between multiple individuals. Generosity was recoded two times, first to a rate by dividing the each value by the maximum possible value for each community. Then, the variable was dichotomized with a cut-off point of 0,5. The new binary variable was used as a dependent variable in the logistical regression.

Analysis plan

In order to test the four hypotheses I want to estimate the following models shown in the table below:

Table 2: Models used to test hypothesis, with variables, dependent, and type of regression

	Variables	Dependent	Regression type
Model 1	Sex and Age	Generosity	Logistical regression
Model 2	Sex, Age, and Wealth	Generosity	Logistical regression
Model 3	Sex, Age, Wealth and Kinship	Generosity	Logistical regression
Model 4	Sex, Age, and Kinship	Wealth	Linear regression
Model 5	Sex, Age, Wealth and Friendship	Generosity	Logistical regression
Model 6	Sex, Age, and Wealth	Friendship	Linear regression
Model 7	Sex, Age, Wealth, Kinship, and Friendship	Generosity	Logistical regression
Model 8	Sex, Age, Wealth, Kinship, and Friendship	Generosity	Logistical regression split by community

In order to see what the effect of the control variables is on generosity, I will look a model 1. To test the first hypothesis (H1a and H1b), whether there is a positive or negative effect of wealth on generosity, I will look at the results of model 2. I will also compare the first and second model to control for sex and age.

The second hypothesis is about whether there is a spurious effect of kinship on the relationship between wealth and generosity. The second hypothesis (H2) can be tested by comparing the results form models 2, 3 and 4. First by looking at the previously discussed relationship between wealth and generosity in model 2. Then by looking if there is a relationship between kinship and wealth in model 4. Finally I will look at the difference in the effect size of wealth on generosity within model 2 and within model 3, were both wealth and kinship are included.

The third hypothesis (H3) is about whether there is a mediating effect of friendship on the relationship between wealth and generosity. I will test this hypothesis by again first looking at the effect of wealth on generosity within model 2. Then I will look if there is an effect of wealth on friendship within model 6. Finally, I will compare the effect size of wealth on generosity in model 2 and model 5.

Model 7 is the effect of all variables on generosity. Model 8 is in essence the same as model 7, except that the results are split per community. By comparing the different confidences intervals around the coefficients within models 7 and 8, it is possible to eyeball if the last hypothesis (H4) is true.

Results

Networks

In figures 3, 4, 5 and 6 are the multiplex networks visualized of each community. The colour of the nodes indicates the level of generosity in the allocation game, with green meaning high, red meaning low and white meaning a non-response. The size is the material wealth of the respondent relative to the rest of the community. Solid lines indicated a friendship nomination and dotted lines are close kinship relationships. These networks can give a quick overview of the general characteristics of each community.

Figure 3 shows the multiplex network for the coastal community. There is no clear correlation visible between node size and colour. The combination of both friendship and kinship networks shows three large clusters who are only connected by two friendship ties. In social network literature these are described as bridges, because they bridge the connection between otherwise disconnected groups. Higher wealth does seem to correlate with a more central position within the network, meaning wealthier individual are more connected then others.

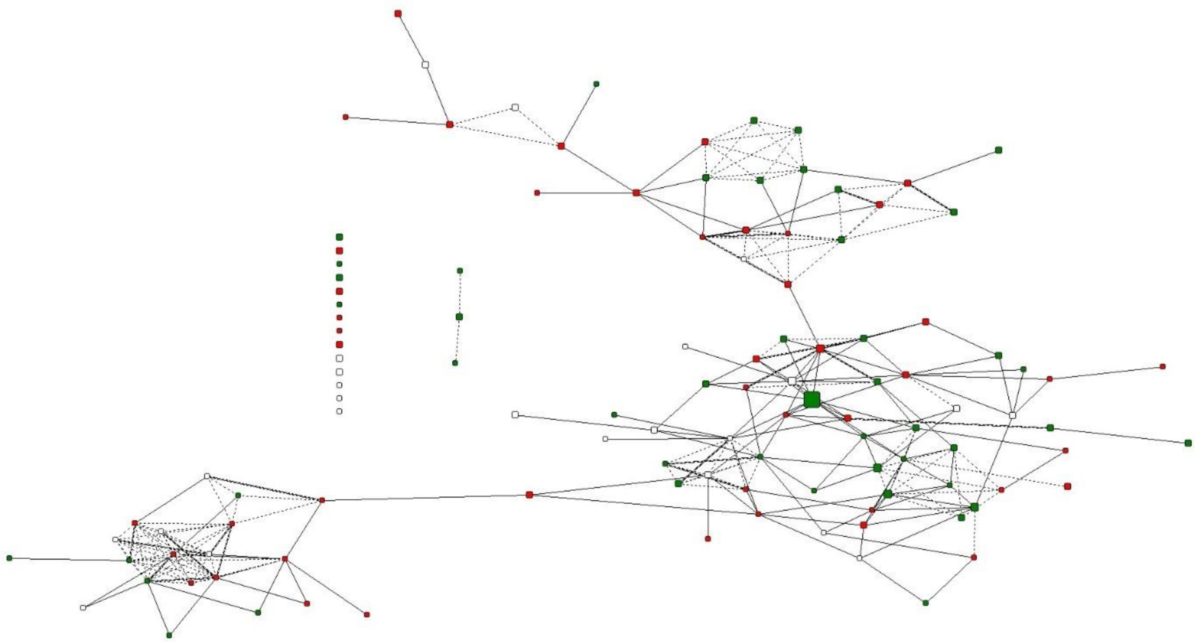

Figure 3: Network visualisation of the coastal community

Figure 4 shows the multiplex network for the lowland community. Again no clear association between generosity and wealth is visible. This community seems to be relatively well connected, with no clear clusters and only a handful of isolated individuals.

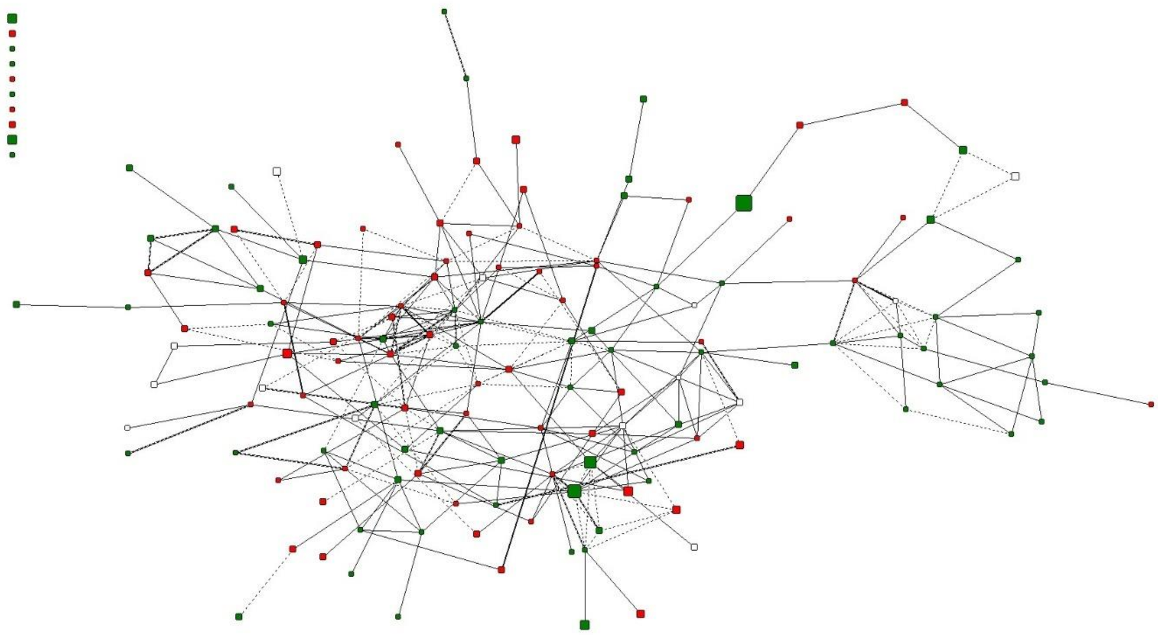

Figure 4: Network visualisation of the lowland community

Figure 5 shows the multiplex network for the highland community. This community is by far the smallest and looks to be relatively close knit, although there are still some isolates as well. Again, no clear association between wealth and generosity is visible.

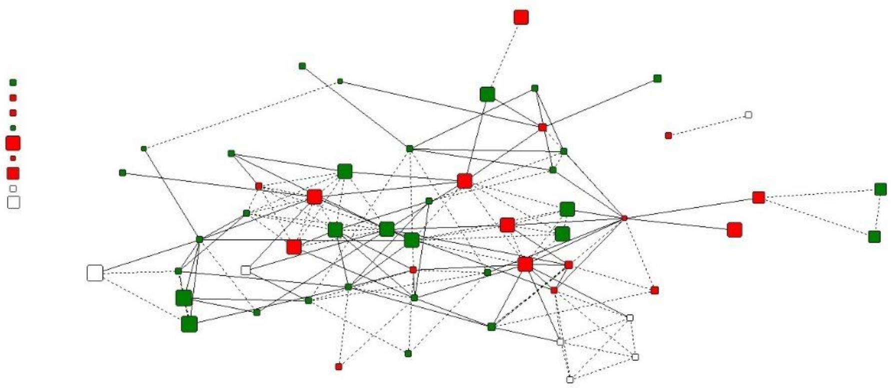

Figure 5: Network visualisation of the highland community

Figure 6 shows the multiplex network for the altiplano community. The friendship network is small within the community and most connections are close kinship relations. This means a lot of smaller isolated groups are visible and if kinship clusters are connected this is because of only one or two friendship nominations. Again, no clear association between wealth and generosity is visible.

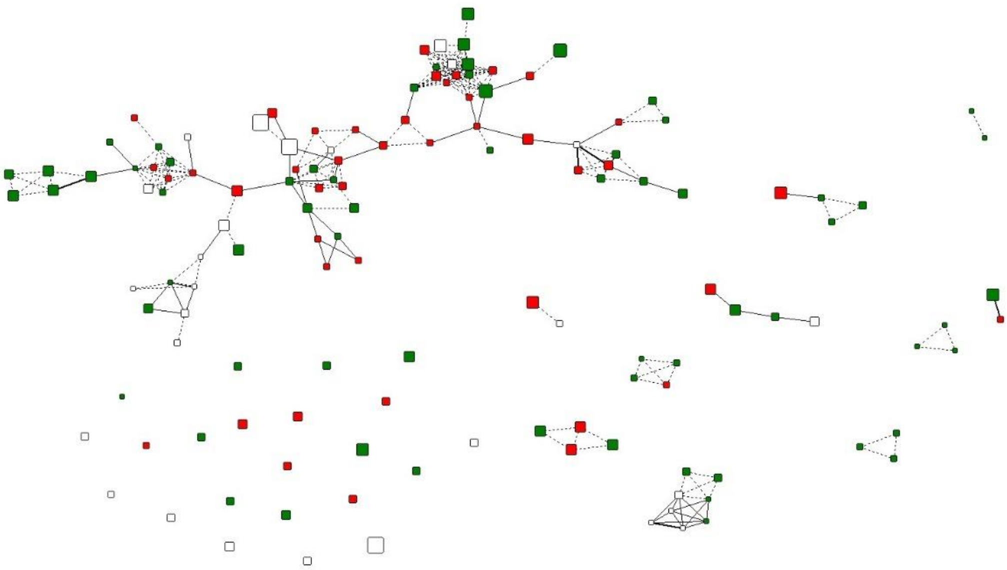

Figure 6: Network visualization of the altiplano community

The tables below show some specific network descriptives for friendship and kinship. Both the friendship and kinship network of the highland community have the highest density, respectively *0,021* and *0,037*. Because the community is also the smallest of the four, it is likely to be a relatively close knitted community. The friendship for the altiplano community is the smallest, with a density of *0,004* and only 68 friendship ties. The transitivity is however relatively high *(0,597)*, which indicated that most friends are also friends with each other's friends. Friendship may play a different role within the altiplano community in comparison to the other communities. Family ties within the altiplano community are in contrast more numerous with 24 distinct family clusters and 372 close kinship ties. The coastal community is relatively average in value compared to the other communities. The kinship network in the lowland community is the least dense of all the communities (*0,009)*, but has the highest number of family clusters. This may indicate relative small family clusters with only the immediate family, like parents and children.

Table 3: Descriptions of friendship network included within the analysis: Density, Transitivity and Reciprocity

Community	*Density*	*Transitivity*	*Reciprocity*	*N Nodes*	*N Ties*
Coastal	0,013	0,214	0,164	117	177
Lowland	0,012	0,134	0,144	149	262
Highland	0,021	0,221	0,178	65	86
Altiplano	0,004	0,597	0,153	136	68

Table 4: Descriptions of Kinship network included within the analysis: Density, Number of clusters, Number of nodes and Number of ties

Community	*Density*	*N Clusters*	*N Nodes*	*N Ties*
Coastal	0,019	13	117	260
Lowland	0,009	21	149	200
Highland	0,037	13	65	154
Altiplano	0,020	24	136	372

Descriptive statistics of variables used within the analysis

In table 5 the descriptive statistics are given for the different variables within the analysis. I will briefly discuss some noteworthy details. The rate for generosity is heavily skewed *(median = 0,90)*, which indicates that most individuals gave away most of their money in the allocation game and at least 25% gave everything away *(Q3 = 1)*. The network variables friendship *(mean = 1,62; max = 9)* and kinship *(mean = 2,16; max = 13)*, are heavily skewed as well. This is meanly because most individuals only have 1 or 2 friends and only a handful of individuals have a lot of friends. Wealth was also heavily skewed, but the log transformation helped to normalize the variation for wealth *(mean = 3,70; SD = 0,63)*. There are a lot more female respondents *(60,5%)*, compared to male respondents. The highest proportion of respondents are from the lowland community *(34,4%)* and the lowest proportion from the highland community *(14,3%).*

Table 5: Descriptions of variables included within the analysis: Mean (standard deviation), five-number summary and number of respondents (excluding respondents with missing data on one or more cases)

Variable	*Mean (Standard deviation)*[a]	*Minium*	*Q1*	*Median*	*Q3*	*Maximum*	*N total*
Age	42,59 (17,58)	14,33	28,38	40,21	55,71	89,00	392
Generosity	0,79 (0,24)	0	0,70	0,90	1	1	392
Friendship	1,31 (1,62)	0	0	1	2	9	392
Close kinship	2,16 (2,64)	0	0	1	3	13	392
Wealth (log)	3,70 (0,63)	1,3	3,52	3,77	4,12	5,01	392
Sex (Male=0, Female=1)	39,5% male 60,5% female	-	-	-	-	-	392
Community (Coastal=1, Lowland=2, Highland=3, Altiplano=4)	23,7% coastal 34,4% lowland 14,3% highland 27,6% altiplano	-	-	-	-	-	392
Generosity: Binary (Low=0, High=1)	14,8% Low 85,2% High	-	-	-	-	-	392

[a] In case of categorical variable, the frequencies in percentages are reported instead.

Table 6 shows the same descriptives as above, but split out per community. These can show some important variation between the different communities. Although generosity is high in all communities, there are some differences. The most generous community is the highland community *(mean = 0,85)* and the lowest is the lowland community *(mean = 0,75).* Friendship and kinship show some variation as well. Respondents from the lowland community *(mean = 1,75)* have more then two times as much friends on average compared to the altiplano community *(mean = 0,80)*. The opposite is true for kinship, where respondents form the altiplano community *(mean = 2,91)* have more the two times as much close family members compared to the lowland site *(mean = 1,37)*. The average of wealth is relatively similar in each community *(means = 3,61; 3,50; 3,88; 3,94),* however the range between the minimum and maximum values does variate a bit. The highest range is the coastal community *(min = 1,30; max = 5,01),* where is the lowest range is in the altiplano community *(min = 2,48; max = 4,54).*

Table 6: Descriptions of variables included within the analysis per community: Mean (standard deviation), five-number summary and number of respondents (excluding respondents with missing data on one or more cases)

Variable	*Mean (Standard deviation)[a]*	*Minium*	*Q1*	*Median*	*Q3*	*Maximum*	*Community*
Age	41,07 *(15,72)*	19,00	29,88	39,50	50,08	87,83	*c*
	47,13 *(18,33)*	18,67	30,08	43,92	63,50	89,00	*l*
	38,22 *(17,94)*	14,33	23,25	34,21	51,83	88,83	*h*
	40,51 *(16,97)*	16,25	24,88	40,58	50,17	81,92	*a*
Generosity	0,78 *(0,24)*	0	0,67	0,87	1,00	1	*c*
	0,75 *(0,25)*	0	0,65	0,85	0,95	1	*l*
	0,85 *(0,19)*	0	0,80	0,90	1,00	1	*h*
	0,80 *(0,27)*	0	0,73	0,90	1,00	1	*a*
Friendship	1,65 *(1,86)*	0	0	1	3	9	*c*
	1,75 *(1,71)*	0	0	1	3	7	*l*
	1,41 *(1,52)*	0	0	1	3	5	*h*
	0,80 *(0,27)*	0	0	0	1	5	*a*
Close kinship	2,30 *(2,81)*	0	0	1	4	10	*c*
	1,37 *(1,76)*	0	0	1	2	7	*l*
	2,41 *(1,98)*	0	1	2	4	6	*h*
	2,91 *(3,38)*	0	0	2	4	13	*a*
Wealth (log)	3,61 *(0,74)*	1,30	3,36	3,82	4,09	5,01	*c*
	3,50 *(0,69)*	1,48	3,35	3,62	3,91	4,86	*l*
	3,88 *(0,42)*	2,85	3,61	3,74	4,37	4,45	*h*
	3,94 *(0,39)*	2,48	3,74	4,05	4,22	4,54	*a*
Sex	43,0% Male; 57,0% Female						*c*
(Male=0,	37,0% Male; 63,0% Female						*l*
Female=1)	48,2% Male; 51,8% Female						*h*
	35,2% Male; 64,8% Female						*a*
Generosity:	9,7% Low; 90,3% High						*c*
Binary	23,0% Low; 77,0% High						*l*
(Low=0, High=1)	7,1% Low; 92,9% High						*h*
	13,0% Low; 87,0% High						*a*

[a] In case of categorical variable, the frequencies in percentages are reported instead.
[c] *Coastal community; N = 93*
[l] *Lowland community; N = 135*
[h] *Highland community; N = 56*
[a] *Altiplano community; N = 108*

In table 7 the correlations between variables are shown. In the upper conner the overall correlations are reported, including community differences. In the bottom conner the correlations for each community are reported. First I will look at the upper conner and secondly at the bottom conner.

