Environmental Long-term Farm Investments of Smallholders in the Agroforestry Sector in Tanzania

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Abbreviations

a.s.l.	above sea-level
AIC	Akaike information criterion
Better-iS	Biofuel Evaluation for Technological Tanzanian Efficiency using Renewables – integrated Strategy
BIC	Schwarz' Bayesian information criterion
BLUE	best linear unbiased estimators
Cook's D	Cook's Distance
e.g.	exempli gratia
et al.	et aliud
etc.	et cetera
GLM	generalized linear model
ha	hectare
HH	household
ICRAF	International Agroforestry Centre
ln	natural logarithm
Max.	maximum
Min.	minimum
NGO	non Governmental Organization
no.	number
Obs.	observations

OLS	ordinary least squares
PRESA	Pro-poor Rewards for Environmental Services in Africa
RESET	regression specification error test
SSE	explained sum of squares
SSR	residual sum of squares
SST	total sum of squares
Std. Dev.	standard deviation
SUA	Sokoine University of Agriculture
TZS	Tanzanian Shilling
VIF	Variance Inflation Factor

1 Introduction

The population of Tanzania grew steadily from 19,253,166 inhabitants in 1981 to 43,739,051 inhabitants in 2009 (World Bank, 2010 , World Bank, 1982). Thus the population density has more than doubled within less than two decades. With an increasing population density the availability of cultivable land becomes scarcer. As a result of this the periods of fallow are shortened which reduces soil fertility. Due to the reduced soil fertility and the increasing population pressure areas which were former covered by forest are cleared to gain new arable areas. In addition, forest areas are partially degraded because the requirements of firewood and timber are at least partly covered by extraction out of the forest. From the reduced forest cover arises among other issues the problem of soil erosion which in turn leads to yield losses.

Agroforestry – in particular tree planting – is a promising solution to the just characterized issues because firewood would be generated on one side and on the other side soil erosion could be alleviated. However, trees need a certain period of time to grow up before they deliver firewood and develop roots that reduce the occurrence of soil erosion. Although the benefits from agroforestry accrue in the future the investment in seeds, seedlings and fertilizer have to be made in the present. Hence, the investment in trees may depend on a persons' rate of time preference by which that person discounts future results.

Due to the benefits accompanied by agroforestry the question raises which factors have an impact on the decision of Tanzanian smallholders to adopt agroforestry? In addition the question arises of whether there is a nexus among long-term farm investments like tree planting and the rate of time preference of smallholders in Tanzania? And finally what are the factors of influencing on the-level of the smallholders' rate of time preference?

These questions are addressed by an empirical analysis based on data compiled through a household survey. The household survey was conducted within the project "Biofuel Evaluation for Technological Tanzanian Efficiency using Renewables – integrated Strategy" (Better-iS). As survey area was the village Tandai selected which is located approximately 200 km in the west of Dar es Salaam – the capital of Tanzania. Since this final paper is written in the context of the Better-iS project the survey data has been available for the empirical analysis regarding the above raised questions.

In the course of entering into the questions the following structure is chosen. In section two a review of the available literature on agroforestry on one hand and time preference on the other hand is provided. In chapter three the influencing factors for agroforestry and the rate of time preference are derived by drawing on results of former empirical studies on agroforestry as well as by theoretical considerations. In section 4 the characteristics of the study village Tandai and the particularities of the poll conducted in Tandai are illustrated. The empirical analysis on the influencing factors on agroforestry is performed in section five followed by the empirical analysis on the smallholders' rate of time preference in chapter six. Finally a conclusion of the obtained results is delivered in section 7.

2 Literature Review

2.1 Agroforestry – its Costs, Benefits and Determinants

2.1.1 Definition of Agroforestry

Agroforestry characterizes the intentional use of trees and other woody perennials at the same unit of productive land where agricultural crops are grown or which is used for pasture or animal keeping to benefit from the resulting ecological and economic interaction (Nair, 1985). The outcome is a mixed spatial arrangement of different land uses at the same place and the same time respectively over a sequence of time (Current et al., 1995). As depicted in figure 1 the three main types of agroforestry systems are agrisilviculture, silvopastural and agrosilvopastoral. Agrisilviculture means that crops and trees are grown on the same unit of productive land. If a silvopastural agroforestry scheme is applied also trees are grown on the area which is used for pasture or animal keeping. And agrosilvopastoral is even a combination of agrisilviculture and a silvopastural agroforestry scheme because crops and trees are grown on the same area which is also used for animal keeping and pasture. However, a plethora of different subtypes of agroforestry schemes arise through the combination of different spatial and temporal arrangements. For instance the applied agroforestry schemes may vary in trees or shrubs which are cultivated as well as in the pattern of growing those trees (Nair, 1985). Moreover the different products like food, fodder, fuelwood or timber that might be produced with the aid of a particular agroforestry scheme give rise to a differentiation of agroforestry schemes. Finally, the smallholders themselves tend to adapt the agroforestry schemes which are introduced to them by scientists to their personal needs, their production possibilities and resource constraints (Adesina and Chianu, 2002). Thereby other and new configurations of agroforestry schemes evolve.

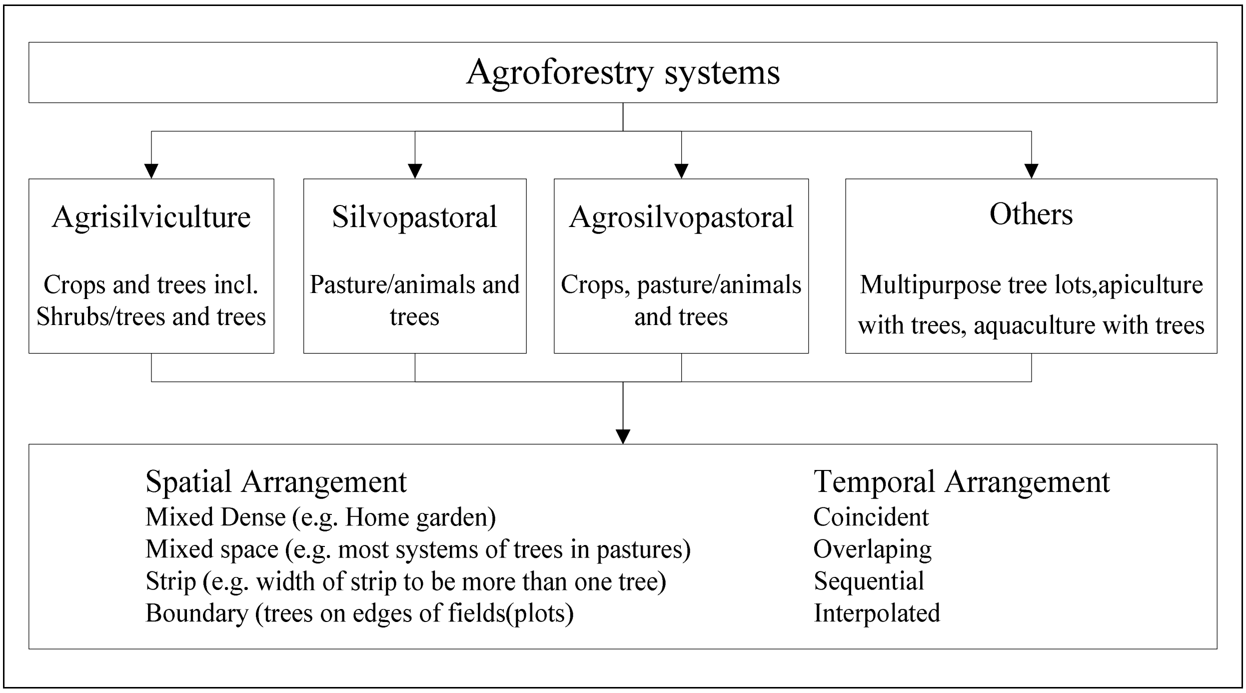

Figure 1: Agroforestry Systems
Source: Own figure following Nair, 1985

2.1.2 Benefits from Agroforestry

Agroforestry systems bear a vast number of benefits for the applying smallholders with respect to the environment, the exposure to risk, the availability of construction material, fodder and fuelwood, as well as the improvement of personal circumstances. A significant environmental advantage results from trees and shrubs because they protect against soil erosion (Gebreegziabher et al., 2010). This becomes obvious if the result of Shively (1998) is taken into account. Shively (1998) observes the erosion rates for established orchards and agroforestry systems being roughly halved compared to cultivating annual field crops. Similar results were found by Benin et al. (2003) who surveyed Ethiopian smallholders. These smallholders reported less erosion problems and higher fertility-levels on plots where trees were planted.