Most correlations are relatively small and non-significant. Excluding community differences, the largest associations are between friendship and age *(r = 0,117; p < 0,05)* and between wealth and kinship *(r = 0,120; p < 0,05).* This indicates that individuals are more likely to befriend others of the same age, and that individuals with more close family members have more household material wealth.

The largest differences are between the different communities. Generosity *(F = 4, 072),* Age *(F = 5,042),* Kinship *(F = 7,526),* Wealth *(F = 13,008)* and *(F = 17,824),* show significant between group differences. In the bottom corner the differences in correlations between communities even more clear. The effect sizes are much greater, and there is a lot of variation between the communities. These results may suggest that different variables or mechanisms are at play within each community.

Table 7: Correlations between variables used within analysis. Upper conner includes all cases used in the analysis, bottom conner shows effects split by community.

	Sex	Age	Kinship	Wealth	Friendship	Generosity	Community[a]
Sex	-	-0,048	0,028	-0,014	0,011	-0,087	0,009 (1,146)
Age	-0,070[c] -0,103[l] 0,190 -0,123	-	-0,066	-0,033	0,117*	-0,087	0,038 (5,042)**
Kinship	0,078[c] 0,110[l] -0,071[h] -0,020[a]	-0,157[c] 0,108[l] -0,148[h] 0,001[a]	-	0,120*	-0,009	0,080	0,055 (7,526)**
Wealth	-0,012[c] 0,019[l] 0,003[h] -0,099[a]	0,088[c] 0,021[l] 0,114[h] -0,159[a]	0,029[c] 0,037[l] 0,390**[h] 0,046[a]	-	-0,037	0,041	0,091 (13,008)**
Friendship	0,033[c] 0,031[l] 0,002[h] 0,036[a]	-0,093[c] 0,278**[l] -0,071[h] 0,069[a]	0,010[c] 0,190*[l] 0,287*[h] -0,107[a]	0,207*[c] 0,000[l] 0,058[h] -0,191*[a]	-	-0,028	0,121 (17,824)**
Generosity	0,156[c] -0,200*[l] -0,268*[h] 0,004[a]	-0,133[c] 0,081[l] -0,381**[h] -0,100[a]	0,244*[c] -0,206*[l] 0,093[h] 0,137[a]	0,088[c] -0,030[l] -0,026[h] 0,010[a]	0,035[c] 0,012[l] 0,075[h] -0,219*[a]	-	0,031 (4,072)**

[a] For the variable community the eta-squared (anova) and F-value are reported instead
[c] *Coastal community*
[l] *Lowland community*
[h] *Highland community*
[a] *Altiplano community*
**significant at $p<0,05$, **significant at $p<0,01$, $N_{total} = 392$, $N^c = 93$, $N^l = 135$, $N^h = 56$, $N^a = 108$*

Model fitness

At first my goal was to estimate a number of models with linear regression. With these I would be able to estimate a path model with all six variables. As can be seen in appendix 3, a number of assumptions did not hold up, so different statistical models where used for the analysis. The main issue was the normal distribution of the residuals. This assumption did not hold, mostly due to the skewed variation of generosity. Therefore I choose to do a binary linear regression instead. The observations where not independent from each other as well. A better fit for the data would be a network analysis, but this goes beyond the scope of the bachelor thesis.

Some data point had a high leverage, cook's distance or standardized residual value. This may indicate that some point had a higher influence within the dataset. When I run the analysis again without the most influential points, no clear difference was found in the results. These values where therefore not excluded from the dataset. One outlier was found for the age variable and was excluded from the dataset. Someone had a reported age of 6 years, which is likely a reporting error.

No indications of multicollinearity where found, the highest Variance Inflations Factor (VIF) found was 1,157. Ethnicity was excluded in a early stage due to possible multicollinearity with the variable community. Ethnic composition of the communities is one of the main characteristics of each community, therefore the concepts measure in theory partially the same thing.

Tabel 8: Results of logistical regression analysis with Generosity as dependent variable, wealth as independent, kinship as spurious, and friendship as mediati variable

	Model 1			Model 2			Model 3			Model 5			Model 7		
	b (SE)	Odds-ratio	*p-value*	*b* (SE)	Odds-ratio	*p-value*	*b* (SE)	Odds-ratio	*p-value*	*b* (SE)	Odds-ratio	*p-value*	*b* (SE)	Odds-ratio	*p-value*
Constant	2,745 (0,455)	15,563	<0,001**	2,125 (0,934)	8,373	0,023*	2,085 (0,938)	8,045	0,026*	2,154 (0,940)	8,619	0,022*	2,111 (0,942)	8,257	0,025*
Sex	-0,559 (0,311)	0,572	0,072	-0,558 (0,311)	0,986	0,073	-0,579 (0,313)	0,560	0,064	-0,557 (0,331)	0,573	0,073	-0,578 (0,313)	0,561	0,064
Age	-0,014 (0,008)	0,986	0,071	-0,014 (0,008)	0,986	0,075	-0,014 (0,008)	0,986	0,087	-0,014 (0,008)	0,986	0,083	-0,013 (0,008)	0,987	0,096
Wealth				0,166 (0,221)	1,180	0,453	0,125 (0,223)	1,133	0,577	0,164 (0,221)	1,178	0,459	0,123 (0,224)	1,131	0,581
Kinship							0,099 (0,066)	1,104	0,135				0,099 (0,066)	0,973	0,755
Friendship										-0,026 (0,087)	0,974	0,974	-0,027 (0,087)	1,104	0,134
Deviance	*322,318*			*321,775*			*319,253*			*321,685*			*319,156*		
X2	*6,298**			*0,543*			*2,522*			*0,089*			*2,529*		
N	*392*			*392*			*392*			*392*			*392*		

**significant by p <0,05; **significant by p <0,01*

Table 9: Results of linear regression, with either wealth or friendship as dependent variable and kinship or wealth as independent variable

	Model 4[a]		Model 6[b]	
	b (SE)	*p-value*	*b* (SE)	*p-value*
Constant	3,696 (0,098)	<0,001**	1,129 (0,546)	0,039*
Sex	-0,023 (0,065)	0,719	0,054 (0,167)	0,748
Age	-0,001 (0,002)	0,606	0,011 (0,005)	0,021*
Kinship	0,028 (0,012)	0,019*		
Wealth			-0,085 (0,130)	0,514
R2 adjusted	*0,008*		*0,007*	
F Change	*2,012*		*1,979*	
N	*392*		*392*	

**significant by p <0,05; **significant by p <0,01*

[a] Dependent is wealth; [b] Dependent is friendship

Table 10: Results of logistical regression with generosity as dependent variable and all other variables as dependents. Results split by community.

	Model 8c			Model 8l			Model 8h			Model 8a		
	b (SE)	Odds-ratio	*p-value*	*b* (SE)	Odds-ratio	*p-value*	*b* (SE)	Odds-ratio	*p-value*	*b* (SE)	Odds-ratio	*p-value*
Constant	2,013 (1,890)	7,486	0,287	1,974 (1,325)	7,201	0,136	2,968 (7,404)	19,450	0,689	4,106 (3,605)	60,729	0,255
Sex	0,878 (0,795)	2,405	0,270	-1,025 (0,508)	0,359	0,043*	-	-	-	-0,003 (0,635)	0,997	0,996
Age	-0,039 (0,028)	0,962	0,163	0,011 (0,012)	1,011	0,374	-0,101 (0,053)	,904	0,055	-0,017 (0,018)	0,983	0,336
Wealth	0,217 (0,443)	1,243	0,624	-0,070 (0,315)	0,933	0,825	1,217 (2,410)	3,378	0,613	-0,376 (0,816)	0,686	0,645
Kinship	0,959 (0,534)	2,610	0,072	-0,268 (0,119)	0,765	0,025*	-0,136 (0,427)	0,873	0,750	0,149 (0,127)	1,160	0,242
Friendship	-0,027 (0,200)	0,973	0,891	0,066 (0,136)	1,068	0,627	0,189 (0,427)	1,208	0,658	-0,583 (0,314	0,558	0,064
Deviance	*45,681*			*133,908*			*20,571*			*76,297*		
X2	*13,455**			*11,576**			*8,249*			*7,010*		
N	*93*			*135*			*56*			*108*		

**significant by p <0,05; **significant by p <0,01*

[c] Coastal community; [l] Lowland community; [h] Highland community; [a] Altiplano community

Model 1 in table 8 show men are somewhat more generous overall then women (*b = -0,572; p = 0,072).* Younger individuals are also more generous then older individuals *(b = -0,014; p = 0,071)*. Both effects are non-significant, but the Chi-square value for this model is significant *(X^2 = 6,298; p < 0,05).* This means sex and age are able to explain the variation of generosity to somewhat.

Model 1 and model 2 where used to test the first two hypotheses:

- *H1a: Wealthier individuals are more likely to show generous behaviour.*

- *H1b: Wealthier individuals are less likely to show generous behaviour.*

Model 2 shows a positive effect of wealth *(b = 0,166; p = 0,453)* on generosity, controlled for sex and age. The effect is small *(OR = 1,180)* and non-significant. Model 2 shows minimal decrease of the deviance *(321,775)* and the Chi-square test for this block shows no significant increase *(X^2 = 0,543).* I do not have enough evidence to reject the null-hypotheses and therefore cannot support hypothesis 1a or 1b.

Models 2 and 3 in table 8 and Model 4 in table 9 were used to test the second hypothesis:

- *H2: Part of the effect of wealth on generosity can be explained by a spurious effect of kinship*

As stated before, model 2 shows a small positive effect of wealth *(b = 0,166; p = 0,453)* on generosity. Model 4 shows that having more close family members in the community, has a positive effect on household wealth *(b = 0,028; p < 0,05)*. Model 3 shows similar effects, with again a positive effect of more close family on wealth *(b = 0,099; OR; 1,104; p = 0,135).* The effect of wealth on generosity in model 4 is somewhat smaller *(b = 0,125),* but still not significant *(p = 0,577).* The proportional explained variance of model 4 is relatively low *(R^2 = 0,008)* and the difference with the empty model is small and non-significant as well *(F_{change} = 2,012).* Model 4 shows no fitness improvement either *(Deviance = 319,253; X^2 = 2,522).* More family members is related to higher levels of material wealth, and the effect size of wealth on generosity somewhat decreases when kinship is added within model 3, which might suggest there is some support for hypothesis 2. However, the low fitness of the models and the non-significant effect sizes of wealth and kinship in model 4 mean I cannot reject the null-hypothesis. Therefore I did not find support for hypothesis 2.

Models 2 and 5 in table 8 and model 6 in table 9 were used tot test the third hypothesis:

- *H3: Part of the effect of wealth on generosity can be explained by a mediation effect of friendship*

Model 6 show that higher levels of material wealth is related to lower number of friends *(b = -0,085)*, but the result was non-significant *(p = 0,514)*. Model 6 has a poor fitness as well *(R^2 = 0,007; F_{change} =*

1,979). Model 5 shows that more friends is related to lower levels of generosity *(b = -0,026; P = 0,974).* The effect size of wealth on generosity increases compared to model 2 *(b = 0,162; p = 0,459).* Model 5 has a poor fitness as well, the deviance decreases almost nothing *(321,685)* and the chi-square test is small as well *(X^2 = 0,089).* Friendship is negatively related to both wealth and generosity and the effect of wealth increasing when friendship is included within the model. These finding suggest a mediation effect of friendship, although it is in the opposite direction I hypothesized before. No strong evidence exist to reject the null-hypothesis again, due to the low increase in model fitness and non-significant effects. Therefore I did not find support for hypothesis 3.

Model 7 in table 8 and models 8c, 8l, 8h and 8a in table 10 where used to test the fourth hypothesis:

- *H4: The effect of Wealth on Generosity differs between the four communities.*

In the model for the highland community, I excluded the variable for sex due to small sample size and extremely high standard error when the variable was included. Figures x, x, and x show a graphical visualisation of the 95% confidence intervals around the effect for wealth, kinship and friendship on generosity. The confidence intervals for wealth overlap quite a bit and the coefficients lay close to zero. The effect of wealth on generosity in the highland community is somewhat higher *(b = 1,217),* but due to the high standard error *(SE = 2,410),* the differences is probably not significant.

The confidence intervals for kinship and friendship do show some variation. Kinship in the coastal community is related to higher levels of generosity *(b = 0,959; p = 0,072),* but in the lowland community this effect is flipped and more family is related to lower levels of generosity *(b = -0,268; p < 0,05)*. Friendship has mostly no effect on generosity, except for the altiplano community where the relationship is negative *(b = 0,583; p = 0,064).*

Because there where no clear differences between the effect of wealth on generosity between the communities, the null-hypothesis cannot be rejected. I do not find support for hypothesis 4 as well.

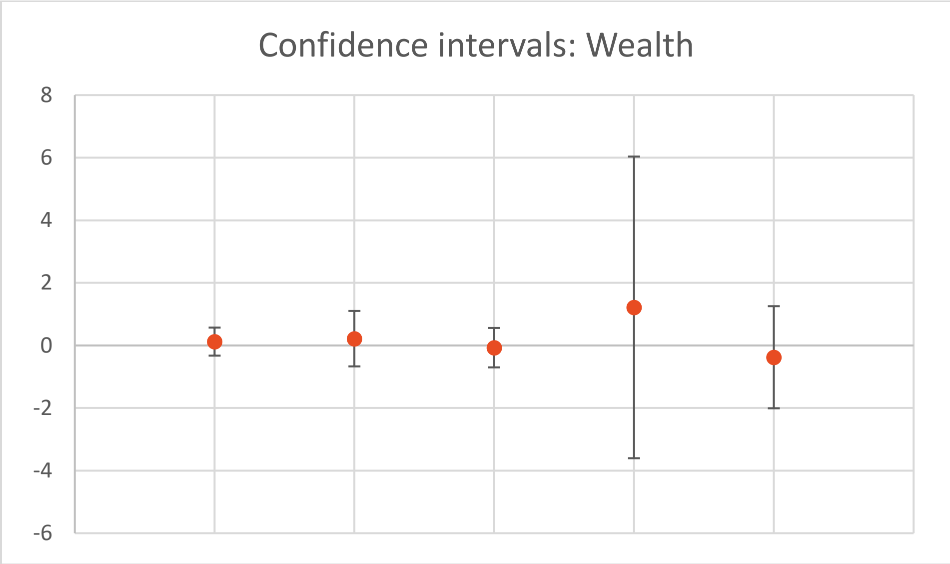

Figure 7: Confidence for the wealth coefficient in model 7 and 8;
From left to right: All cases, coastal, lowland, highland, and altiplano

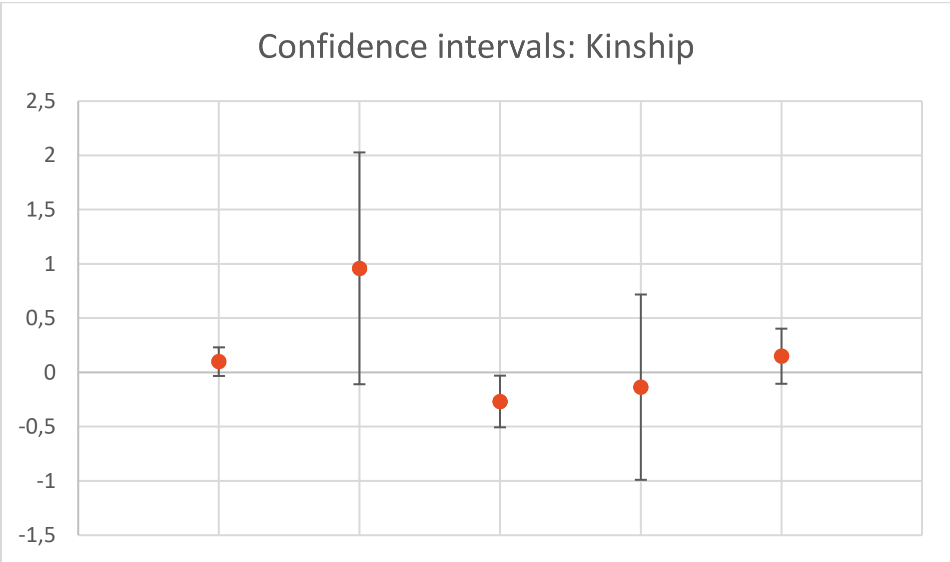

Figure 8: Confidence for the kinship coefficient in model 7 and 8;
From left to right: All cases, coastal, lowland, highland, and altiplano

Figure 9: Confidence for the Friendship coefficient in model 7 and 8;
From left to right: All cases, coastal, lowland, highland, and altiplano

Discussion and conclusion

The analysis did not find any clear support for the hypotheses. The effects found are relatively small, which makes it difficult to say anything clear about them. I see three potential possibilities why this may be the case.

First off, when looking at the main effect, I hypothesized opposite effects due to mixed results in previous research. When no clear results are found, it is difficult to infer if this means no mechanism is at play or if maybe both are at play at the same time. If this is the case, no statistical difference is visible with no result at all.

Secondly, the measurements used for the different variables are more reliable for network data then for normal regression analysis. This is particularly a problem for the network variables kinship and friendship. In my analysis the number of friends and family was compared with the sum of shared money during the allocation game. However my model cannot see the difference between sharing having 1 friend and sharing 5 peso's or having 5 friends and sharing 1 peso with each of them. A better model would be a dyadic network analysis where friendship and kinship ties are compared with generous giving ties (Borgatti et al., 2018). In other words, comparing if who you share money with are the same individuals as your friends and family.

Thirdly, the absence of variation for wealth and generosity might explain why no clear relationship was found. Most individuals where extremely generous, with more then half of them giving away 90% of their money. However this does mean very little data was collected for less generous individuals, which makes predictions for less generous individuals less reliable. For wealth the same problem might play a role. Although there is some variation of wealth within the communities, if we compare wealth with urban area's within Colombia almost all respondents live in poverty. This means a lot of data was missing for actually rich individuals.

What was found is some variation between the four communities when it comes to the network variables. The differences are likely due to the variation in the networks themselves. For example, the negative relationship between friendship and wealth in the altiplano community may be explained by the fragmented friendship network within the community itself. Further research into the relationship between friendship and generosity has already been done with the same dataset by Redhead et. al. (2023). As far as I know, the relationship between kinship and generosity has not been researched yet with these datasets.

When looking back at the research question: *"What is the relationship between wealth and generosity within the rural Colombian context?"* I can say that there is no clear relationship between wealth and generosity based on my findings. More research with network analysis might gain some insights in the future.

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Smith, C., & Davidson, H. (2014). *The Paradox of Generosity*. https://doi.org/10.1093/acprof:oso/9780199394906.001.0001

Van Vugt, M., & Van Lange, P. A. M. (2006). The Altruism Puzzle: Psychological adaptations for Prosocial Behavior. In *Evolution and Social Psychology* (pp. 237–261).

Waal, F. B. M. (2020). *De aap in ons: waarom we zijn wie we zijn*.

Appendix 1

In this appendix I have reported the descriptives and frequencies of the variables included within the analysis. First I will show what the variables looked like before any changes where computed, secondly I will show which changes were made, and lastly I will show the descriptives and frequencies of these new computed variables. Most calculations and transformations where made with SPSS and some with Ucinet. If calculations or transformations where made with ucinet, this will be reported. If no specifics are given, calculations and transformations where done in SPSS.

Variable 1: Sex

Syntax

```
FREQUENCIES VARIABLES=Sex
  /ORDER=ANALYSIS.

RECODE Sex ('M'=0) ('F'=1) INTO Sex_bi.
EXECUTE.

FREQUENCIES VARIABLES=Sex_bi
  /ORDER=ANALYSIS.
```

Reported sex of respondents. Male is coded “M” and Female is coded “F”.

Sex

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	F	272	58,2	58,2	58,2
	M	195	41,8	41,8	100,0
	Total	467	100,0	100,0	

Sex was recoded to a binary variable with M = 0 and F = 1.

Sex_bi

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	,00	195	41,8	41,8	41,8
	1,00	272	58,2	58,2	100,0
	Total	467	100,0	100,0	

Variable 2: Age

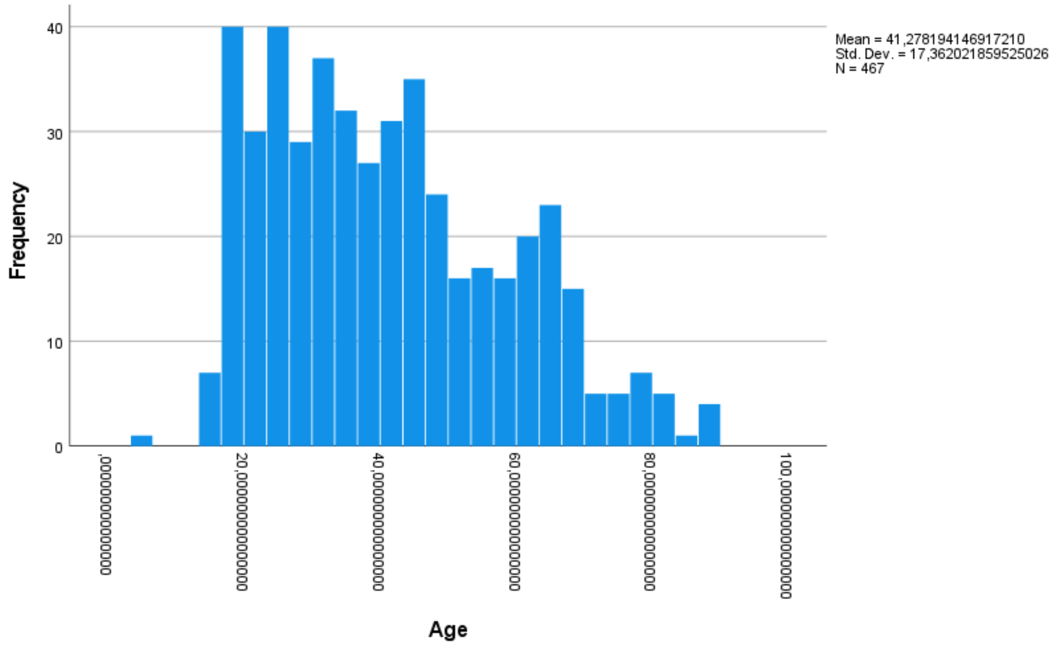
Syntax

```
DESCRIPTIVES VARIABLES=Age
  /STATISTICS=MEAN STDDEV MIN MAX.

GRAPH
  /HISTOGRAM=Age.
```

Reported age of respondents in years. No further transformations where made.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Age	467	6,416666667000000	89,000000000000000	41,278194146917170	17,362021859525033
Valid N (listwise)	467				



Variable 3: Kinship

Ucinet

```
Transform -> Dichotomize… -> input dataset (coastal_kinship):

       Dichotomization rule -> If x(i,j) Greater than or equal to value 0,25 then
       y(i,j)= 1 else y(i,j) =0

Network -> Centrality -> Degree -> input Network (coastal_kinship_GE_0,25):

       Output -> Raw totals

Transform -> Dichotomize… -> input dataset (lowland_kinship):

       Dichotomization rule -> If x(i,j) Greater than or equal to value 0,25 then
       y(i,j)= 1 else y(i,j) =0

Network -> Centrality -> Degree -> input Network (lowland_kinship_GE_0,25):

       Output -> Raw totals

Transform -> Dichotomize… -> input dataset (highland_kinship):

       Dichotomization rule -> If x(i,j) Greater than or equal to value 0,25 then
       y(i,j)= 1 else y(i,j) =0

Network -> Centrality -> Degree -> input Network (highland_kinship_GE_0,25):

       Output -> Raw totals

Transform -> Dichotomize… -> input dataset (altiplano_kinship):

       Dichotomization rule -> If x(i,j) Greater than or equal to value 0,25 then
       y(i,j)= 1 else y(i,j) =0

Network -> Centrality -> Degree -> input Network (altiplano_kinship_GE_0,25):

       Output -> Raw totals

Network -> Whole network & cohesion -> Multiple whole network measures -> Input
dataset (coastal_kinship_GE_0,25)

Network -> Whole network & cohesion -> Multiple whole network measures -> Input
dataset (lowland_kinship_GE_0,25)

Network -> Whole network & cohesion -> Multiple whole network measures -> Input
dataset (highland_kinship_GE_0,25)

Network -> Whole network & cohesion -> Multiple whole network measures -> Input
dataset (altiplano_kinship_GE_0,25)
```

For each community a kinship network was constructed with the tie value indicating the rate of relatedness between two individuals. These networks where dichotomized with the cutoff point of 0,25. Then the number of ties was calculated per individual with the degree centrality option, which gives the number of close relatives within the community a respondent has. These values where added to the SPSS dataset.

```
Whole network measures

                                1
                         coastal_
                         kinship_
                          GE_0,25
                         --------
   1            # of nodes     117
   2             # of ties     260
   3            Avg Degree   2.222
   4         Indeg H-Index       9
   5          K-core index       7
   6 Deg Centralization      0.068
   7 Out-Centralization      0.068
   8  In-Centralization      0.068
   9            Indeg Corr  -0.099
  10           Outdeg Corr  -0.099
  11               Density   0.019
  12            Components      68
  13       Component Ratio   0.578
  14          Connectedness  0.029
  15         Fragmentation   0.971
  16               Closure   0.855
  17          Avg Distance   1.406
  18         Prop within 3   0.029
  19              # w/in 3     388
  20           SD Distance   0.635
  21              Diameter       4
  22          Wiener Index     554
  23        Dependency Sum     160
  24               Breadth   0.976
  25           Compactness   0.024
  26       Small Worldness
  27               Mutuals   0.019
  28           Asymmetrics       0
  29                 Nulls   0.981
  30       Arc Reciprocity       1
  31      Dyad Reciprocity       1

31 rows, 1 columns, 1 levels.
```

```
Whole network measures

                                1
                         lowland_
                         kinship_
                          GE_0,25
                         --------
   1            # of nodes     149
   2             # of ties     200
   3            Avg Degree   1.342
   4         Indeg H-Index       5
   5          K-core index       4
   6 Deg Centralization      0.039
   7 Out-Centralization      0.038
   8  In-Centralization      0.038
   9            Indeg Corr  -0.037
  10           Outdeg Corr  -0.037
  11               Density   0.009
  12            Components      89
  13       Component Ratio   0.595
  14         Connectedness   0.018
  15         Fragmentation   0.982
  16               Closure   0.667
  17          Avg Distance   1.696
  18         Prop within 3   0.017
  19              # w/in 3     380
  20           SD Distance   0.822
  21              Diameter       4
  22          Wiener Index     658
  23        Dependency Sum     270
  24               Breadth   0.987
  25           Compactness   0.013
  26       Small Worldness
  27               Mutuals   0.009
  28           Asymmetrics       0
  29                 Nulls   0.991
  30       Arc Reciprocity       1
  31      Dyad Reciprocity       1

31 rows, 1 columns, 1 levels.
```

Whole network measures

		1 highland_kinship_GE_0,25
1	# of nodes	65
2	# of ties	154
3	Avg Degree	2.369
4	Indeg H-Index	5
5	K-core index	5
6	Deg Centralization	0.059
7	Out-Centralization	0.058
8	In-Centralization	0.058
9	Indeg Corr	-0.217
10	Outdeg Corr	-0.217
11	Density	0.037
12	Components	29
13	Component Ratio	0.438
14	Connectedness	0.041
15	Fragmentation	0.959
16	Closure	0.921
17	Avg Distance	1.106
18	Prop within 3	0.041
19	# w/in 3	170
20	SD Distance	0.344
21	Diameter	3
22	Wiener Index	188
23	Dependency Sum	18
24	Breadth	0.961
25	Compactness	0.039
26	Small Worldness	
27	Mutuals	0.037
28	Asymmetrics	0
29	Nulls	0.963
30	Arc Reciprocity	1
31	Dyad Reciprocity	1

31 rows, 1 columns, 1 levels.

Whole network measures

		1 altiplano_kinship_GE_0,25
1	# of nodes	136
2	# of ties	372
3	Avg Degree	2.735
4	Indeg H-Index	9
5	K-core index	9
6	Deg Centralization	0.077
7	Out-Centralization	0.077
8	In-Centralization	0.077
9	Indeg Corr	-0.068
10	Outdeg Corr	-0.068
11	Density	0.020
12	Components	63
13	Component Ratio	0.459
14	Connectedness	0.027
15	Fragmentation	0.973
16	Closure	0.840
17	Avg Distance	1.316
18	Prop within 3	0.027
19	# w/in 3	488
20	SD Distance	0.615
21	Diameter	4
22	Wiener Index	650
23	Dependency Sum	156
24	Breadth	0.977
25	Compactness	0.023
26	Small Worldness	
27	Mutuals	0.020
28	Asymmetrics	0
29	Nulls	0.980
30	Arc Reciprocity	1
31	Dyad Reciprocity	1

31 rows, 1 columns, 1 levels.

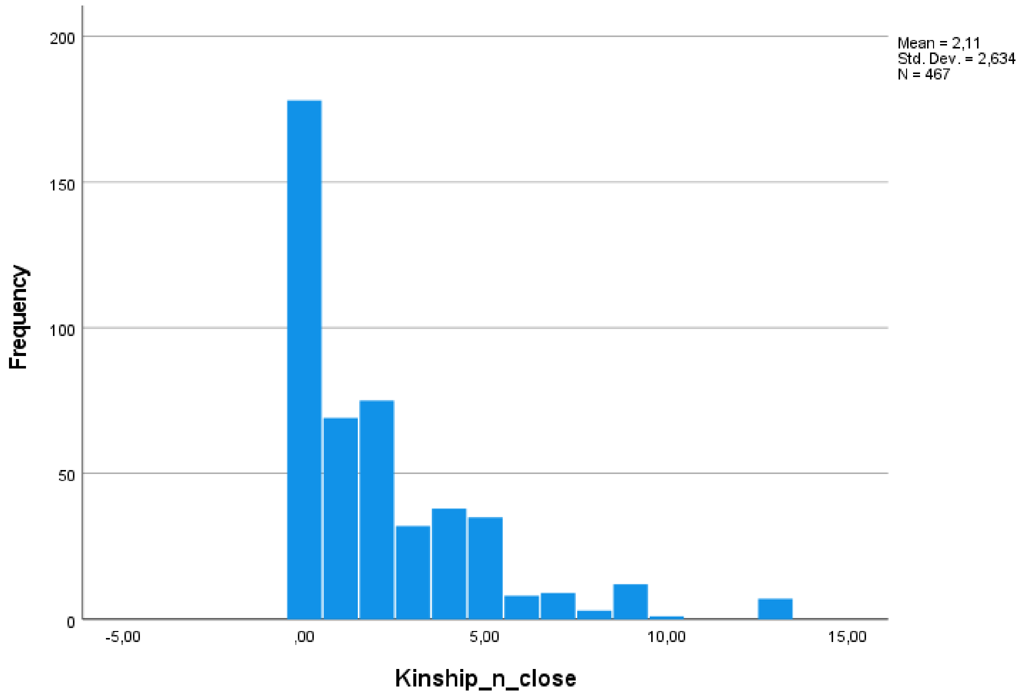
SPSS syntax

```
DESCRIPTIVES VARIABLES=Kinship_n_close
  /STATISTICS=MEAN STDDEV MIN MAX.

GRAPH
  /HISTOGRAM=Kinship_n_close.
```

Value indicates reported close family members within the community. No further transformations where made within SPSS.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Kinship_n_close	467	,00	13,00	2,1113	2,63446
Valid N (listwise)	467				



Variable 4: Wealth

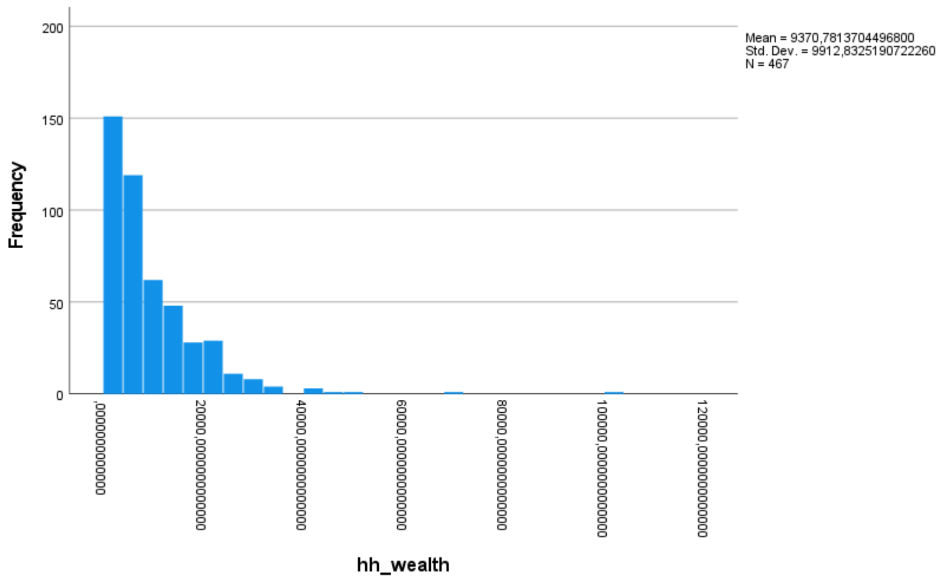
Syntax

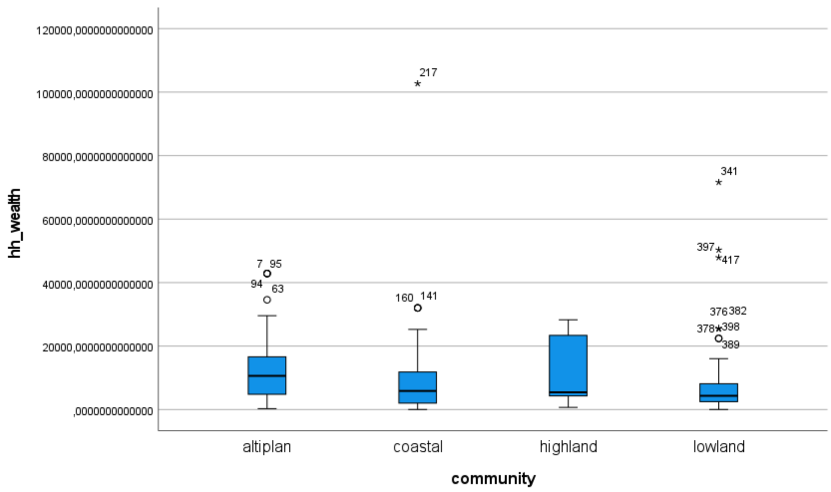
```
DESCRIPTIVES VARIABLES=hh_wealth
  /STATISTICS=MEAN STDDEV MIN MAX.

GRAPH
  /HISTOGRAM=hh_wealth.

EXAMINE VARIABLES=hh_wealth BY community
  /PLOT=BOXPLOT
  /STATISTICS=NONE
  /NOTOTAL.

COMPUTE log_wealth=LG10(hh_wealth).
EXECUTE.

DESCRIPTIVES VARIABLES=log_wealth
  /STATISTICS=MEAN STDDEV MIN MAX.

GRAPH
  /HISTOGRAM=log_wealth.

EXAMINE VARIABLES=log_wealth BY community
  /PLOT=BOXPLOT
  /STATISTICS=NONE
  /NOTOTAL.
```

Estimated value of material wealth within the household of respondent. Natural log of wealth was calculated due to extreme skewed distribution of wealth which caused problems for the assumption of a linear relationship (see: appendix 3).