Due to the application of agroforestry schemes like alley cropping nutrients can be recycled and captured within the soil (Adesina et al., 2000). The pruning of the shrubs or hedgerow trees delivers considerable amounts of mulch. Applying the mulch on the crops helps to fixate nitrogen and alleviates land degradation in general (Adesina et al., 2000). If tree planting increases, the availability of firewood rises which may lead to a reduced use of dung and crop residues for fuels (Benin et al., 2003). Consequently, dung and crop residuals could get disseminated on the cultivable area and act as fertilizer which would lead to an enrichment of nutrients within the soil. The consideration of substituting the use of dung as fuel by firewood is contrasted by the finding of woody biomass and dung being either complements or independent goods (Mekonnen, 1999). Hence, if fuelwood and dung are complements the use of dung for fuel would also increase when additional fuelwood is generated by tree planting. If fuelwood and dung are independent an increasing availability of fuelwood would have no impact on a declining use of dung and crop residues as fuels. However, Mekonnen found also that scarcity of fuels affects the fuel choice and fuel mix of Ethiopian farmers. He argued that a policy which encourages the use of dung as fertilizer and aims at the same time at reducing the relative price of wood might reduce land degradation resulting from nutrient depletion (Mekonnen, 1999).

A benefit from agroforestry can also emerge because needed firewood and building timber that was former extracted from natural forests is now provided by the trees on the farm. Therefore, agroforestry schemes can lower the pressure on ecosystems. One such example is given by smallholders in Honduras who depended for a 100% of their tree products on natural forests and meet now the majority of their needs for tree products from trees they planted on their farms (Current et al., 1995). Another gain that should be stressed in this context is that farms which integrate trees provide microhabitats that better support local wildlife than farms which merely grow annual crops (Shively, 1998). According to Shively even a small number of trees on a farm can have a measurable impact on the observed diversity of species.

Moreover planting trees for fruits or timber is a benefit due to the provision of food and building material (Gebreegziabher et al., 2010). Besides, selling tree products which are not needed for the own consumption could be a source to generate income (Shively, 1999). In stressful periods can farmers who apply agroforestry harvest the trees and sell the tree products on the market to generate cash income immediately (Nibbering, 1999). Referring to Nibbering that is why trees can also function as a security. Naturally this is only viable if farmers have access to a market for tree products.

Finally, Shively (2001) mentions that soil erosion events can be a shock to the long-run yields and income of a farm if erosion events are stochastic shocks to the soil stock. Therefore investments in soil conservation means like agroforestry are an opportunity to reduce the exposure to risk from such adverse shocks.

2.1.3 Costs related to Agroforestry

Despite all the positive effects going along with agroforestry there are some facts that hinder smallholders to apply this means of soil conservation. One issue mentioned by Shively (2001) is that agroforestry conservation structures require initial investments for their establishment and further occupy some of the cultivable area. If smallholders have little or no savings and have limited possibilities to receive a loan, the decision to invest in soil conservation incorporates tensions between the objectives to protect yields in the long run and avoid a shortfall of liquidity in the short run(Shively, 2001).

Therefore the utilization and performance of subsidies, food-for-work programs and loans is investigated in several studies. Current et al. (1995) state for example that credits offered to the adopters of agroforestry should be integrated in the offer to introduce agroforestry and not targeted on specific crops or trees. This is particularly reasonable because smallholders employ tree species that fulfill their personal requirements and resource constraints best (Current et al., 1995). These might be other tree species than the ones the credit targeted on.

Regarding the value from food-for-work programs to support the implementation of soil conservation measures the positions are ambiguous. Benin et al. (2003) find food-for-work programs to be an appropriate alternative within their study area in the Ethiopian highlands to induce substantial increases in conservation of cropland as well as in income. An opposing argumentation is that food-for-work programs might lead to difficulties in maintaining introduced agroforestry after incentives by food-for-work programs are not given any longer (Current et al., 1995). In addition, Current et al. (1995) find aversions to make more efforts in agroforestry without payments as soon as payments for the use of agroforestry systems were offered once.

Moreover opportunity costs accrue to the smallholders because the period of time in between of the establishment of agroforestry systems and the accumulation of benefits is longer compared to annual crops (Adesina and Chianu, 2002). The latter provide food or cash income in the year in which they are planted (Adesina and Chianu, 2002). Since the credit markets often function improperly in developing countries the interest rates for loans taken out to establish agroforestry may be very high (Hoff and Stiglitz, 1990). This circumstance even increases the opportunity costs for smallholders who borrow money to establish agroforestry.

Besides monetary and opportunity costs the potential competition of crops and trees or shrubs on the cultivable plots has to be taken into account when evaluating the costs and benefits of agroforestry. Due to the self-sufficient food production of many small scale farmers in developing countries Scherr (2000) stresses that the introduced agroforestry system must not endanger a households' ability to meet its consumption needs self-sufficiently. A solution to this is the application of trees and shrubs that provide among other benefits tree products and food. But as mentioned with respect to the benefits from agroforestry the agricultural productivity often increases through nutrient recycling, improved soil fertility and reduced soil erosion due to the application of agroforestry (Akinnifesi and Kang, 2000). As a result of this the adoption of agroforestry cannot only endanger but even ensure the subsistent production of food because yields can be stabilized in the long-run. A competition of shrubs or trees and crops can be mitigated by ensuring that the intercropped plants fit together. A positive example is given by a study conducted in Indonesia where cassava was cultivated below trees (Nibbering, 1999). The cassava tolerates shade better than cereal crops and therewith the trees were less competitive to the crops grown beyond (Nibbering, 1999).

2.1.4 Determinants of the Adoption of Agroforestry

The adoption of a new technology like agroforestry is a procedure that happens in subsequent stages individuals pass through. A framework for the agroforestry adoption process which is subdivided into subsequent stages is for instance introduced by Neupane et al. (2002). In figure 2 an overview of that adoption framework is provided. It consists out of the stages awareness of agroforestry, attitude towards agroforestry, and adoption of agroforestry. From figure 2 becomes obvious that the each stage of the agroforestry adoption process can be influenced by a variety of factors. Factors of influence are the community characteristics, the household characteristics as well as institutional factors consisting out of the impact of local NGOs and external agroforestry organizations (Neupane et al., 2002). Superordinated structures like the characteristics of the community or the impact of external agroforestry organizations exert their influence on the local NGOs or the household characteristics. The household characteristics as well as the local NGOs in turn have an immediate impact on the decision to adopt agroforestry.