Descriptive Statistics

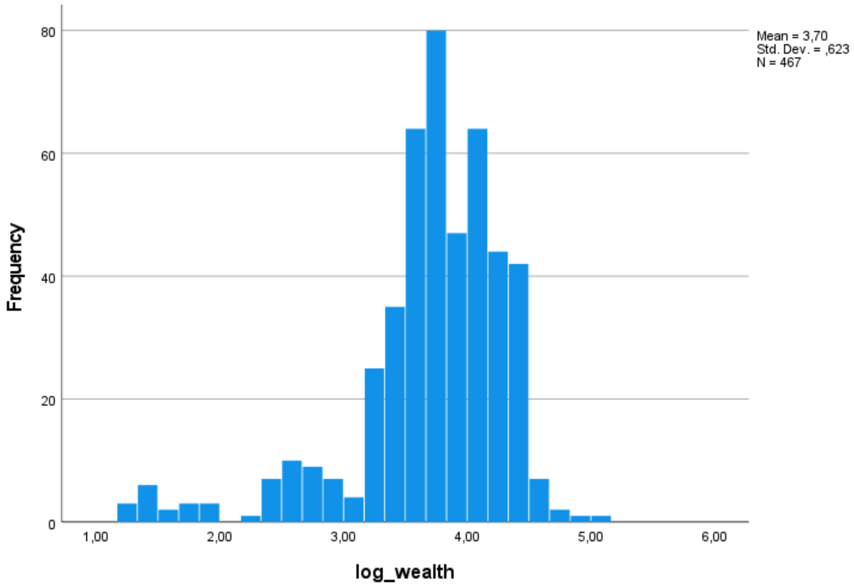
	N	Minimum	Maximum	Mean	Std. Deviation
hh_wealth	467	20,0000000000000 0	102720,00000000 00000	9223,3720368547 77000	9223,3720368547 77000
Valid N (listwise)	467				

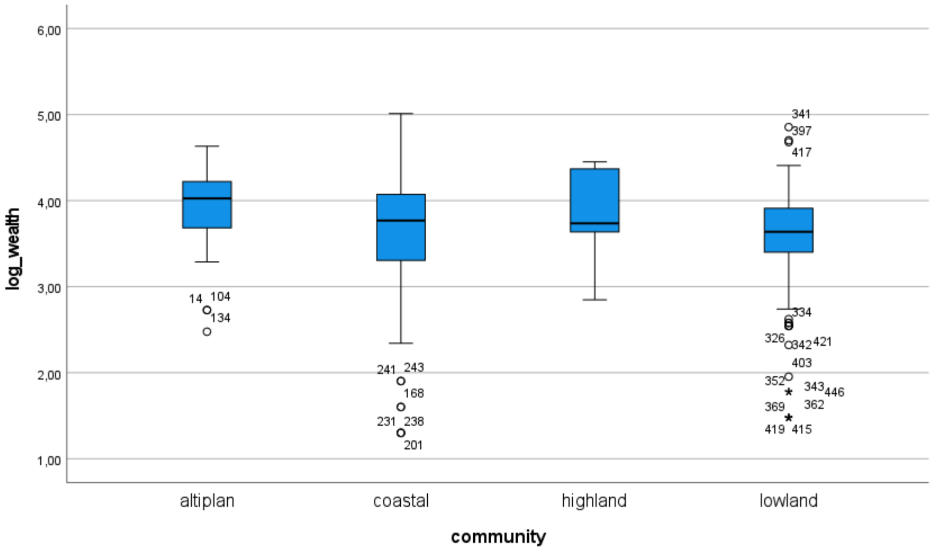




Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
log_wealth	467	1,30	5,01	3,7009	,62284
Valid N (listwise)	467				


Mean = 3,70
Std. Dev. = ,623
N = 467
Frequency
log_wealth


log_wealth
altiplan
coastal
highland
lowland
community

Variable 5: Friendship

Ucinet

```
Network -> Centrality -> Degree -> input Network (coastal_friendship):

       Output -> Raw totals

Network -> Centrality -> Degree -> input Network (lowland_ friendship):

       Output -> Raw totals

Network -> Centrality -> Degree -> input Network (highland_ friendship):

       Output -> Raw totals

Network -> Centrality -> Degree -> input Network (altiplano_ friendship):

       Output -> Raw totals

Network -> Whole network & cohesion -> Multiple whole network measures -> Input
dataset (coastal_friendship)

Network -> Whole network & cohesion -> Multiple whole network measures -> Input
dataset (lowland_friendship)

Network -> Whole network & cohesion -> Multiple whole network measures -> Input
dataset (highland_friendship)

Network -> Whole network & cohesion -> Multiple whole network measures -> Input
dataset (altiplano_friendship)
```

For each community a friendship network was constructed with self-reported friendship of individuals. I calculated the number of reported number friends per respondents by using the degree centrality option. The outdegree values (ties reported by ego themselves) where added to the SPSS dataset.

Whole network measures

		1 coastal_friends
1	# of nodes	117
2	# of ties	177
3	Avg Degree	1.513
4	Indeg H-Index	6
5	K-core index	3
6	Deg Centralization	0.074
7	Out-Centralization	0.065
8	In-Centralization	0.065
9	Indeg Corr	0.047
10	Outdeg Corr	0.045
11	Density	0.013
12	Components	84
13	Component Ratio	0.716
14	Connectedness	0.116
15	Fragmentation	0.884
16	Closure	0.214
17	Avg Distance	3.756
18	Prop within 3	0.056
19	# w/in 3	760
20	SD Distance	1.850
21	Diameter	10
22	Wiener Index	5919
23	Dependency Sum	4343
24	Breadth	0.957
25	Compactness	0.043
26	Small Worldness	
27	Mutuals	0.004
28	Asymmetrics	0.019
29	Nulls	0.978
30	Arc Reciprocity	0.282
31	Dyad Reciprocity	0.164

31 rows, 1 columns, 1 levels.

Whole network measures

		1 lowland_friends
1	# of nodes	149
2	# of ties	262
3	Avg Degree	1.758
4	Indeg H-Index	5
5	K-core index	4
6	Deg Centralization	0.068
7	Out-Centralization	0.036
8	In-Centralization	0.042
9	Indeg Corr	0.021
10	Outdeg Corr	0.013
11	Density	0.012
12	Components	88
13	Component Ratio	0.588
14	Connectedness	0.335
15	Fragmentation	0.665
16	Closure	0.134
17	Avg Distance	5.279
18	Prop within 3	0.073
19	# w/in 3	1606
20	SD Distance	2.185
21	Diameter	13
22	Wiener Index	39011
23	Dependency Sum	31621
24	Breadth	0.918
25	Compactness	0.082
26	Small Worldness	
27	Mutuals	0.003
28	Asymmetrics	0.018
29	Nulls	0.979
30	Arc Reciprocity	0.252
31	Dyad Reciprocity	0.144

31 rows, 1 columns, 1 levels.

Whole network measures

		1 highland_friends
1	# of nodes	65
2	# of ties	86
3	Avg Degree	1.323
4	Indeg H-Index	5
5	K-core index	3
6	Deg Centralization	0.109
7	Out-Centralization	0.058
8	In-Centralization	0.106
9	Indeg Corr	0.091
10	Outdeg Corr	0.025
11	Density	0.021
12	Components	50
13	Component Ratio	0.766
14	Connectedness	0.122
15	Fragmentation	0.878
16	Closure	0.221
17	Avg Distance	3.338
18	Prop within 3	0.072
19	# w/in 3	299
20	SD Distance	1.860
21	Diameter	9
22	Wiener Index	1689
23	Dependency Sum	1183
24	Breadth	0.948
25	Compactness	0.052
26	Small Worldness	
27	Mutuals	0.006
28	Asymmetrics	0.029
29	Nulls	0.965
30	Arc Reciprocity	0.302
31	Dyad Reciprocity	0.178

31 rows, 1 columns, 1 levels.

Whole network measures

		1 altiplano_friends
1	# of nodes	136
2	# of ties	68
3	Avg Degree	0.500
4	Indeg H-Index	3
5	K-core index	4
6	Deg Centralization	0.031
7	Out-Centralization	0.034
8	In-Centralization	0.026
9	Indeg Corr	0.022
10	Outdeg Corr	0.041
11	Density	0.004
12	Components	129
13	Component Ratio	0.948
14	Connectedness	0.005
15	Fragmentation	0.995
16	Closure	0.597
17	Avg Distance	1.330
18	Prop within 3	0.005
19	# w/in 3	94
20	SD Distance	0.572
21	Diameter	3
22	Wiener Index	125
23	Dependency Sum	31
24	Breadth	0.996
25	Compactness	0.004
26	Small Worldness	
27	Mutuals	0.001
28	Asymmetrics	0.005
29	Nulls	0.994
30	Arc Reciprocity	0.265
31	Dyad Reciprocity	0.153

31 rows, 1 columns, 1 levels.

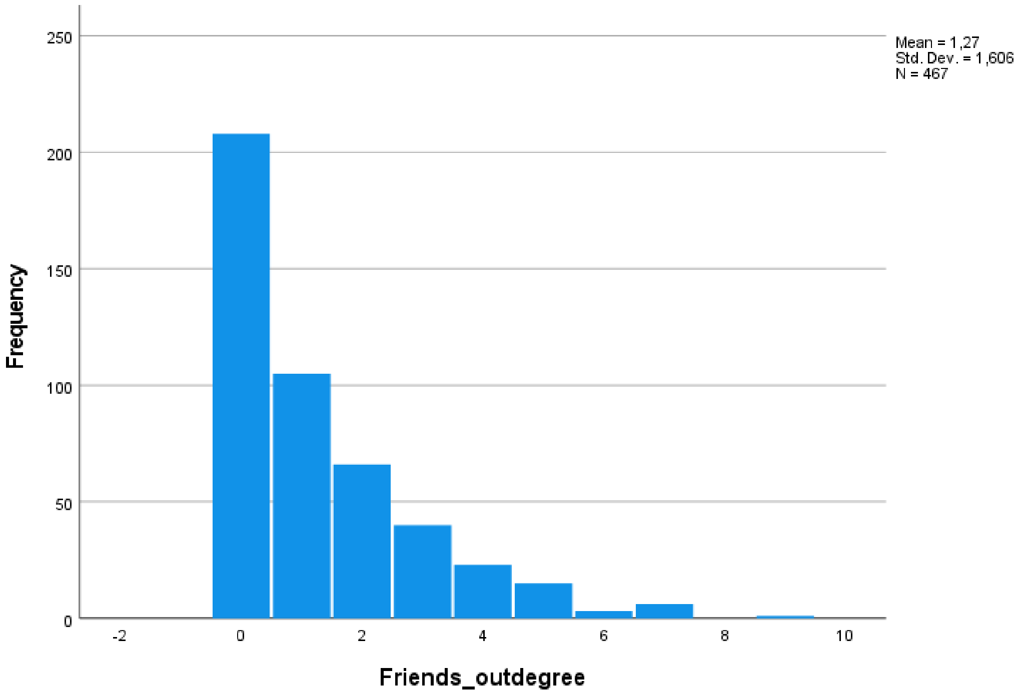
SPSS syntax

```
DESCRIPTIVES VARIABLES=Friends_outdegree
  /STATISTICS=MEAN STDDEV MIN MAX.

GRAPH
  /HISTOGRAM=Friends_outdegree.
```

Value indicates self-reported friends within the community. No further transformations where made within SPSS.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Friends_outdegree	467	0	9	1,27	1,606
Valid N (listwise)	467				



Variable 6: Generosity

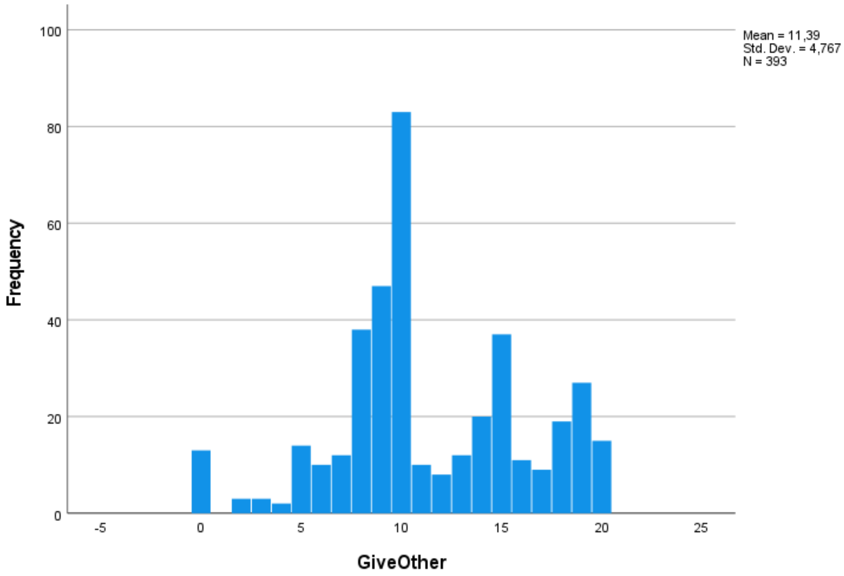
Syntax

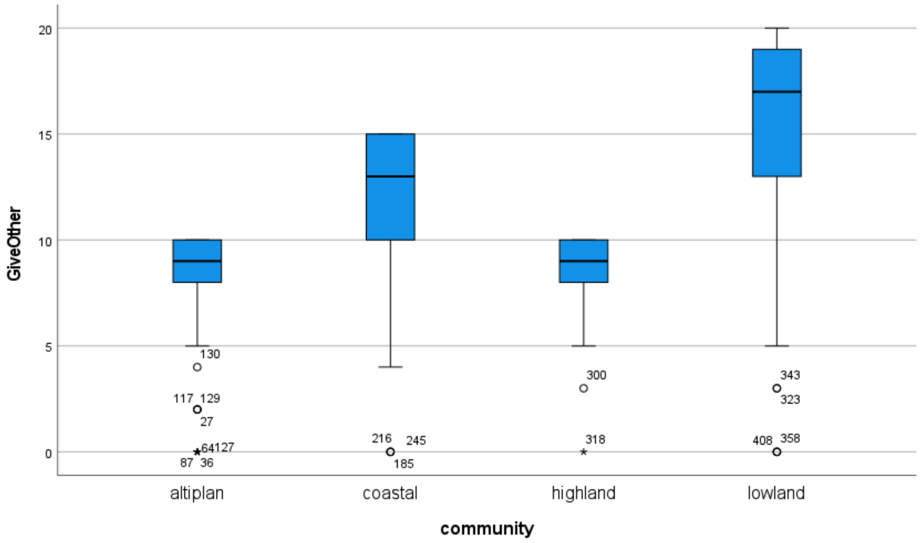
```
DESCRIPTIVES VARIABLES=GiveOther
  /STATISTICS=MEAN STDDEV MIN MAX.

GRAPH
  /HISTOGRAM=GiveOther.

EXAMINE VARIABLES=GiveOther BY community
  /PLOT=BOXPLOT
  /STATISTICS=NONE
  /NOTOTAL.

IF  (coastal = 1) Gen_c=GiveOther / 15.
EXECUTE.
IF  (lowland = 1) Gen_l=GiveOther / 20.
EXECUTE.
IF  (highland = 1) Gen_h=GiveOther / 10.
EXECUTE.
IF  (altiplano = 1) Gen_a=GiveOther / 10.
EXECUTE.

COMPUTE Generosity=SUM(Gen_c,Gen_l,Gen_h,Gen_a).
EXECUTE.

DESCRIPTIVES VARIABLES=Generosity
  /STATISTICS=MEAN STDDEV MIN MAX.

DESCRIPTIVES VARIABLES=Generosity
  /STATISTICS=MEAN STDDEV MIN MAX.

EXAMINE VARIABLES=Generosity BY community
  /PLOT=BOXPLOT
  /STATISTICS=NONE
  /NOTOTAL.

RECODE Generosity (SYSMIS=SYSMIS) (Lowest thru 0.5=0) (ELSE=1) INTO
Generosity_01.
EXECUTE.

FREQUENCIES VARIABLES=Generosity_01
  /ORDER=ANALYSIS.
```

GiveOther is the number of peso's respondents gave away during the RICH allocation game (with 1000 steps increments). Because the maximum people were able to give was different per community, the dependent had to be recoded to a rate with 0 meaning nothing was given and 1 meaning everything was given. The residuals of this new dependent were not distributed normally and I decided to preform a binary logistic regression. The variable generosity was dichotomized with all values lower or equal to 0,5 coded as 0 and all above values coded as 1.

Descriptive Statistics

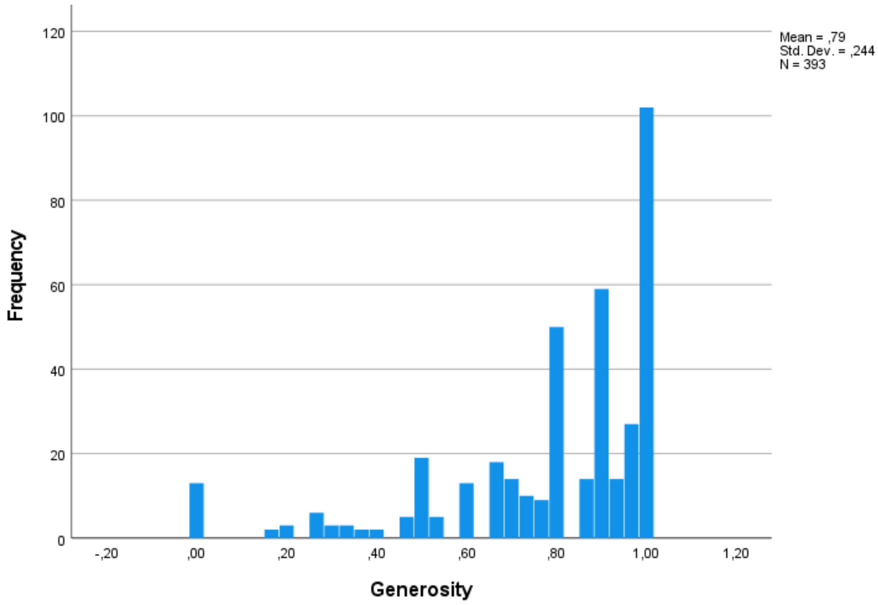
	N	Minimum	Maximum	Mean	Std. Deviation
GiveOther	393	0	20	11,39	4,767
Valid N (listwise)	393				

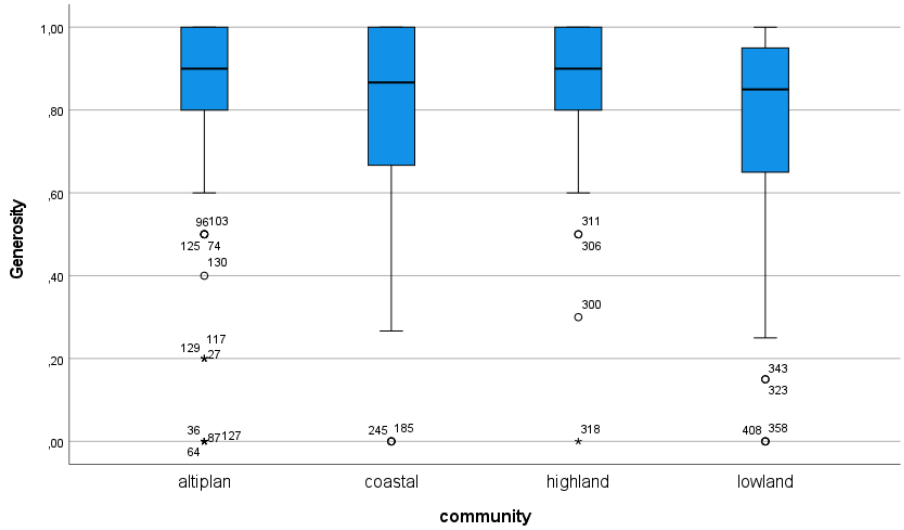




Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Generosity	393	,00	1,00	,7879	,24442
Valid N (listwise)	393				





Generosity_01

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	,00	58	12,4	14,8	14,8
	1,00	335	71,7	85,2	100,0
	Total	393	84,2	100,0	
Missing	System	74	15,8		
Total		467	100,0		

Variable 7: Community

Syntax

```
FREQUENCIES VARIABLES=community
  /ORDER=ANALYSIS.

SORT CASES  BY community.
SPLIT FILE LAYERED BY community.

FREQUENCIES VARIABLES=Ethnicity
  /ORDER=ANALYSIS.

SPLIT FILE OFF.

RECODE community ('coastal'=1) ('lowland'=2) ('highland'=3) ('altiplano'=4) INTO
community_ANOVA.
EXECUTE.
```

Community is a simple nominal variable indicating which community a respondent belongs to. The descriptives for ethnicity are also added for the method paragraph. An extra variable was constructed so community could be used within an ANOVA analysis.

community

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	altiplano	136	29,1	29,1	29,1
	coastal	117	25,1	25,1	54,2
	highland	65	13,9	13,9	68,1
	lowland	149	31,9	31,9	100,0
	Total	467	100,0	100,0	

Ethnicity

community			Frequency	Percent	Valid Percent	Cumulative Percent
altiplano	Valid	MESTIZO	136	100,0	100,0	100,0
coastal	Valid	AFROCOLOMBIAN	80	68,4	68,4	68,4
		AFROEMBERA	1	,9	,9	69,2
		EMBERA	28	23,9	23,9	93,2
		MESTIZO	8	6,8	6,8	100,0
		Total	117	100,0	100,0	
highland	Valid	AFROCOLOMBIAN	3	4,6	4,6	4,6
		EMBERA	1	1,5	1,5	6,2
		MESTIZO	61	93,8	93,8	100,0
		Total	65	100,0	100,0	
lowland	Valid	AFROCOLOMBIAN	116	77,9	77,9	77,9
		EMBERA	21	14,1	14,1	91,9
		MESTIZO	12	8,1	8,1	100,0
		Total	149	100,0	100,0	

Without missing data

Syntax

```
USE ALL.
COMPUTE filter_$=(obs = 1).
VARIABLE LABELS filter_$ 'obs = 1 (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.

DESCRIPTIVES VARIABLES=Age Kinship_n_close log_wealth Friends_outdegree
Generosity
  /STATISTICS=MEAN STDDEV MIN MAX.

FREQUENCIES VARIABLES=Sex_bi Generosity_01 community
  /ORDER=ANALYSIS.

FREQUENCIES VARIABLES=Age Kinship_n_close log_wealth Friends_outdegree Generosity
  /NTILES=4
  /STATISTICS=STDDEV MAXIMUM MEAN MEDIAN
  /ORDER=ANALYSIS.

SORT CASES  BY community.
SPLIT FILE LAYERED BY community.

DESCRIPTIVES VARIABLES=Age Kinship_n_close log_wealth Friends_outdegree
Generosity
  /STATISTICS=MEAN STDDEV MIN MAX.

FREQUENCIES VARIABLES=Sex_bi Generosity_01
  /ORDER=ANALYSIS.

SPLIT FILE OFF.
FREQUENCIES VARIABLES=Age Kinship_n_close log_wealth Friends_outdegree Generosity
  /NTILES=4
  /STATISTICS=STDDEV MAXIMUM MEAN MEDIAN
  /ORDER=ANALYSIS.

SPLIT FILE OFF.
```

Descriptives and frequencies of variables without missing data and split by community.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Age	392	14,333333330000000	89,000000000000000	42,598001700527206	17,579869324309428
Kinship_n_close	392	,00	13,00	2,1633	2,64021
log_wealth	392	1,30	5,01	3,7034	,62928
Friends_outdegree	392	0	9	1,31	1,624
Generosity	392	,00	1,00	,7873	,24450
Valid N (listwise)	392				

Sex_bi

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	,00	155	39,5	39,5	39,5
	1,00	237	60,5	60,5	100,0
	Total	392	100,0	100,0	

Generosity_01

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	,00	58	14,8	14,8	14,8
	1,00	334	85,2	85,2	100,0
	Total	392	100,0	100,0	

community

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	altiplano	108	27,6	27,6	27,6
	coastal	93	23,7	23,7	51,3
	highland	56	14,3	14,3	65,6
	lowland	135	34,4	34,4	100,0
	Total	392	100,0	100,0	

Descriptive Statistics

community		N	Minimum	Maximum	Mean	Std. Deviation
altiplano	Age	108	16,250000000000000	81,916666666666700	40,510802469043210	16,972165429006090
	Kinship_n_close	108	,00	13,00	2,9074	3,37815
	log_wealth	108	2,48	4,54	3,9415	,38829
	Friends_outdegree	108	0	5	,41	,798
	Generosity	108	,00	1,00	,8019	,26545
	Valid N (listwise)	108				
coastal	Age	93	19,000000000000000	87,833333333333300	41,073476702508970	15,717812988717740
	Kinship_n_close	93	,00	10,00	2,3011	2,80831
	log_wealth	93	1,30	5,01	3,6135	,74418
	Friends_outdegree	93	0	9	1,65	1,863
	Generosity	93	,00	1,00	,7842	,23782
	Valid N (listwise)	93				
highland	Age	56	14,333333330000000	88,833333330000000	38,223214284821420	17,943416304225163
	Kinship_n_close	56	,00	6,00	2,4107	1,97969
	log_wealth	56	2,85	4,45	3,8807	,41907
	Friends_outdegree	56	0	5	1,41	1,523
	Generosity	56	,00	1,00	,8518	,18780
	Valid N (listwise)	56				
lowland	Age	135	18,666666666666700	89,000000000000000	47,132716049382700	18,334826647391970
	Kinship_n_close	135	,00	7,00	1,3704	1,75661
	log_wealth	135	1,48	4,86	3,5013	,69079
	Friends_outdegree	135	0	7	1,75	1,709
	Generosity	135	,00	1,00	,7511	,24824
	Valid N (listwise)	135				

Sex_bi

community			Frequency	Percent	Valid Percent	Cumulative Percent
altiplano	Valid	,00	38	35,2	35,2	35,2
		1,00	70	64,8	64,8	100,0
		Total	108	100,0	100,0	
coastal	Valid	,00	40	43,0	43,0	43,0
		1,00	53	57,0	57,0	100,0
		Total	93	100,0	100,0	
highland	Valid	,00	27	48,2	48,2	48,2
		1,00	29	51,8	51,8	100,0
		Total	56	100,0	100,0	
lowland	Valid	,00	50	37,0	37,0	37,0
		1,00	85	63,0	63,0	100,0
		Total	135	100,0	100,0	

Generosity_01

community			Frequency	Percent	Valid Percent	Cumulative Percent
altiplano	Valid	,00	14	13,0	13,0	13,0
		1,00	94	87,0	87,0	100,0
		Total	108	100,0	100,0	
coastal	Valid	,00	9	9,7	9,7	9,7
		1,00	84	90,3	90,3	100,0
		Total	93	100,0	100,0	
highland	Valid	,00	4	7,1	7,1	7,1
		1,00	52	92,9	92,9	100,0
		Total	56	100,0	100,0	
lowland	Valid	,00	31	23,0	23,0	23,0
		1,00	104	77,0	77,0	100,0
		Total	135	100,0	100,0	

Statistics

community			Age	Kinship_n_close	log_wealth	Friends_outdegree	Generosity
altiplano	N	Valid	108	108	108	108	108
		Missing	0	0	0	0	0
	Mean		40,510802469043210	2,9074	3,9415	,41	,8019
	Median		40,583333335000000	2,0000	4,0507	,00	,9000
	Std. Deviation		16,972165429006086	3,37815	,38829	,798	,26545
	Maximum		81,916666666666700	13,00	4,54	5	1,00
	Percentiles	25	24,875000000000000	,0000	3,7419	,00	,7250
		50	40,583333335000000	2,0000	4,0507	,00	,9000
		75	50,166666665000000	4,0000	4,2164	1,00	1,0000
coastal	N	Valid	93	93	93	93	93
		Missing	0	0	0	0	0
	Mean		41,073476702508955	2,3011	3,6135	1,65	,7842
	Median		39,500000000000000	1,0000	3,8156	1,00	,8667
	Std. Deviation		15,717812988717737	2,80831	,74418	1,863	,23782
	Maximum		87,833333333333300	10,00	5,01	9	1,00
	Percentiles	25	29,875000000000000	,0000	3,3555	,00	,6667
		50	39,500000000000000	1,0000	3,8156	1,00	,8667
		75	50,083333333333310	4,0000	4,0881	3,00	1,0000
highland	N	Valid	56	56	56	56	56
		Missing	0	0	0	0	0
	Mean		38,223214284821430	2,4107	3,8807	1,41	,8518
	Median		34,208333330000000	2,0000	3,7397	1,00	,9000
	Std. Deviation		17,943416304225160	1,97969	,41907	1,523	,18780

	Maximum		88,833333330000000	6,00	4,45	5	1,00
	Percentiles	25	23,250000000000000	1,0000	3,6090	,00	,8000
		50	34,208333330000000	2,0000	3,7397	1,00	,9000
		75	51,833333335000000	4,0000	4,3687	3,00	1,0000
lowland	N	Valid	135	135	135	135	135
		Missing	0	0	0	0	0
	Mean		47,132716049382715	1,3704	3,5013	1,75	,7511
	Median		43,916666666666690	1,0000	3,6160	1,00	,8500
	Std. Deviation		18,334826647391967	1,75661	,69079	1,709	,24824
	Maximum		89,000000000000000	7,00	4,86	7	1,00
	Percentiles	25	30,083333333333300	,0000	3,3522	,00	,6500
		50	43,916666666666690	1,0000	3,6160	1,00	,8500
		75	63,500000000000000	2,0000	3,9112	3,00	,9500

Appendix 2

In this appendix I will first show the bivariate statistics for all cases, then for all cases without missing data and finally split by community. Bivariate correlations for most variables were used and oneway ANOVA for communities.

The different models were then estimated with logistic and linear regression according to the statistical analysis plan in the method paragraph.

Bivariate statistics

Syntax

```
CORRELATIONS
  /VARIABLES=Sex_bi Age Kinship_n_close log_wealth Friends_outdegree
Generosity_01
  /PRINT=TWOTAIL NOSIG FULL
  /MISSING=PAIRWISE.


ONEWAY Sex_bi Age Kinship_n_close log_wealth Friends_outdegree Generosity_01 BY
community_ANOVA
  /ES=OVERALL
  /STATISTICS DESCRIPTIVES
  /PLOT MEANS
  /MISSING ANALYSIS
  /CRITERIA=CILEVEL(0.95).
```

Correlations and ANOVA for all cases (n = 467)

Correlations

		Sex_bi	Age	Kinship_n_close	log_wealth	Friends_outdegree	Generosity_01
Sex_bi	Pearson Correlation	1	-,062	,042	-,015	-,017	-,086
	Sig. (2-tailed)		,179	,360	,749	,709	,088
	N	467	467	467	467	467	393
Age	Pearson Correlation	-,062	1	-,024	-,045	,149**	-,089
	Sig. (2-tailed)	,179		,606	,329	,001	,079
	N	467	467	467	467	467	393
Kinship_n_close	Pearson Correlation	,042	-,024	1	,065	-,026	,081
	Sig. (2-tailed)	,360	,606		,160	,569	,108
	N	467	467	467	467	467	393
log_wealth	Pearson Correlation	-,015	-,045	,065	1	-,035	,041
	Sig. (2-tailed)	,749	,329	,160		,450	,417
	N	467	467	467	467	467	393
Friends_outdegree	Pearson Correlation	-,017	,149**	-,026	-,035	1	-,028
	Sig. (2-tailed)	,709	,001	,569	,450		,573
	N	467	467	467	467	467	393
Generosity_01	Pearson Correlation	-,086	-,089	,081	,041	-,028	1
	Sig. (2-tailed)	,088	,079	,108	,417	,573	
	N	393	393	393	393	393	393

**. Correlation is significant at the 0.01 level (2-tailed).

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Sex_bi	Between Groups	,456	3	,152	,622	,601
	Within Groups	113,120	463	,244		
	Total	113,576	466			
Age	Between Groups	5820,723	3	1940,241	6,672	,000
	Within Groups	134650,225	463	290,821		
	Total	140470,948	466			
Kinship_n_close	Between Groups	146,835	3	48,945	7,340	,000
	Within Groups	3087,375	463	6,668		
	Total	3234,210	466			
log_wealth	Between Groups	16,780	3	5,593	15,792	,000
	Within Groups	163,992	463	,354		
	Total	180,773	466			
Friends_outdegree	Between Groups	123,256	3	41,085	17,634	,000
	Within Groups	1078,748	463	2,330		
	Total	1202,004	466			
Generosity_01	Between Groups	1,514	3	,505	4,095	,007
	Within Groups	47,927	389	,123		
	Total	49,440	392			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
Sex_bi	Eta-squared	,004	,000	,016
	Epsilon-squared	-,002	-,006	,010
	Omega-squared Fixed-effect	-,002	-,006	,010
	Omega-squared Random-effect	-,001	-,002	,003
Age	Eta-squared	,041	,010	,078
	Epsilon-squared	,035	,004	,072
	Omega-squared Fixed-effect	,035	,004	,071
	Omega-squared Random-effect	,012	,001	,025
Kinship_n_close	Eta-squared	,045	,012	,083
	Epsilon-squared	,039	,006	,077
	Omega-squared Fixed-effect	,039	,006	,077
	Omega-squared Random-effect	,013	,002	,027
log_wealth	Eta-squared	,093	,045	,141
	Epsilon-squared	,087	,039	,136
	Omega-squared Fixed-effect	,087	,039	,135

	Omega-squared Random-effect	,031	,013	,050
Friends_outdegree	Eta-squared	,103	,053	,152
	Epsilon-squared	,097	,046	,147
	Omega-squared Fixed-effect	,097	,046	,147
	Omega-squared Random-effect	,034	,016	,054
Generosity_01	Eta-squared	,031	,003	,065
	Epsilon-squared	,023	-,005	,058
	Omega-squared Fixed-effect	,023	-,005	,058
	Omega-squared Random-effect	,008	-,002	,020

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

Syntax

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT GiveOther
  /METHOD=ENTER Age Sex_bi Friends_outdegree Kinship_n hh_wealth coastal lowland
highland altiplano
  /SAVE RESID.