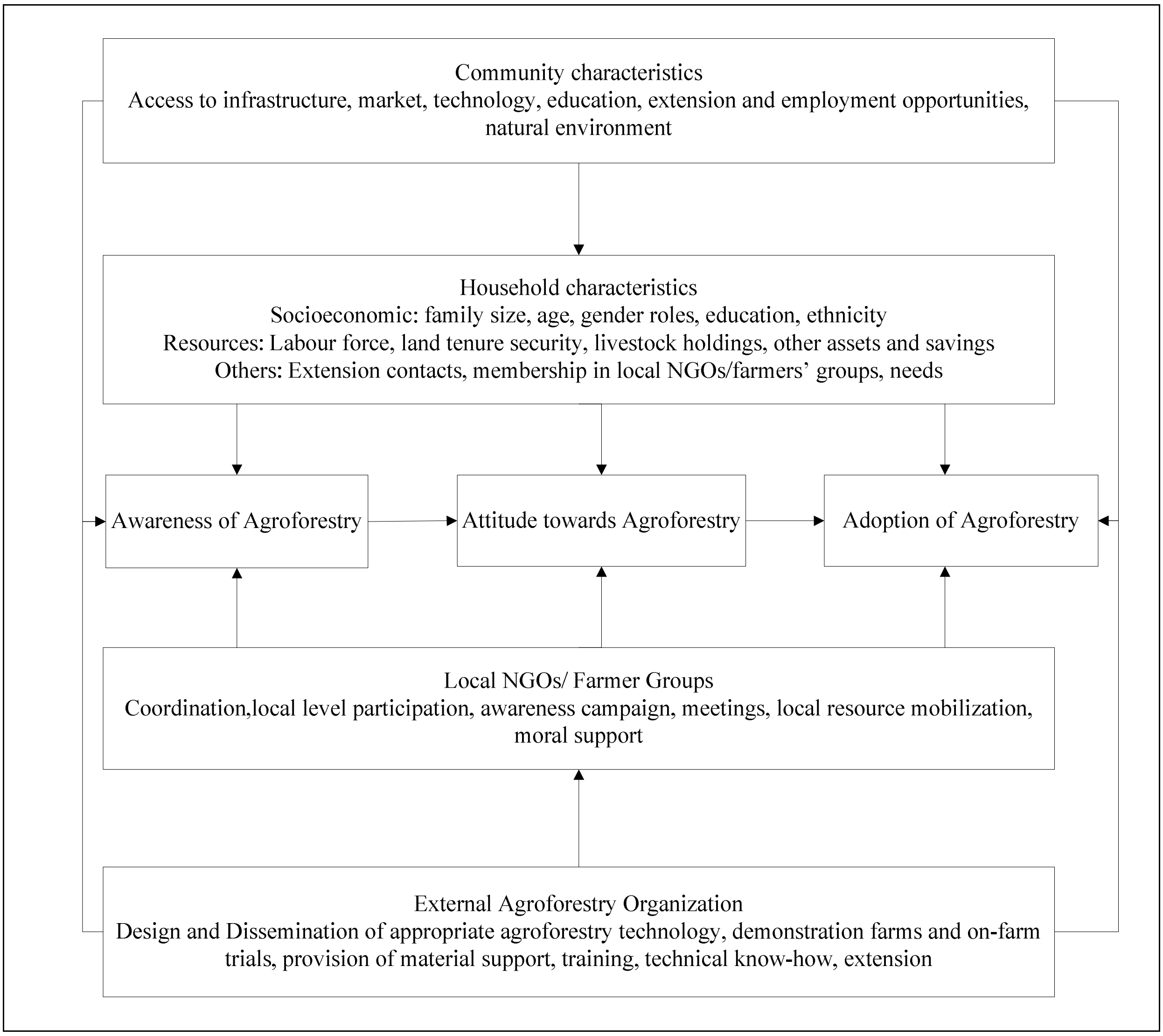

Figure 2: Agroforestry Adoption Framework
Source: Neupane, Sharma, Thapa, 2002

The characteristics of the community comprise access to extension, education, market and infrastructure as well as environmental factors. The community characteristics have an impact on household characteristics which again influence the decision process of a potential adopter itself. The impact of the community characteristics on the household characteristics is for instance given by the fact that if access to education is limited for the whole community also each household member is less likely to receive an education. Furthermore, if the land tenure system within a community involves tenure insecurity, the probability for a single household to face tenure insecurity might be higher. Apart from socioeconomic factors like education and the resource base of a household the characteristics of the households comprise other household specific factors like individual needs or contact to extension services (Neupane et al., 2002).

The third category of influencing characteristics is the one of institutional factors. The institutional factors can be subdivided into external agroforestry organizations as well as farmers' groups and local NGO's. External agroforestry organizations design and disseminate appropriate agroforestry technologies, establish demonstration farms and should provide material support and training (Neupane et al., 2002). Through this action the external agroforestry organizations may influence the local action of NGO's and the farmers groups which in turn may have an impact on the adoption decision itself. With the help of the local action of NGO's and participation of farmers in farmers' groups, the awareness of agroforestry can be strengthened, moral support for the adopters can be delivered as well as local resources can be mobilized (Neupane et al., 2002).

In addition, Caveness and Kurtz (1993) underline that for a positive attitude towards a new technology this technology has to be perceived as needed and realizable under the given social and environmental circumstances. The perception of the soil conserving technology again depends on the information on the soil conserving technology which is available to the smallholder (Caveness and Kurtz, 1993). Scherr (2000) argues similar to Caveness and Kurtz (1993). She stresses that the awareness of a degradation process is crucial for perceiving a new technology as needed. Moreover the respective degradation process has to be considered by the persons, who are supposed to apply the conservation measure, as a threat towards their livelihood (Scherr, 2000). Thus the awareness of an environmental problem and the need for a soil conserving measure is – additional to the above mentioned determinants of the agroforestry adoption process – a crucial determinant for the acceptance of agroforestry.

2.2 Rate of Time Preference – its Definition and Application

The rate of time preference denotes in general a specific pattern for the appreciation of income or consumption over time. A high rate of time preference stands for a high value that is attributed to consumption now compared to consumption in the future (Holden et al., 1998). To put it another way the rate of time preference indicates the amount of consumption a person requires in the future for giving up a specific amount of consumption today; so to say the willingness to accept for a consumption delay. Conversely, the rate of time preference represents also the amount of consumption a person is willing to give up in the future to consume now. In other words the rate of time preference is the willingness to pay to consume now instead of in the future. According to the just said the rate of time preference of a person is defined as the marginal rate of intertemporal substitution at which consumption can be shifted in time while the utility of the person remains unaltered (Fisher, 1930).

The scope of the rate of time preference – also named discount rate – ranges from theories of savings and investment to economic growth as well as from interest rate determination and asset pricing to public policies tackling environmental concerns like climate change or soil degradation (Becker and Mulligan, 1997 , Atkinson et al., 2009). Articles with respect to the savings and investment theory were the first which included discounting. In those articles was argued that in the presence of perfectly functioning loan markets the rate of interest for loans without risk would equal each persons' discount rate (Fisher, 1930). Beyond that, considering on one hand the use of the interest rate to compute future values out of present values and on the other hand the use of the interest rate for discounting future values into present values, Fisher (1930) regards the latter being more relevant.

The assumption that each person's discount rate is equal to the rate of interest holds solely if the neoclassical conditions of perfect functioning markets, perfect information and no externalities are fulfilled (Fisher, 1930 , Holden et al., 1998). Within developing countries, like the study area in the Morogoro region in Tanzania, imperfect information and high transaction costs lead often to market imperfections (Holden et al., 1998). This is in particular true for credit markets in rural areas of developing countries, where interest rates above 75 percentages were observed and sometime credit is not available at all (Hoff and Stiglitz, 1990). As a result of this another opportunity apart from choosing the interest rate as the discount rate has to be found to elicit the time preference of the rural population in Tanzania. For this purpose either the pure rate of time preference or the social rate of discount can be chosen. The social rate of time preference is defined by Markandya and Pearce (1991) as:

$$\rho = \delta + \mu g \tag{1}$$

The social rate depends on the rate by which consumption grows (g), on how fast utility falls when consumption grows (μ) as well as on the pure rate of time preference (δ). The purpose of the social rate of discount is to measure at which rate social utility from consumption falls over time (Markandya and Pearce, 1991). The social rate of discount is in particular applicable for cost benefit analyses e.g. of policy measures that induce e.g. environmental conservation (Markandya and Pearce, 1991). By contrast, the pure rate of time preference δ is the rate at which individuals discount future utility (Holden et al., 1998). The use agroforestry is an individual decision which is based on the expected utility from this decision. As a result of this the smallholders' pure rate of time preference is examined on its impact on the application of agroforestry..

Apart from the issues how to determine the rate of time preference and which rate of time preference to choose it also has to be defined how individuals discount future utility. The choice of the functional form for the discount function depends upon the assumptions made with respect to the structure of time preference as well as on the suitability of a functional for modelling a specific behaviour of a decision maker (Rubinstein, 2003).

A widely used theoretical framework for discounting was developed by Samuelson (1937). Within Samuelson's discounted utility model the following four assumptions are formulated:

i. "Utility is only measurable as […] marginal utility." (Samuelson, 1937, p. 156) This implies that the decision maker integrates a new alternative into already existing plans to evaluate the utility emerging from this new alternative (Frederick et al., 2002).
ii. "During any specified period of time, the individual behaves so as to maximise the sum of all future utilities, they being reduced to comparable magnitudes by suitable time discounting." (Samuelson, 1937, p. 156)
iii. "The individual discounts future utilities in some simple regular fashion which is known to us." (Samuelson, 1937, p. 156)
iv. A set of ideal experimental conditions under which the decision maker acts has to be defined (Samuelson, 1937).

Under the above formulated conditions Samuelson receives equation (2) as the equation according to which individuals discount utility. Within that equation the marginal utilities obtained in the future are referred to today with the aid of discounting (Samuelson, 1937):

$$J = \int_0^b U(x) e^{-\pi t} dt, \ where \ \pi = \left(\frac{1}{1+\delta} \right). \tag{2}$$

The decision maker maximizes the overall utility J that results out of the integral of the discounted utilities over the specified period of time from 0 till b. The decision maker's instantaneous utility function U(x) is dependent upon the income x and exhibits diminishing returns to scale. The discount function $e^{-\pi t}$ depends on the current period of time t and π which in turn depends on the constant discount rate δ. Samuelson (1937) stresses that his choice of the exponential function as the discount function was arbitrary and further that "it is completely arbitrary to assume that the individual behaves so as to maximise an integral [of discounted utilities] of the form envisaged [in equation (2)]".

Nevertheless, several empirically observed behaviours contradict the assumptions of the discounted utility model. The following inconsistencies with respect to the discounted utility model are compiled by Loewenstein and Prelec(1992):

1. The discount rate for large amounts is observed to be lower than the discount rate for small amounts.
2. Gains are discounted at a higher rate of discount than losses.
3. Asymmetric preferences are observed between speeding up and delaying consumption.
4. The preference for two delayed outcomes often switches if both outcomes are increased by a common constant amount. For instance on one hand a person prefers an apple today to two apples tomorrow. On the other hand the same person prefers two apples in one year and one day to one apple in a year.

In addition, Dasgupta and Maskin (2005) stress the results of studies in economics and behavioural ecology in which discount rates are found to increase if the time in between of today and a consumption delay becomes shorter. A model which appears to suit the by Dasgupta and Maskin (2005) mentioned sensitivity in time delay better is hyperbolical discounting. In distinction from the above presented discounted utility model the discount rate of a hyperbolic discount function decreases when the time in between of today and a consumption delay increases (Loewenstein and Prelec, 1992). That is why, a person’s time preference can also be explained by hyperbolic discounting if that persons’ discount rate for a consumption delay in the near future is higher than the discount rate applied for a consumption delay in the distant future. Loewenstein and Prelec (1992) deliver the first general formulation of a discount function with such features. An intuitive formulation of hyperbolic utility discounting can be given in the following way (Ainslie, 2002):

$$V=\frac{\text{Value if immediate}}{\text{Constant (1)}+(\text{Delay}\cdot\text{Constant (2)})} \tag{3}$$

Where V stands for the value attributed to the delayed event, constant (2) is a factor describing individual steepness of discounting which is multiplied with the time of delay (Ainslie, 2002). Constant (2) is bigger if the consumption delay occurs in the near future compared to a consumption delay occurring in the distant future. Constant (1) is a small constant added to the denominator to reflect the fact that values do not approach infinity as delays approach zero (Ainslie, 2002). Constant (1) usually amounts to 1. The problem arising from this formula is that over the course of time constant (2) has to be defined newly at each point in time (Ainslie, 2002). Furthermore, a new computation of the time of delay is needed at every point in time. To avoid this bother Laibson (1997) proposes to apply quasi-hyperbolic discounting instead of hyperbolic discounting:

$$U_t = E_t\left[u(c_t) + \beta\sum_{i=1}^{T\text{-}t}\delta^i u(c_{t+i})\right], where\ 0 < \beta, \delta < 1. \tag{4}$$

U_t is the utility in period t which depends upon the utility from consumption in the present period $u(c_t)$ as well as the utilities arising from consumption in future periods $u(c_{t+i})$. Since the expected value is included in equation 4 this function is not only valid for secure consumption levels in the respective periods but also for uncertain consumption levels (Laibson, 1997). The quasi-hyperbolic discount function is discrete over time and the utilities from consumption in periods 0, 1, 2, 3, ... are discounted by 1, $\beta\delta$, $\beta\delta^2$, $\beta\delta^3$, … (Rubinstein, 2003). The not discounted utility in the current period t=0 in combination with the discounted future utilities reflects the empirically observed decline in the discount rate if the consumption delay is more remote in the future. As a result of this, the discount parameters β and δ capture the drop of the discount rate in between of the adjacent period and more distant periods that is characteristic for hyperbolic discount functions (Diamond and Köszegi, 2003).

3 Conceptual Framework

3.1 Influencing Factors on the Application of Agroforestry

The decision to plant trees and therewith to apply agroforestry is caused by various influencing factors resulting from the personal circumstances of a smallholder. The factors which may influence the decision to apply agroforestry are hereafter derived either by drawing on results of previously conducted empirical studies or by theoretical considerations. In the below depicted cause-effect-diagram the possibly influencing factors are listed. Single influencing factors are subsumed under umbrella terms as far as possible. Whether smallholders apply agroforestry or not will be captured in the econometric analysis by the tree density which is observed for each smallholder. The tree density measures the number of trees grown on one acre (=4,046m²) of cultivable land. The results of the econometric model on agroforestry are presented in section 5.3. A factor which influences tree planting among others is a smallholder's rate of time preference because tree planting is rather a long-term farm investment. Since the smallholders' rate of time preference are an own object of study, the factors that might influence the rate of time preference are also depicted in figure 3.