RECODE RES_1 (MISSING=0) (ELSE=1) INTO obs.
EXECUTE.

USE ALL.
COMPUTE filter_$=(obs = 1).
VARIABLE LABELS filter_$ 'obs = 1 (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.

*Manually add case 321 to obs = 0, because the value of 6,4166 is a error.

CORRELATIONS
  /VARIABLES=Sex_bi Age Kinship_n_close log_wealth Friends_outdegree
Generosity_01
  /PRINT=TWOTAIL NOSIG FULL
  /MISSING=PAIRWISE.


ONEWAY Sex_bi Age Kinship_n_close log_wealth Friends_outdegree Generosity_01 BY
community_ANOVA
  /ES=OVERALL
  /STATISTICS DESCRIPTIVES
  /PLOT MEANS
  /MISSING ANALYSIS
  /CRITERIA=CILEVEL(0.95).
```

Correlations and ANOVA for all cases without missing data:

Correlations

		Sex_bi	Age	Kinship_n_close	log_wealth	Friends_outdegree	Generosity_01
Sex_bi	Pearson Correlation	1	-,048	,028	-,014	,011	-,087
	Sig. (2-tailed)		,345	,576	,789	,827	,085
	N	392	392	392	392	392	392
Age	Pearson Correlation	-,048	1	-,066	-,033	,117*	-,087
	Sig. (2-tailed)	,345		,196	,514	,020	,086
	N	392	392	392	392	392	392
Kinship_n_close	Pearson Correlation	,028	-,066	1	,120*	-,009	,080
	Sig. (2-tailed)	,576	,196		,018	,854	,112
	N	392	392	392	392	392	392
log_wealth	Pearson Correlation	-,014	-,033	,120*	1	-,037	,041
	Sig. (2-tailed)	,789	,514	,018		,465	,414
	N	392	392	392	392	392	392
Friends_outdegree	Pearson Correlation	,011	,117*	-,009	-,037	1	-,028
	Sig. (2-tailed)	,827	,020	,854	,465		,585
	N	392	392	392	392	392	392
Generosity_01	Pearson Correlation	-,087	-,087	,080	,041	-,028	1
	Sig. (2-tailed)	,085	,086	,112	,414	,585	
	N	392	392	392	392	392	392

*. Correlation is significant at the 0.05 level (2-tailed).

ANOVA

		Sum of Squares	df	Mean Square	F	Sig.
Sex_bi	Between Groups	,823	3	,274	1,146	,330
	Within Groups	92,889	388	,239		
	Total	93,712	391			
Age	Between Groups	4534,501	3	1511,500	5,042	,002
	Within Groups	116304,755	388	299,755		
	Total	120839,256	391			
Kinship_n_close	Between Groups	149,872	3	49,957	7,526	,000
	Within Groups	2575,679	388	6,638		
	Total	2725,551	391			
log_wealth	Between Groups	14,149	3	4,716	13,008	,000
	Within Groups	140,685	388	,363		
	Total	154,835	391			
Friends_outdegree	Between Groups	124,910	3	41,637	17,824	,000
	Within Groups	906,355	388	2,336		
	Total	1031,265	391			
Generosity_01	Between Groups	1,508	3	,503	4,072	,007
	Within Groups	47,910	388	,123		
	Total	49,418	391			

ANOVA Effect Sizes[a,b]

		Point Estimate	95% Confidence Interval	
			Lower	Upper
Sex_bi	Eta-squared	,009	,000	,029
	Epsilon-squared	,001	-,008	,021
	Omega-squared Fixed-effect	,001	-,008	,021
	Omega-squared Random-effect	,000	-,003	,007
Age	Eta-squared	,038	,006	,075
	Epsilon-squared	,030	-,002	,068
	Omega-squared Fixed-effect	,030	-,002	,068
	Omega-squared Random-effect	,010	-,001	,024
Kinship_n_close	Eta-squared	,055	,015	,099
	Epsilon-squared	,048	,008	,092
	Omega-squared Fixed-effect	,048	,008	,092
	Omega-squared Random-effect	,016	,003	,033
log_wealth	Eta-squared	,091	,040	,144
	Epsilon-squared	,084	,032	,137
	Omega-squared Fixed-effect	,084	,032	,137

	Omega-squared Random-effect	,030	,011	,050
Friends_outdegree	Eta-squared	,121	,063	,178
	Epsilon-squared	,114	,055	,172
	Omega-squared Fixed-effect	,114	,055	,171
	Omega-squared Random-effect	,041	,019	,064
Generosity_01	Eta-squared	,031	,003	,065
	Epsilon-squared	,023	-,005	,058
	Omega-squared Fixed-effect	,023	-,005	,058
	Omega-squared Random-effect	,008	-,002	,020

a. Eta-squared and Epsilon-squared are estimated based on the fixed-effect model.

b. Negative but less biased estimates are retained, not rounded to zero.

Syntax

```
SORT CASES  BY community.
SPLIT FILE LAYERED BY community.

CORRELATIONS
  /VARIABLES=Sex_bi Age Kinship_n_close log_wealth Friends_outdegree
Generosity_01
  /PRINT=TWOTAIL NOSIG FULL
  /MISSING=PAIRWISE.

SPLIT FILE OFF.

FILTER OFF.
USE ALL.
EXECUTE.
```

Correlations split by community:

Correlations

community			Sex_bi	Age	Kinship_n_close	log_wealth	Friends_outdegree	Generosity_01
altiplano	Sex_bi	Pearson Correlation	1	-,123	-,020	-,099	,036	,004
		Sig. (2-tailed)		,203	,835	,309	,710	,965
		N	108	108	108	108	108	108
	Age	Pearson Correlation	-,123	1	,001	-,159	,069	-,100
		Sig. (2-tailed)	,203		,993	,100	,481	,305
		N	108	108	108	108	108	108
	Kinship_n_close	Pearson Correlation	-,020	,001	1	,046	-,107	,137

		Sig. (2-tailed)	,835	,993		,639	,269	,158
		N	108	108	108	108	108	108
	log_wealth	Pearson Correlation	-,099	-,159	,046	1	-,191*	,010
		Sig. (2-tailed)	,309	,100	,639		,048	,922
		N	108	108	108	108	108	108
	Friends_outdegree	Pearson Correlation	,036	,069	-,107	-,191*	1	-,219*
		Sig. (2-tailed)	,710	,481	,269	,048		,023
		N	108	108	108	108	108	108
	Generosity_01	Pearson Correlation	,004	-,100	,137	,010	-,219*	1
		Sig. (2-tailed)	,965	,305	,158	,922	,023	
		N	108	108	108	108	108	108
coastal	Sex_bi	Pearson Correlation	1	-,070	,078	-,012	,033	,156
		Sig. (2-tailed)		,506	,457	,908	,754	,134
		N	93	93	93	93	93	93
	Age	Pearson Correlation	-,070	1	-,157	,088	-,093	-,133
		Sig. (2-tailed)	,506		,133	,401	,374	,204
		N	93	93	93	93	93	93
	Kinship_n_close	Pearson Correlation	,078	-,157	1	,029	,010	,244*
		Sig. (2-tailed)	,457	,133		,785	,922	,019
		N	93	93	93	93	93	93
	log_wealth	Pearson Correlation	-,012	,088	,029	1	,207*	,088
		Sig. (2-tailed)	,908	,401	,785		,046	,402
		N	93	93	93	93	93	93
	Friends_outdegree	Pearson Correlation	,033	-,093	,010	,207*	1	,035
		Sig. (2-tailed)	,754	,374	,922	,046		,736
		N	93	93	93	93	93	93
	Generosity_01	Pearson Correlation	,156	-,133	,244*	,088	,035	1
		Sig. (2-tailed)	,134	,204	,019	,402	,736	
		N	93	93	93	93	93	93
highland	Sex_bi	Pearson Correlation	1	,178	-,071	,003	,002	-,268*
		Sig. (2-tailed)		,190	,602	,984	,988	,046

		N	56	56	56	56	56	56
	Age	Pearson Correlation	,178	1	-,148	,114	-,071	-,381**
		Sig. (2-tailed)	,190		,276	,405	,602	,004
		N	56	56	56	56	56	56
	Kinship_n_close	Pearson Correlation	-,071	-,148	1	,390**	,287*	,093
		Sig. (2-tailed)	,602	,276		,003	,032	,494
		N	56	56	56	56	56	56
	log_wealth	Pearson Correlation	,003	,114	,390**	1	,058	-,026
		Sig. (2-tailed)	,984	,405	,003		,670	,852
		N	56	56	56	56	56	56
	Friends_outdegree	Pearson Correlation	,002	-,071	,287*	,058	1	,075
		Sig. (2-tailed)	,988	,602	,032	,670		,580
		N	56	56	56	56	56	56
	Generosity_01	Pearson Correlation	-,268*	-,381**	,093	-,026	,075	1
		Sig. (2-tailed)	,046	,004	,494	,852	,580	
		N	56	56	56	56	56	56
lowland	Sex_bi	Pearson Correlation	1	-,103	,110	,019	,031	-,200*
		Sig. (2-tailed)		,233	,205	,828	,724	,020
		N	135	135	135	135	135	135
	Age	Pearson Correlation	-,103	1	,108	,021	,278**	,081
		Sig. (2-tailed)	,233		,213	,808	,001	,353
		N	135	135	135	135	135	135
	Kinship_n_close	Pearson Correlation	,110	,108	1	,037	,190*	-,206*
		Sig. (2-tailed)	,205	,213		,670	,027	,016
		N	135	135	135	135	135	135
	log_wealth	Pearson Correlation	,019	,021	,037	1	,000	-,030
		Sig. (2-tailed)	,828	,808	,670		,999	,727
		N	135	135	135	135	135	135
	Friends_outdegree	Pearson Correlation	,031	,278**	,190*	,000	1	,012
		Sig. (2-tailed)	,724	,001	,027	,999		,887
		N	135	135	135	135	135	135

Generosity_01	Pearson Correlation	-,200*	,081	-,206*	-,030	,012	1
	Sig. (2-tailed)	,020	,353	,016	,727	,887	
	N	135	135	135	135	135	135

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Models

Syntax

```
USE ALL.
COMPUTE filter_$=(obs = 1).
VARIABLE LABELS filter_$ 'obs = 1 (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.

LOGISTIC REGRESSION VARIABLES Generosity_01
  /METHOD=ENTER Sex_bi Age
  /METHOD=ENTER Sex_bi Age log_wealth
  /METHOD=ENTER Sex_bi Age log_wealth Kinship_n_close
  /METHOD=ENTER Sex_bi Age log_wealth Kinship_n_close Friends_outdegree
  /SAVE=COOK LEVER DFBETA ZRESID DEV
  /CLASSPLOT
  /PRINT=GOODFIT CORR CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).

LOGISTIC REGRESSION VARIABLES Generosity_01
  /METHOD=ENTER Sex_bi Age
  /METHOD=ENTER Sex_bi Age log_wealth
  /METHOD=ENTER Sex_bi Age log_wealth Friends_outdegree
  /METHOD=ENTER Sex_bi Age log_wealth Kinship_n_close Friends_outdegree
  /SAVE=COOK LEVER DFBETA ZRESID DEV
  /CLASSPLOT
  /PRINT=GOODFIT CORR CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).


REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT log_wealth
  /METHOD=ENTER Sex_bi Age Kinship_n_close.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Friends_outdegree
  /METHOD=ENTER Sex_bi Age log_wealth.
```

Empty model:

Block 0: Beginning Block

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	1,751	,142	151,464	1	,000	5,759

Model 1: Sex, Age -> Generosity

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	6,298	2	,043
	Block	6,298	2	,043
	Model	6,298	2	,043

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	322,318[a]	,016	,028

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	5,336	8	,721

Classification Table[a]

Observed			Predicted Generosity_01 ,00	Predicted Generosity_01 1,00	Percentage Correct
Step 1	Generosity_01	,00	0	58	,0
		1,00	0	334	100,0
	Overall Percentage				85,2

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Sex_bi	-,559	,311	3,234	1	,072	,572	,311	1,052
	Age	-,014	,008	3,258	1	,071	,986	,971	1,001
	Constant	2,745	,455	36,394	1	,000	15,563		

a. Variable(s) entered on step 1: Sex_bi, Age.

Model 2: Sex, Age, Wealth -> Generosity

Block 2: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	,543	1	,461
	Block	,543	1	,461
	Model	6,841	3	,077

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	321,775[a]	,017	,030

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	8,250	8	,409

Classification Table[a]

	Observed	Predicted Generosity_01

			,00	1,00	Percentage Correct
Step 1	Generosity_01	,00	0	58	,0
		1,00	0	334	100,0
	Overall Percentage				85,2

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Sex_bi	-,558	,311	3,215	1	,073	,572	,311	1,053
	Age	-,014	,008	3,172	1	,075	,986	,971	1,001
	log_wealth	,166	,221	,563	1	,453	1,180	,765	1,821
	Constant	2,125	,934	5,173	1	,023	8,373		

a. Variable(s) entered on step 1: Sex_bi, Age, log_wealth.

Model 3: Sex, Age, Wealth, Kinship -> Generosity

Block 3: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	2,522	1	,112
	Block	2,522	1	,112
	Model	9,363	4	,053

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	319,253[a]	,024	,042

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.

1	7,087	8	,527

Classification Table[a]

Observed			Predicted		
			Generosity_01		Percentage Correct
			,00	1,00	
Step 1	Generosity_01	,00	0	58	,0
		1,00	0	334	100,0
	Overall Percentage				85,2

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Sex_bi	-,579	,313	3,433	1	,064	,560	,304	1,034
	Age	-,014	,008	2,937	1	,087	,986	,971	1,002
	log_wealth	,125	,223	,312	1	,577	1,133	,731	1,755
	Kinship_n_close	,099	,066	2,235	1	,135	1,104	,970	1,256
	Constant	2,085	,938	4,944	1	,026	8,045		

a. Variable(s) entered on step 1: Sex_bi, Age, log_wealth, Kinship_n_close.

Model 7: Sex, Age, Wealth, Kinship, Friendship -> Generosity

Block 4: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	,096	1	,757
	Block	,096	1	,757
	Model	9,459	5	,092

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	319,156[a]	,024	,042

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	4,297	8	,829

Classification Table[a]

	Observed		Predicted Generosity_01 ,00	Predicted Generosity_01 1,00	Percentage Correct
Step 1	Generosity_01	,00	0	58	,0
		1,00	0	334	100,0
	Overall Percentage				85,2

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	Sex_bi	-,578	,313	3,418	1	,064	,561	,304	1,035
	Age	-,013	,008	2,765	1	,096	,987	,971	1,002
	log_wealth	,123	,224	,304	1	,581	1,131	,730	1,754
	Kinship_n_close	,099	,066	2,241	1	,134	1,104	,970	1,257
	Friends_outdegree	-,027	,087	,097	1	,755	,973	,821	1,153
	Constant	2,111	,942	5,018	1	,025	8,257		

a. Variable(s) entered on step 1: Sex_bi, Age, log_wealth, Friends_outdegree.

Model 5: Sex, Age, Wealth, Friendship -> Generosity

Block 3: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	,089	1	,765
	Block	,089	1	,765
	Model	6,930	4	,140

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	321,685[a]	,018	,031

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	8,319	8	,403

Classification Table[a]

Observed			Predicted		
			Generosity_01		Percentage Correct
			,00	1,00	
Step 1	Generosity_01	,00	0	58	,0
		1,00	0	334	100,0
	Overall Percentage				85,2

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Sex_bi	-,557	,311	3,207	1	,073	,573	,311	1,054
	Age	-,014	,008	3,003	1	,083	,986	,971	1,002
	log_wealth	,164	,221	,550	1	,459	1,178	,764	1,818
	Friends_outdegree	-,026	,087	,091	1	,763	,974	,821	1,155
	Constant	2,154	,940	5,250	1	,022	8,619		

a. Variable(s) entered on step 1: Sex_bi, Age, log_wealth, Friends_outdegree.

Model 7: Sex, Age, Wealth, Kinship, Friendship -> Generosity

Block 4: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	2,529	1	,112
	Block	2,529	1	,112
	Model	9,459	5	,092

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	319,156[a]	,024	,042

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	4,297	8	,829

Classification Table[a]

	Observed		Predicted		
			Generosity_01		Percentage Correct
			,00	1,00	
Step 1	Generosity_01	,00	0	58	,0
		1,00	0	334	100,0
	Overall Percentage				85,2

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
Step 1[a]	Sex_bi	-,578	,313	3,418	1	,064	,561	,304	1,035
	Age	-,013	,008	2,765	1	,096	,987	,971	1,002
	log_wealth	,123	,224	,304	1	,581	1,131	,730	1,754
	Friends_outdegree	-,027	,087	,097	1	,755	,973	,821	1,153
	Kinship_n_close	,099	,066	2,241	1	,134	1,104	,970	1,257
	Constant	2,111	,942	5,018	1	,025	8,257		

a. Variable(s) entered on step 1: Sex_bi, Age, log_wealth, Friends_outdegree, Kinship_n_close.

Model 4: Sex, Age, Kinship -> Wealth

Regression

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,124[a]	,015	,008	,62685

a. Predictors: (Constant), Kinship_n_close, Sex_bi, Age

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2,372	3	,791	2,012	,112[b]
	Residual	152,463	388	,393		
	Total	154,835	391			

a. Dependent Variable: log_wealth

b. Predictors: (Constant), Kinship_n_close, Sex_bi, Age

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	3,696	,098		37,644	,000
	Sex_bi	-,023	,065	-,018	-,361	,719
	Age	-,001	,002	-,026	-,517	,606
	Kinship_n_close	,028	,012	,119	2,349	,019

a. Dependent Variable: log_wealth

Model 6: Sex, Age, Wealth -> Friendship

Regression

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,123[a]	,015	,007	1,618

a. Predictors: (Constant), log_wealth, Sex_bi, Age

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	15,543	3	5,181	1,979	,117[b]
	Residual	1015,722	388	2,618		
	Total	1031,265	391			

a. Dependent Variable: Friends_outdegree

b. Predictors: (Constant), log_wealth, Sex_bi, Age

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	1,129	,546		2,067	,039
	Sex_bi	,054	,167	,016	,322	,748
	Age	,011	,005	,117	2,314	,021
	log_wealth	-,085	,130	-,033	-,654	,514

a. Dependent Variable: Friends_outdegree

Syntax

```
SORT CASES  BY community.
SPLIT FILE LAYERED BY community.