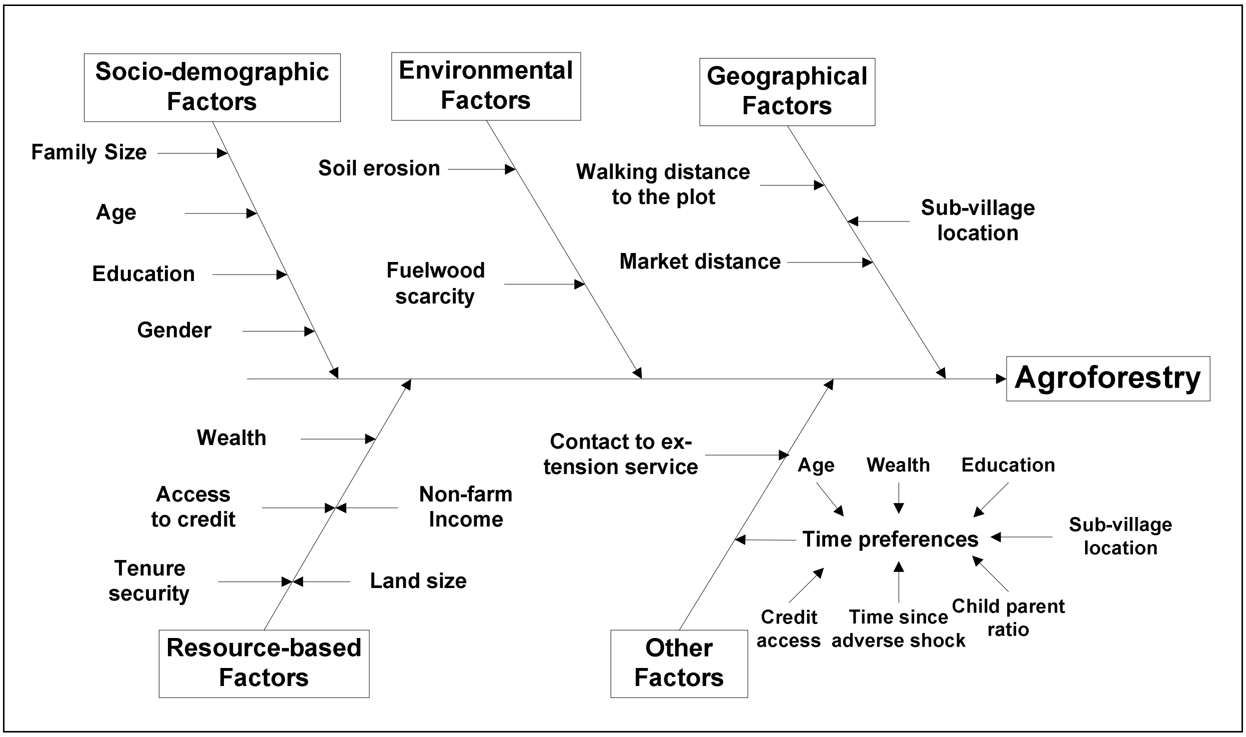

Figure 3: Factors of Influence on Agroforestry
Source: Own figure

3.1.1 Socio-demographic Factors of Influence

It is broadly found that agroforestry increases soil fertility and accompanied by this yields increase often, too (Bannister et al., 2002). Nonetheless, smallholders might be critical to a land use change whereby they have to devote space to trees instead of growing food or cash crops. This is due to the fact that smallholders might fear a loss in food security, if less land is used to grow food crops (Cavatassi and Lipper, 2004). The need to grow food crops and thus to generate food may be perceived the stronger the larger the family is. With respect to this is assumed that with a rising number of family members the tree density on the plots decreases.

In addition the age of smallholders could be relevant to the application of agroforestry because younger smallholders may be more receptive to try new technologies instead of sticking to the traditional way of agriculture. For instance, in a study from Polson and Spencer (1991) younger smallholders were found to have higher probabilities to adopt improved cassava technologies. Due to this is assumed that the age of the household (HH) head is negatively related to the tree density on the smallholders' plots.

Scherr (1995) mentions furthermore that male smallholders in western Kenya had 50% more trees on their farms and a by 30% higher tree density compared to farms run by women. A higher number of trees on cropland were observed on men's farms, too. Moreover Adesina (1996) finds that women apply new technologies like agroforestry less likely compared to men. Hence, the gender of the household head may potentially be included in the regression model. The variable *gender HH head* takes the value 1 if the respective household head is male and 0 otherwise. Therefore, it is presumed that this variable influences the observed tree density positively.

It is likely that better educated smallholders are also better informed about soil conserving measures and the consequences to productivity that coincide with erosion (Ervin and Ervin, 1982). That is why the hypothesis is constructed that the education of the household head is positively related to the tree density.

3.1.2 Environmental Factors of Influence

The stabilizing feature of agroforestry regarding soil degradation and soil erosion may be also vital to smallholders for the adoption decision. At least one of the predominant responses in a survey of farmers in Senegal was that they adopted agroforestry to benefit from the advantages for the soil (Caveness and Kurtz, 1993). Hence, a variable that characterizes yield losses due to soil degradation or erosion is examined on its impact on the tree density. The smallholders had to indicate for each plot whether they face yield losses on that specific plot or not. The variable *area yield loss* is the total land size of the plots for which smallholders stated to face yield losses on. It is hypothesized that the variable *area yield loss* influences the tree density with a negative sign meaning fewer yield losses go along with a higher tree density.

Firewood is needed by the rural population in the study village Tandai for cooking and heating. To become more independent from collecting and buying firewood smallholders may plant trees in areas where firewood is scarce. Therefore scarcity of firewood is likely to induce an increase in the number of planted trees as well as the tree density. The sufficiency of the own firewood production is determined by deducting for each household the weekly consumed amount of firewood from the weekly collected amount of firewood. If the result from that arithmetic operation is positive or 0 that household's firewood production is sufficient because more firewood is collected than used. If more firewood is consumed than collected the value of the variable firewood sufficiency is negative and indicates a lack of firewood from the own production. It is hypothesized that the variable *firewood sufficiency* has a positive impact on the tree density. Accordingly households who exhibit a higher positive value for the variable *firewood sufficiency* are expected to have a higher tree density than households with a lower positive or even negative value for that variable.

3.1.3 Geographical Factors of Influence

In addition the location of a village in the proximity of a market place may induce tree planting because tree products which are not needed for subsistence can be sold on the market place. This would coincide with the statement of farmers' polled by Caveness and Kurtz (1993) who applied agroforestry mainly to obtain wood or fruits for sale. The closer the farmers live to the market the easier it becomes for them to transport their goods derived from trees to the market. Therefore it is presumed that the variable *market distance* shows a negative relation to the tree density. The distance to the market is measured in minutes needed to reach the market by foot.

In a study by Otsuka et al. (2001) a larger walking distance from the homestead to the plot had a negative impact on tree planting. To plant trees in the proximity of the homestead can be interpreted as a strategy to cope with the risk of theft of tree products or even trees itself. To account for this circumstance the mean walking distance from the homestead to the plot is computed. The distance is measured in minutes the smallholders require to reach their plots by foot. The variable *mean plots distance* is assumed to be negatively related to the smallholders' decision to apply agroforestry and thus to the tree density.

If firewood is scarce and the location of a farm is close to the forest some smallholders may collect firewood in the proximity of the forest. Eventually the smallholders go even into the forest to collect firewood, although every kind of extraction from the forest is forbidden in the Morogoro region. Thus it is assumed that the distance to the forest has a negative impact on the tree density. The distance to the forest is again measured in minutes required to reach the forest by foot.

Moreover, the belonging of a polled household to a certain sub-village is captured by dummy variables that take the value 1 if the observed household belongs to a respective sub-village and 0 otherwise. Through the sub-village dummy variables for differing conditions among the sub-villages is accounted, although for this information was not explicitly asked. These differences may influence the decision to apply agroforestry are included in the regression For instance overall differences in the wealth of the sub-villages are taken into account by including the sub-village dummy variables in the regression on the acceptance of agroforestry. Aside from wealth also the fact whether a sub-village is located on steep hills may be important for the decision to use agroforestry. This results from the circumstance that sub-villages which are located on steep hills are more endangered to experience soil erosion than in the valley situated sub-villages.

3.1.4 Resource-based Factors of Influence

Assets which wealthy smallholders possess, like savings or livestock, can be sold in stressful periods to receive cash for buying food immediately. This may lower the wealthy smallholders' perception of the risk of a consumption shortfall due to a cultivation of arable land applying agroforestry schemes. Furthermore, wealthy smallholders may be able to finance the establishment of agroforestry without taking out a loan. Accordingly they may have fewer difficulties to overcome the barrier of the initial costs of growing trees which are e.g. given by the costs for seedlings. Besides, wealthy smallholders may own assets which are suitable as collateral when asking for a loan. That is why the interest payments a wealthy smallholder has to pay for a loan to establish agroforestry are likely to be lower compared to the interest payments a poor smallholder has to pay. Based on this wealth is assumed to be positively related to the tree density. The wealth of a smallholder is captured by a wealth index which is computed along the lines of Carletto et al. (2000):

$$wealth\ score = \sum_{g=1}^{G} f_{gi} \cdot w_g \tag{5}$$

The index g stands for a specific item, whereas i is the index for the households. A weight (w_g) is assigned to each item in the list of all assets (g) (Carletto et al., 2000). The weight w_g equals the reciprocal value of the proportion of study households who own this item (Carletto et al., 2000). w_g is multiplied by the number of units a household owns from that specific asset f_g (Carletto et al., 2000). The sum over the product out of w_g and f_{gi} over all possible assets yields the wealth index for each household.

Poor smallholders cannot finance the establishment of agroforestry from own resources (Fakhrul Islam and Monayem Miah, 2007). Therefore, they need access to credit by NGO's at reduced interest rates to finance the initial costs for tree seedlings, seeds, fertilizer, etc. (Fakhrul Islam and Monayem Miah, 2007). Thus the variable *credit access* is hypothesized to influence the tree density positively. The variable credit access is a dummy variable that takes on the value 1 if credit is available and 0 otherwise.

Income which a member of a family derives from other sources than farming was identified to have a significantly positive relation to the adoption of new agricultural practices (Adesina, 1996). A possible reason is that with more sources to generate income also more income is obtained in total. This coincides with the results of several studies conducted in Africa regarding off-farm employment. For instance Barrett et al. (2001) find a positive relation between non-farm income and a household's wealth. With more income it is possible to invest into new ways of farming like establishing agroforestry or purchasing fertilizer (Alavalapati and Thangata, 2003). The variable *off-farm employment* is a dummy variable that becomes 1 if a household shows off-farm income and 0 otherwise. It is hypothesized that the variable *off-farm employment* has a positive effect on the farmer's decision to plant trees and hence on the tree density.

Although the adoption rates for agroforestry are quite similar across different tenure types (Bannister et al., 2002), tenure security might be also important to a smallholder to decide whether to adopt agroforestry or not. Bannister et al. (2001) provided information that the most trees are planted on plots with a higher tenure security like purchased and inherited plots. This may result from the fact that a smallholder who planted trees also wants to obtain the gains from tree planting that accrue several years after planting. Hence, the perception of tenure security is hypothesized to have a positive impact on the tree density as the proxy for the smallholders' decision to plant trees. Within the present household survey smallholders were asked for each plot they cultivate whether from their perception the tenure for that plot is secure or not. The variable *tenure security* is the mean of the smallholders' answers for all plots. It ranges between 0 and 1 and gives the percentage of plots which are perceived to be secure by a smallholder.

A survey in the Philippines found that the total land size managed by a household as well as the number of plots are positively correlated with the number of trees a single household intends to plant (Emtage and Suh, 2004). A reason for this result could be that the pressure to grow food crops for own consumption on the majority of the available space is perceived less if a larger area is available for cultivation. Thus the hypothesis is constructed that the variable *land size* influences the tree density in a positive way.

3.1.5 Other Factors of Influence

Agroforestry schemes are often disseminated by staff of extension services. Therefore, a positive impact on the willingness to apply agroforestry may arise from contact to extension service. In addition, farmers who were taught new ways to conduct agriculture by the extension staff may be more open-minded to apply new technologies (Adesina et al., 2000). The contact to extension service is measured in visits per year by extension officers. It is hypothesized that the variable *extension visits* has a positive impact on the tree density.

As already mentioned benefits and revenues from agroforestry measures usually accrue to the smallholders several years after the establishment of agroforestry. If a smallholder has a high rate of discount benefits and revenues in the future are less esteemed compared to benefits and revenues today. Hence, lower discount rates are likely to increase the intensity of the application of agroforestry because soil conservation measures often require making investments in the short run while the productivity is stabilized or increased in the long run. Due to this the rate of time preference is presumed to be negatively related to the number of trees grown by a household and, hence also to the tree density which can be observed on the plots.

3.2 Factors of Influence on the Rate of Time Preference

The pure rate of time preference is not only vital for tree planting but also for every long-term investment executed by an individual. Resulting from this overall significance of the rate of discount the theoretically influencing factors on the rate of time preference are identified in this section. The actual factors of influence on the smallholders' rate of time preference as well as their extent are identified through a regression on the rate of time preference. The results of that regression are presented in section 6.3.

3.2.1 Socio-demographic Factors of Influence

Ervin and Ervin (1982) state that lower discount rates imply longer effective planning periods, whereas higher discount rates indicate a shorter planning horizon. As a person grows older the planning period in general becomes shorter and the rate of time preference is supposed to increase. Therefore, it is hypothesized that the variable *age HH head* has a positive impact on the extent of time preference.

If a person attends school for a longer time the opportunity to generate income immediately is interchanged for the prospect to receive a higher income after further education. Thus more years of education could be a reflection of a longer planning period and more farsightedness of a person. That is why it is presumed that the variable *education HH head* influences the-level of time preference negatively.

The composition of the family of smallholders' could be a factor of influence on the rate of time preference, too. If a family has relatively many children compared to adults the respondent may perceive future benefits as important, too. A reason for this is that the children of a family are the next generation which also needs to have a basis of life. Due to this the respondent of a household comprising many children could put a higher emphasis on future benefits compared to present benefits than the respondent of a household comprising fewer children.

To account for this the variable *child parent ratio* is generated. By that variable the number of children living in a household is put in relation to the number of adults of that household. The hypothesis is constructed that the variable *child parent ratio* is negatively related to the rate of time preference. This implies that a higher number of children is accompanied by lower rate of time preference.

3.2.2 Resource-based Factors of Influence

Wealth respectively income was identified several times as one of the most crucial factors that influences the extent of the rate of time preference (Becker and Mulligan, 1997 , Fisher, 1930). A permanently small income or a low-level of wealth is interlinked with a high preference for consumption now, because basic present needs have to be satisfied before a person can give thoughts about the future (Fisher, 1930). To capture the exact-level of wealth of the smallholders in Tandai the in section 3.1.4 introduced wealth indicator is applied. A higher value for that wealth indicator is expected to be negatively related to the magnitude of the rate of time preference.

In addition, wealthy people have better access to loan and face lower discount rates, because they might be able to give collateral (Holden et al., 1998). As a consequence it is likely that poor people who have neither savings nor access to loans and thus face liquidity constraints cannot smooth their consumption over time (Holden et al., 1998). This implies the risk of a shortfall of basic needs which, in turn, increases the preference for consumption now. Hence, it is likely that people who report credit constraints exhibit higher rates of time preference (Holden et al., 1998). As a result of this is assumed that the variable *credit access* is negatively related to the magnitude of time preference. The variable *credit access* is a dummy variable that takes on the value 1 if credit is available for a household and 0 otherwise.