LOGISTIC REGRESSION VARIABLES Generosity_01
  /METHOD=ENTER Sex_bi Age
  /METHOD=ENTER Sex_bi Age log_wealth
  /METHOD=ENTER Sex_bi Age log_wealth Kinship_n_close
  /METHOD=ENTER Sex_bi Age log_wealth Friends_outdegree
  /METHOD=ENTER Sex_bi Age log_wealth Kinship_n_close Friends_outdegree
  /CLASSPLOT
  /PRINT=GOODFIT CORR CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).


SPLIT FILE OFF.
```

Models split by community:
Block 4: Method = Enter

Omnibus Tests of Model Coefficients

community			Chi-square	df	Sig.
altiplano	Step 1	Step	3,461	1	,063
		Block	3,461	1	,063
		Model	7,010	5	,220
coastal	Step 1	Step	,018	1	,892
		Block	,018	1	,892
		Model	13,455	5	,019
highland	Step 1	Step	,303	1	,582
		Block	,303	1	,582
		Model	12,329	5	,031
lowland	Step 1	Step	,242	1	,623
		Block	,242	1	,623
		Model	11,576	5	,041

Model Summary

community	Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
altiplano	1	76,297[a]	,063	,117
coastal	1	45,681[b]	,135	,286
highland	1	16,491[c]	,198	,491
lowland	1	133,908[d]	,082	,125

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001 for split file community = altiplano.

b. Estimation terminated at iteration number 8 because parameter estimates changed by less than ,001 for split file community = coastal.

c. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found for split file community = highland.

d. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001 for split file community = lowland.

Hosmer and Lemeshow Test

community	Step	Chi-square	df	Sig.
altiplano	1	7,319	8	,503
coastal	1	5,996	8	,648
highland	1	1,886	7	,966
lowland	1	3,659	8	,886

Classification Table[a]

				Predicted		
				Generosity_01		Percentage
community		Observed		,00	1,00	Correct
altiplano	Step 1	Generosity_01	,00	0	14	,0
			1,00	1	93	98,9
		Overall Percentage				86,1
coastal	Step 1	Generosity_01	,00	0	9	,0
			1,00	0	84	100,0
		Overall Percentage				90,3
highland	Step 1	Generosity_01	,00	1	3	25,0
			1,00	1	51	98,1
		Overall Percentage				92,9
lowland	Step 1	Generosity_01	,00	0	31	,0
			1,00	4	100	96,2
		Overall Percentage				74,1

a. The cut value is ,500

Variables in the Equation

community			B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
altiplano	Step 1[a]	Sex_bi	-,003	,635	,000	1	,996	,997	,287	3,457
		Age	-,017	,018	,926	1	,336	,983	,948	1,018
		log_wealth	-,376	,816	,212	1	,645	,686	,139	3,400
		Kinship_n_close	,149	,127	1,367	1	,242	1,160	,904	1,488
		Friends_outdegree	-,583	,314	3,441	1	,064	,558	,301	1,034
		Constant	4,106	3,605	1,298	1	,255	60,729		
coastal	Step 1[a]	Sex_bi	,878	,795	1,218	1	,270	2,405	,506	11,435
		Age	-,039	,028	1,947	1	,163	,962	,911	1,016
		log_wealth	,217	,443	,240	1	,624	1,243	,521	2,963
		Kinship_n_close	,959	,534	3,229	1	,072	2,610	,917	7,432
		Friends_outdegree	-,027	,200	,019	1	,891	,973	,658	1,439
		Constant	2,013	1,890	1,134	1	,287	7,486		
highland	Step 1[a]	Sex_bi	-18,931	6931,298	,000	1	,998	,000	,000	.
		Age	-,092	,052	3,169	1	,075	,912	,825	1,009
		log_wealth	,965	2,787	,120	1	,729	2,624	,011	618,065
		Kinship_n_close	-,079	,484	,026	1	,871	,924	,358	2,388
		Friends_outdegree	,253	,469	,291	1	,590	1,288	,514	3,228
		Constant	21,487	6931,304	,000	1	,998	2145365219,625		
lowland	Step 1[a]	Sex_bi	-1,025	,508	4,076	1	,043	,359	,133	,970
		Age	,011	,012	,789	1	,374	1,011	,987	1,036
		log_wealth	-,070	,315	,049	1	,825	,933	,503	1,731
		Kinship_n_close	-,268	,119	5,058	1	,025	,765	,606	,966
		Friends_outdegree	,066	,136	,236	1	,627	1,068	,819	1,393
		Constant	1,974	1,325	2,221	1	,136	7,201		

a. Variable(s) entered on step 1: Sex_bi, Age, log_wealth, Friends_outdegree.

Block 5: Method = Enter

Omnibus Tests of Model Coefficients

community			Chi-square	df	Sig.
altiplano	Step 1	Model	7,010	5	,220
coastal	Step 1	Model	13,455	5	,019
highland	Step 1	Model	12,329	5	,031
lowland	Step 1	Model	11,576	5	,041

Model Summary

community	Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
altiplano	1	76,297[a]	,063	,117
coastal	1	45,681[b]	,135	,286
highland	1	16,491[c]	,198	,491
lowland	1	133,908[d]	,082	,125

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001 for split file community = altiplano.

b. Estimation terminated at iteration number 8 because parameter estimates changed by less than ,001 for split file community = coastal.

c. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found for split file community = highland.

d. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001 for split file community = lowland.

Hosmer and Lemeshow Test

community	Step	Chi-square	df	Sig.
altiplano	1	7,319	8	,503
coastal	1	5,996	8	,648
highland	1	1,886	7	,966
lowland	1	3,659	8	,886

Classification Table[a]

community		Observed		Predicted: Generosity_01 ,00	Predicted: Generosity_01 1,00	Predicted: Percentage Correct
altiplano	Step 1	Generosity_01	,00	0	14	,0
			1,00	1	93	98,9
		Overall Percentage				86,1
coastal	Step 1	Generosity_01	,00	0	9	,0
			1,00	0	84	100,0
		Overall Percentage				90,3
highland	Step 1	Generosity_01	,00	1	3	25,0
			1,00	1	51	98,1
		Overall Percentage				92,9
lowland	Step 1	Generosity_01	,00	0	31	,0
			1,00	4	100	96,2
		Overall Percentage				74,1

a. The cut value is ,500

Variables in the Equation

community			B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
altiplano	Step 1[a]	Sex_bi	-,003	,635	,000	1	,996	,997	,287	3,457
		Age	-,017	,018	,926	1	,336	,983	,948	1,018
		log_wealth	-,376	,816	,212	1	,645	,686	,139	3,400
		Kinship_n_close	,149	,127	1,367	1	,242	1,160	,904	1,488
		Friends_outdegree	-,583	,314	3,441	1	,064	,558	,301	1,034
		Constant	4,106	3,605	1,298	1	,255	60,729		
coastal	Step 1[a]	Sex_bi	,878	,795	1,218	1	,270	2,405	,506	11,435
		Age	-,039	,028	1,947	1	,163	,962	,911	1,016
		log_wealth	,217	,443	,240	1	,624	1,243	,521	2,963
		Kinship_n_close	,959	,534	3,229	1	,072	2,610	,917	7,432
		Friends_outdegree	-,027	,200	,019	1	,891	,973	,658	1,439
		Constant	2,013	1,890	1,134	1	,287	7,486		

highland	Step 1[a]	Sex_bi	-18,931	6931,298	,000	1	,998	,000	,000	.
		Age	-,092	,052	3,169	1	,075	,912	,825	1,009
		log_wealth	,965	2,787	,120	1	,729	2,624	,011	618,065
		Kinship_n_close	-,079	,484	,026	1	,871	,924	,358	2,388
		Friends_outdegree	,253	,469	,291	1	,590	1,288	,514	3,228
		Constant	21,487	6931,304	,000	1	,998	2145365219,625		
lowland	Step 1[a]	Sex_bi	-1,025	,508	4,076	1	,043	,359	,133	,970
		Age	,011	,012	,789	1	,374	1,011	,987	1,036
		log_wealth	-,070	,315	,049	1	,825	,933	,503	1,731
		Kinship_n_close	-,268	,119	5,058	1	,025	,765	,606	,966
		Friends_outdegree	,066	,136	,236	1	,627	1,068	,819	1,393
		Constant	1,974	1,325	2,221	1	,136	7,201		

a. Variable(s) entered on step 1: Sex_bi, Age, log_wealth, Kinship_n_close, Friends_outdegree.

Extra analysis without sex

I did one extra analysis for the Highland community without the variable sex due to an extreme high standard error.

Syntax

```
USE ALL.
COMPUTE filter_$=(obs = 1).
VARIABLE LABELS filter_$ 'obs = 1 (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE
.
SORT CASES  BY community.
SPLIT FILE LAYERED BY community.

LOGISTIC REGRESSION VARIABLES Generosity_01
  /METHOD=ENTER Age log_wealth Kinship_n_close Friends_outdegree
  /SAVE=COOK LEVER DFBETA ZRESID DEV
  /CLASSPLOT
  /PRINT=GOODFIT CORR CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).


SPLIT FILE OFF.
```

Block 0: Beginning Block

Classification Table[a,b]

community		Observed		Predicted: Generosity_01 ,00	Predicted: Generosity_01 1,00	Predicted: Percentage Correct
altiplano	Step 0	Generosity_01	,00	0	14	,0
			1,00	0	94	100,0
		Overall Percentage				87,0
coastal	Step 0	Generosity_01	,00	0	9	,0
			1,00	0	84	100,0
		Overall Percentage				90,3
highland	Step 0	Generosity_01	,00	0	4	,0
			1,00	0	52	100,0
		Overall Percentage				92,9
lowland	Step 0	Generosity_01	,00	0	31	,0
			1,00	0	104	100,0
		Overall Percentage				77,0

a. Constant is included in the model.

b. The cut value is ,500

Variables in the Equation

community			B	S.E.	Wald	df	Sig.	Exp(B)
altiplano	Step 0[a]	Constant	1,904	,286	44,185	1	,000	6,714
coastal	Step 0[a]	Constant	2,234	,351	40,555	1	,000	9,333
highland	Step 0[a]	Constant	2,565	,519	24,436	1	,000	13,000
lowland	Step 0[a]	Constant	1,210	,205	34,988	1	,000	3,355

a. Variable(s) entered on step 1: Age, log_wealth, Kinship_n_close, Friends_outdegree.

Block 1: Method = Enter

Omnibus Tests of Model Coefficients

community			Chi-square	df	Sig.
altiplano	Step 1	Step	7,010	4	,135

		Block	7,010	4	,135
		Model	7,010	4	,135
coastal	Step 1	Step	12,182	4	,016
		Block	12,182	4	,016
		Model	12,182	4	,016
highland	Step 1	Step	8,249	4	,083
		Block	8,249	4	,083
		Model	8,249	4	,083
lowland	Step 1	Step	7,019	4	,135
		Block	7,019	4	,135
		Model	7,019	4	,135

Model Summary

community	Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
altiplano	1	76,297[a]	,063	,117
coastal	1	46,954[b]	,123	,261
highland	1	20,571[c]	,137	,340
lowland	1	138,464[d]	,051	,077

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than ,001 for split file community = altiplano.

b. Estimation terminated at iteration number 8 because parameter estimates changed by less than ,001 for split file community = coastal.

c. Estimation terminated at iteration number 8 because parameter estimates changed by less than ,001 for split file community = highland.

d. Estimation terminated at iteration number 4 because parameter estimates changed by less than ,001 for split file community = lowland.

Hosmer and Lemeshow Test

community	Step	Chi-square	df	Sig.
altiplano	1	7,320	8	,503
coastal	1	8,291	8	,406
highland	1	3,376	7	,848
lowland	1	6,634	8	,577

Classification Table[a]

community	Observed	Predicted

				Generosity_01		Percentage Correct
				,00	1,00	
altiplano	Step 1	Generosity_01	,00	0	14	,0
			1,00	1	93	98,9
		Overall Percentage				86,1
coastal	Step 1	Generosity_01	,00	0	9	,0
			1,00	0	84	100,0
		Overall Percentage				90,3
highland	Step 1	Generosity_01	,00	1	3	25,0
			1,00	0	52	100,0
		Overall Percentage				94,6
lowland	Step 1	Generosity_01	,00	0	31	,0
			1,00	2	102	98,1
		Overall Percentage				75,6

a. The cut value is ,500

Variables in the Equation

community			B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	Upper
altiplano	Step 1[a]	Age	-,017	,018	,961	1	,327	,983	,949	1,018
		log_wealth	-,376	,815	,213	1	,644	,687	,139	3,390
		Kinship_n_close	,149	,127	1,367	1	,242	1,160	,904	1,488
		Friends_outdegree	-,583	,314	3,459	1	,063	,558	,302	1,032
		Constant	4,102	3,525	1,354	1	,245	60,484		
coastal	Step 1[a]	Age	-,039	,026	2,222	1	,136	,961	,913	1,013
		log_wealth	,169	,436	,150	1	,699	1,184	,504	2,781
		Kinship_n_close	1,025	,548	3,497	1	,061	2,788	,952	8,164
		Friends_outdegree	-,005	,200	,001	1	,980	,995	,672	1,473
		Constant	2,555	1,826	1,957	1	,162	12,866		
highland	Step 1[a]	Age	-,101	,053	3,689	1	,055	,904	,815	1,002
		log_wealth	1,217	2,410	,255	1	,613	3,378	,030	380,239
		Kinship_n_close	-,136	,427	,102	1	,750	,873	,378	2,016

		Friends_outdegree	,189	,427	,197	1	,658	1,208	,523	2,791
		Constant	2,968	7,404	,161	1	,689	19,450		
lowland	Step 1[a]	Age	,014	,012	1,217	1	,270	1,014	,990	1,038
		log_wealth	-,081	,302	,073	1	,788	,922	,510	1,666
		Kinship_n_close	-,280	,115	5,911	1	,015	,756	,603	,947
		Friends_outdegree	,045	,134	,113	1	,737	1,046	,804	1,360
		Constant	1,232	1,208	1,040	1	,308	3,428		

a. Variable(s) entered on step 1: Age, log_wealth, Kinship_n_close, Friends_outdegree.

Appendix 3

Assumption 1: Independent observations

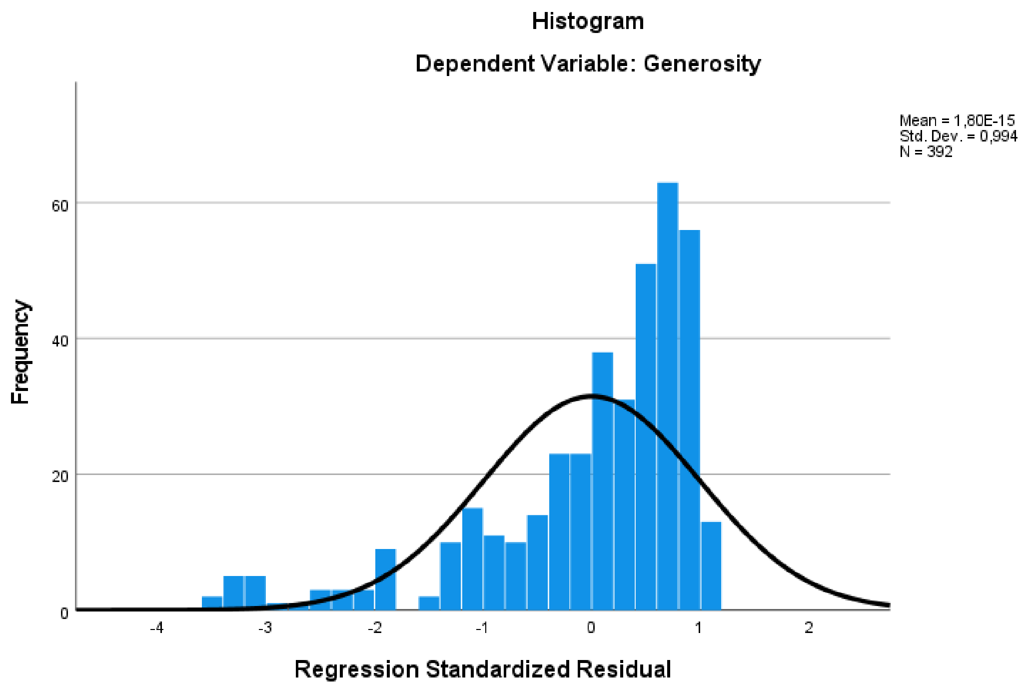
The data used within the analysis was not independently observed. The research design was originally for network analysis. Therefore this assumptions has clearly been violated. In the method and discussion paragraphs I have gone more in depth about the implications.

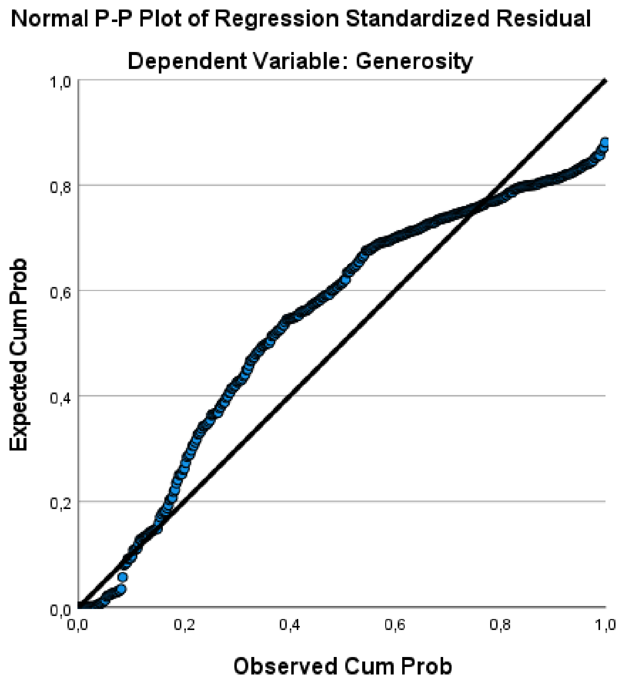
Assumption 2: Normal distribution of residuals

The dependent generosity is a continues variable so my first idea was to do a normal linear regression. However, it became clear that the residuals of generosity were not normally distributed. This can be seen in the histogram of the standardized residuals and the normal P-P Plot below. I decided to perform a binary logistic regression and dichotomized the variable for generosity (see appendix 1)

Syntax

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA CHANGE ZPP
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Generosity
  /METHOD=ENTER Sex_bi Age Kinship_n_close log_wealth Friends_outdegree
  /PARTIALPLOT ALL
  /RESIDUALS HISTOGRAM(ZRESID) NORMPROB(ZRESID).
```