3.2.3 Other Factors of Influence

The experience of idiosyncratic shocks may affect the rate of time preference of smallholders in Tandai. Idiosyncratic shocks are uncertain events, such as illness or the loss of a job, which affect an individual or a household (Del Ninno et al., 2008). The shocks are uncertain in their realization, timing or magnitude. For instance, the loss of a job may be accompanied by a loss of income which might lead to a shortfall of consumption in the year of the occurrence of the shock and also in the following years. The consumption shortfall may imply an increase in the preference for immediate consumption. Furthermore, the necessity to reacquire the lost assets may lead to a neglect of long-term needs like investment in education, soil conservation, etc.

The result is a shortening of planning horizons that coincides with higher discount rates. Presumably, the just described implications of an adverse shock are the bigger the more recent the shock is. That is why the variable *time since shock* is assumed to be positively related to the extent of time preference.

Finally, the dummy variables for the belonging of a polled household to a certain sub-village are considered to be included in the regression on the rate of time preference, too. Again circumstances for which was not explicitly asked are considered by including the sub-village dummy variables into the regression on the pure rate of time preference.

4 Study site and data collection

4.1 Characteristics of the Study Site

The data on which the analysis of the sections 5 and 6 is based on is cross sectional and originates from a household survey that has been conducted in the context of the project Better-iS. The study site is located in the Uluguru Mountains which are a chain of cool, wet highland forests in central Tanzania (PRESA, 2010). The Uluguru Mountains are located in the Morogoro region between latitude 7°-8°S and longitude 37°-38°E (Faße and Hoffmann, 2011).

The population within the Uluguru Mountains currently stands at over 100,000 people. This has led to a significantly reduced forest cover due to pressure from farming and logging activities (PRESA, 2010). However, the Uluguru Mountains are of crucial importance for the forest and water provision for the Morogoro region and other regions. In response to the Uluguru's importance for the water supply as well as the increased environmental pressure arising from the high population density, the Uluguru Nature Reserve was established in November 2008 (World Wildlife Fund, 2009). It has a size of approximately 25.000 ha (World Wildlife Fund, 2009). The Uluguru Nature Reserve ensures the provision of water to the Ruvu River, which is the main water supply to the capital city of Dar es Salaam (World Wildlife Fund, 2009). In figure 4 the location of the Uluguru Mountains within Tanzania as well as the location of the study village within the Uluguru Mountains is depicted.

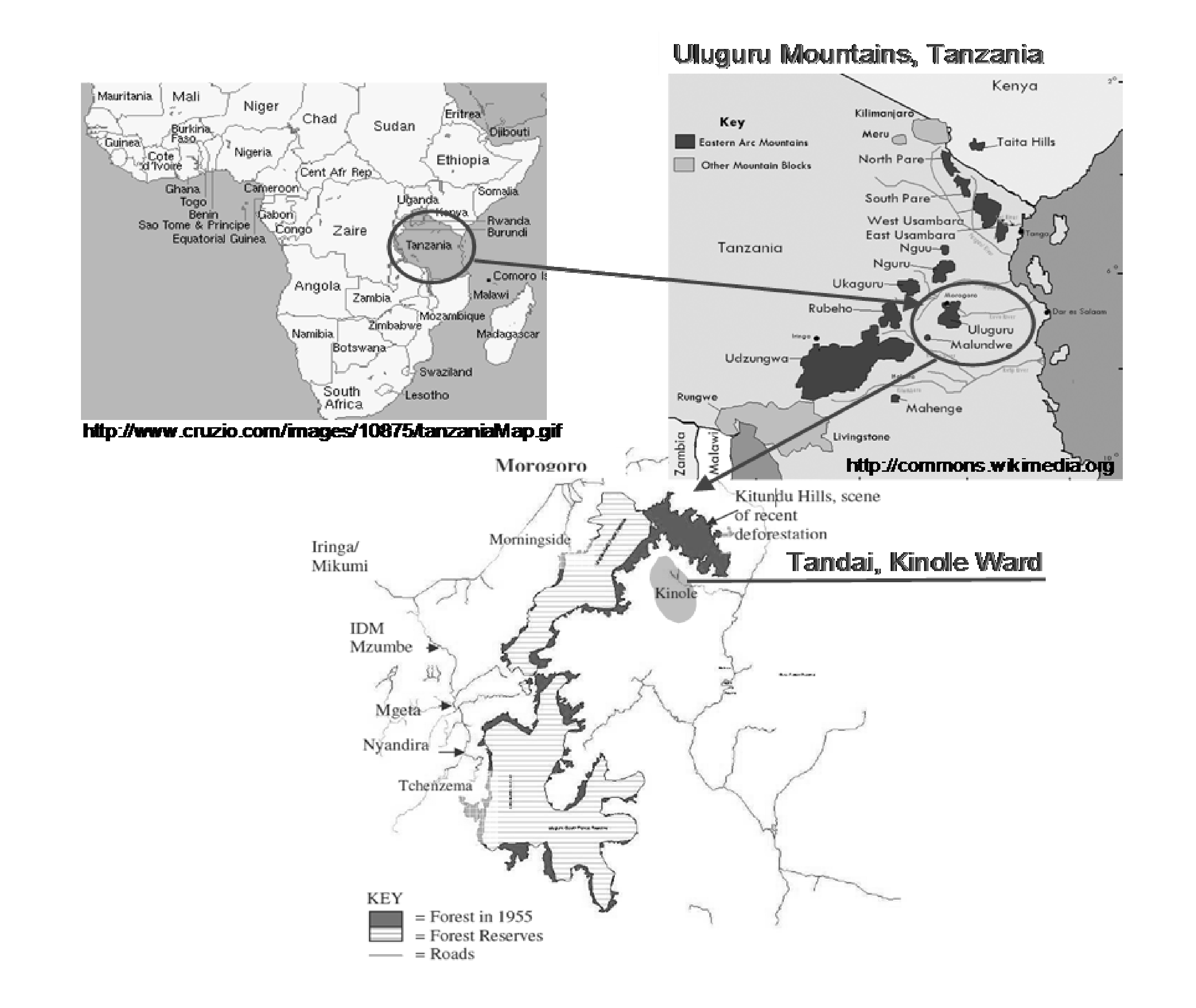

Figure 4: Study Area
Source: Faße and Hoffmann 2011

As becomes obvious from figure 4 the study village Tandai is located in the northern Uluguru Mountains (Kinole Ward, Morogoro region) (Faße and Hoffmann, 2011). The study village was selected by the Better-iS project partner International Agroforestry Centre (ICRAF) in collaboration with the Sokoine University of Agriculture (SUA) of Morogoro. Tandai comprises 1055 households in total and is subdivided into seven sub-villages (see figure 5). The altitude of the sub-villages varies between 314m above sea-level (a.s.l.) in the sub-village Doga and 1128m a.s.l. in the in the sub-village Nyange. The sub-villages Lukenge and Nyange neighbour on the natural forest reserve which is part of the Uluguru Nature Reserve as well as on the community (Faße and Hoffmann, 2011). The community forest is by 80% degraded and is not part of the Uluguru Nature Reserve forest (Faße and Hoffmann, 2011). On one side Lukenge and Nyange feature more fertile cultivable land than sub-villages situated in the valley like Doga or Tonya due to their location close to the forest (Faße and Hoffmann, 2011). On the other side are Lukenge and Nyange located in the uphill area which increases the risk of soil erosion for these sub-villages. An overview of the location of the respective sub-villages is given in figure 5. The abbreviation FC indicates that food crops are grown in this area whereas CC stands for cash crops. Fw stands for trees which are grown for the purpose of firewood and T indicates trees for timber production are grown in that area.