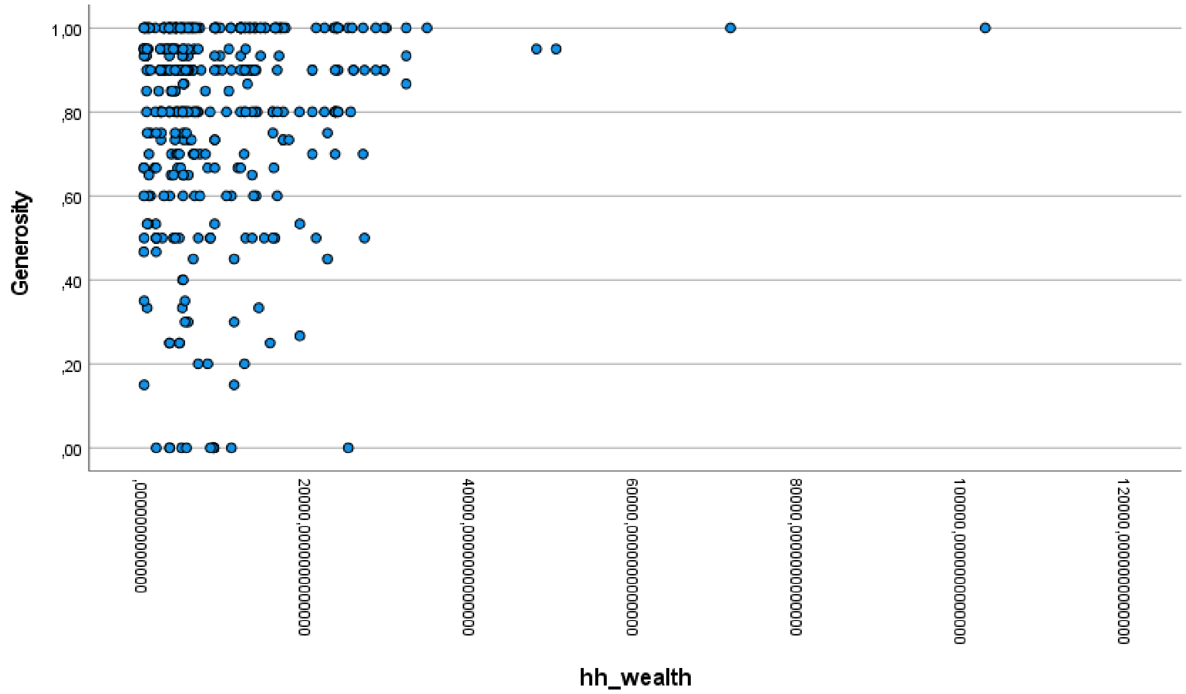


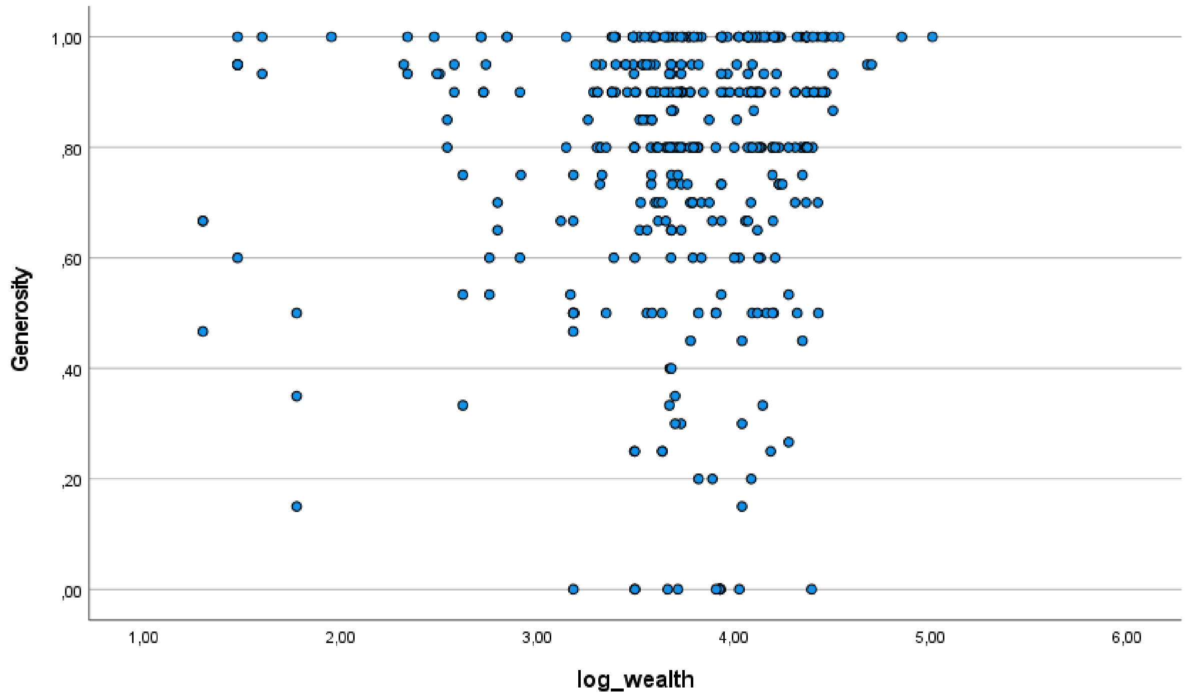
Assumption 3: Linear relationship

One of the assumption within a logistical regression is that there is a linear relationship with the log-odd transformed dependent. The relationship between generosity and wealth is not linear but logistic due to the highly skewed distribution of wealth. This can be seen when comparing the scatterplots of hh_wealth with generosity and log_wealth with generosity. That is why the natural log function of wealth was used in the analysis (see appendix 1).

Syntax

```
GRAPH
  /SCATTERPLOT(BIVAR)=hh_wealth WITH Generosity
  /MISSING=LISTWISE.

GRAPH
  /SCATTERPLOT(BIVAR)=log_wealth WITH Generosity
  /MISSING=LISTWISE.
```





Multicollinearity

No extreme high values of multicollinearity were found in the model.

Syntax

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COLLIN TOL ZPP
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Generosity_01
  /METHOD=ENTER Sex_bi Age Kinship_n_close log_wealth Friends_outdegree coastal
lowland highland
    altiplano.
```

Coefficients[a]

Model		Correlations			Collinearity Statistics	
		Zero-order	Partial	Part	Tolerance	VIF
1	Sex_bi	-,087	-,083	-,081	,986	1,014
	Age	-,087	-,059	-,058	,950	1,052
	Kinship_n_close	,080	,051	,050	,936	1,068
	log_wealth	,041	,004	,004	,902	1,109
	Friends_outdegree	-,028	-,004	-,004	,864	1,157
	coastal	,080	,121	,119	,744	1,344
	highland	,088	,115	,113	,754	1,326
	altiplano	,032	,079	,078	,596	1,677

a. Dependent Variable: Generosity_01

Outliers and influential points

I took a look at potential outliers and influential points. I saved the residuals, cook distance, leverage and DFBETA values. Then I looked at the descriptives which values were extreme and discarded the DFBETA's due to them being relatively low. Then I looked at the most extreme values for the cook distance, leverage and residuals, and I plotted the leverage with the cook distance. Finally I run the analysis again, which resulted in no major differences.

Syntax

```
LOGISTIC REGRESSION VARIABLES Generosity_01
  /METHOD=ENTER Sex_bi Age
  /METHOD=ENTER Sex_bi Age log_wealth
  /METHOD=ENTER Sex_bi Age log_wealth Kinship_n_close
  /METHOD=ENTER Sex_bi Age log_wealth Friends_outdegree
  /METHOD=ENTER Sex_bi Age log_wealth Kinship_n_close Friends_outdegree
  /SAVE=COOK LEVER DFBETA ZRESID DEV
  /CLASSPLOT
  /PRINT=GOODFIT CORR CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).


DESCRIPTIVES VARIABLES=COO_1 LEV_1 ZRE_1 DEV_1 DFB0_1 DFB1_1 DFB2_1 DFB3_1 DFB4_1
DFB5_1
  /STATISTICS=MEAN STDDEV MIN MAX.

GRAPH
  /SCATTERPLOT(BIVAR)=LEV_1 WITH COO_1 BY V1 (IDENTIFY)
  /MISSING=LISTWISE.

RECODE obs (ELSE=Copy) INTO obs2.
EXECUTE.

*Manually recoded values VI = 36, 47, 52, 58, 72, 141, 161, 197, 200, 223, 227,
308, 374, 425 to 0.

COMPUTE filter_$=(obs2 = 1).
VARIABLE LABELS filter_$ 'obs2 = 1 (FILTER)'.
VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
FORMATS filter_$ (f1.0).
FILTER BY filter_$.
EXECUTE.

LOGISTIC REGRESSION VARIABLES Generosity_01
  /METHOD=ENTER Sex_bi Age
  /METHOD=ENTER Sex_bi Age log_wealth
  /METHOD=ENTER Sex_bi Age log_wealth Kinship_n_close
  /METHOD=ENTER Sex_bi Age log_wealth Friends_outdegree
  /METHOD=ENTER Sex_bi Age log_wealth Kinship_n_close Friends_outdegree
  /PRINT=GOODFIT CORR CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).


FILTER OFF.
USE ALL.
EXECUTE.
```

Descriptive Statistics

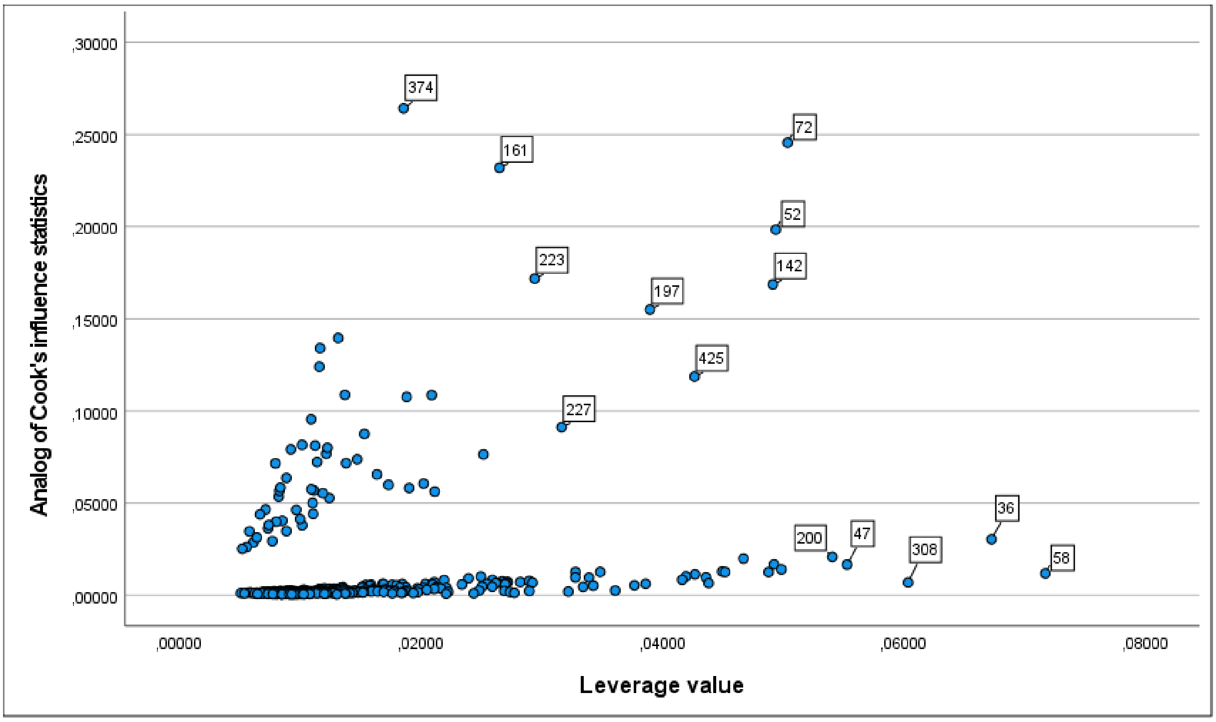
	N	Minimum	Maximum	Mean	Std. Deviation
COO_1 Analog of Cook's influence statistics	392	,00050	,26424	,0146412	,03519198
LEV_1 Leverage value	392	,00514	,07171	,0153061	,01044627
ZRE_1 Normalized residual	392	-3,73480	,64971	,0020707	,99163345
DEV_1 Deviance value	392	-2,32578	,83923	,1864029	,88398081
DFB0_1 DFBETA for constant	392	-,43586	,19766	-,0000026	,05132275
DFB1_1 DFBETA for Sex_bi	392	-,02968	,06723	,0000016	,01602332
DFB2_1 DFBETA for Age	392	-,00229	,00168	-,0000001	,00042027

DFB3_1 DFBETA for log_wealth	392	-,03644	,09960	-,0000001	,01186861
DFB4_1 DFBETA for Kinship_n_close	392	-,02923	,00762	,0000006	,00293607
DFB5_1 DFBETA for Friends_outdegree	392	-,03594	,01065	,0000052	,00419941
Valid N (listwise)	392				

V1	COO_1
374	,26424
72	,24556
161	,23201
52	,19841
223	,17184
142	,16870
197	,15502
194	,13957
136	,13408
285	,12398
425	,11864
34	,10876
88	,10863
28	,10762

V1	LEV_1
58	,07171
36	,06725
308	,06034
47	,05529
200	,05407
72	,05037
140	,04986
52	,04940
178	,04926
142	,04915
203	,04879
82	,04672
187	,04520

V1	ZRE_1
374	-3,73480
136	-3,36793
285	-3,24675
194	-3,23228
128	-2,98020
328	-2,93838
161	-2,91788
9	-2,90954
239	-2,81430
34	-2,79351
363	-2,66649
351	-2,66091
184	-2,62698
139	-2,59851
359	-2,54602
188	-2,53863
240	-2,53585
248	-2,53316
230	-2,50105



Block 5: Method = Enter

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Model	9,304	5	,098

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	282,272[a]	,024	,045

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than ,001.

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	1,003	8	,998

Classification Table[a]

Observed			Predicted: Generosity_01 ,00	Predicted: Generosity_01 1,00	Predicted: Percentage Correct
Step 1	Generosity_01	,00	0	49	,0
		1,00	0	329	100,0
	Overall Percentage				87,0

a. The cut value is ,500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	Sex_bi	-,542	,334	2,625	1	,105	,582	,302	1,120
	Age	-,013	,009	2,010	1	,156	,987	,970	1,005
	log_wealth	-,257	,313	,676	1	,411	,773	,419	1,427
	Kinship_n_close	,150	,079	3,613	1	,057	1,162	,995	1,357
	Friends_outdegree	-,001	,099	,000	1	,996	,999	,822	1,215
	Constant	3,504	1,303	7,229	1	,007	33,257		

a. Variable(s) entered on step 1: Sex_bi, Age, log_wealth, Kinship_n_close, Friends_outdegree.