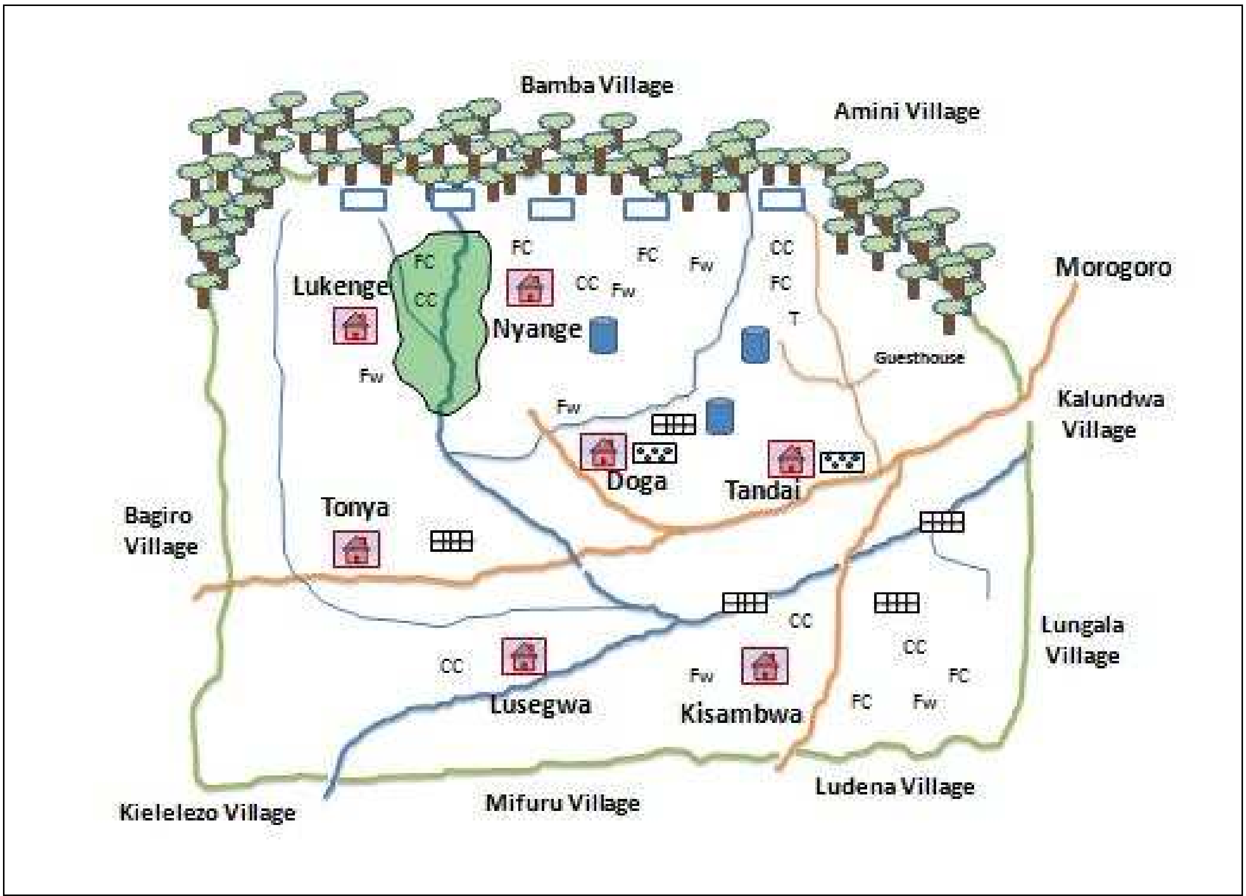

Figure 5: Map of Tandai Source: Faße, 2010

Due to the establishment of the Uluguru Nature Reserve any extraction out of the protected forest is prohibited (Faße et al., 2010). The circumstance that Tandai is situated within a valley surrounded by mountains and the protected forest let environmental resources – particularly arable land and firewood – become scarce (Faße and Hoffmann, 2011). This is challenging to the population of Tandai because rural households often accrued as far as 70% of their income and 90% of the required energy from the forest (Faße et al., 2010). As a result of this challenge to the rural population of Tandai, new ways of income and energy generation have to be detected. For instance the production of biofuels out of Jatropha may be such a way. It bears the potential to supply income on one hand and energy services like cooking, lightning and transportation on the other hand (Better-iS, 2010).

Owing to the implications of excluding the residents of Tandai from the forest resources, the major purpose of Better-iS is to identify opportunities to link smallholders to small and medium enterprises on decentralized biomass concepts (Better-iS, 2010). In order to do so it is intended to perform feasibility studies on advanced biomass value chains, which may ensure the income and energy supply of the inhabitants of Tandai (Better-iS, 2010). The feasibility studies will be based on a social accounting matrix as well as a general equilibrium model on village-level. These two models will be built up employing the data that has been collected in Tandai by means of a poll.

Previously to the initialization of the project Better-iS the project “Pro-poor Rewards for Environmental Services in Africa” (PRESA) was carried out in the Uluguru Mountains. As a result of this tree planting is already spread among the smallholders of Tandai. The focus was to offer direct payments for environmental services, so farmers receive economic incentives for providing watershed services through their conservation efforts (PRESA, 2010). To counteract the problem of deforestation and its implications for the water quality, tree planting was strongly promoted by the PRESA project. An auction study was conducted in which 268 households had to submit their bids on receiving tree planting contracts. A bid represented the amount of money the farmers estimated to need for changing their cultivation from seasonal crops to woodlots with trees (PRESA, 2010). At the end of the auction 32 smallholders obtained tree seedlings in combination with payments for taking up new woodlots (PRESA, 2010). All other participants received just tree seedlings as an incentive to continue their efforts towards conserving the local landscape (PRESA, 2010).

4.2 Questionnaire Design and Data Collection

The households which were supposed to be polled were selected employing stratified random sampling. The strata of a stratified random sample out of which the random samples are taken have to be non-overlapping (e.g. geographical areas or genders) and collectively exhaustive so no element can be excluded (Hunt and Tyrrell, 2001). To ensure that all different household types and farming conditions are included in the survey sample, the sample frame was divided into strata accounting for different agro-ecological zones (Faße and Hoffmann, 2011). Overall nearly one third (n=314) out of all households of Tandai were selected randomly for being polled. A household was defined for the purposes of this study as an economically independent unit, consisting out of the household head his or her spouse their children and other directly dependent members (Faße and Hoffmann, 2011). The interviewees were heads of households or other adult household members if the household head was not present at the time of the interview (Faße and Hoffmann, 2011). All in all, the key respondent was not the household head in 75 out of the 314 polled households. This equals a fraction of 24%.

To account for the different environmental and economic conditions in the seven sub-villages of Tandai, households from every sub-village were polled. For instance, such differences are that the plots in the sub-villages Lukenge and Nyange are steeper and more fertile than in the other sub-villages. Moreover, the households from the sub-villages Doga and Tonya appeared poorer to the interviewers than the households from the remaining sub-villages. Out of each sub-village 30% of the households were surveyed. As a result of this procedure, the empirical results for the whole sample can be computed straightforward instead of weighing the results obtained for each sub-village according to its size (Bortz and Döring, 2005). In Table 1 an overview of the number of households polled from each sub-village and the equivalent percentage of the whole sample is given.

	Doga	Kisambwa	Lukenge	Lusegwa	Nyange	Tandai	Tonya	Σ
no.	32	50	34	42	30	95	31	314
%	10.2%	15.9%	10.8%	13.4%	9.6%	30.3%	9.8%	100%

Table 1: Origin of the polled households
Source: Own table

The questionnaire contains questions on household characteristics like the number of household members, their education, the farm size and the crops cultivated on a farm. Questions on the availability of labour as well as the owned assets are also part of the questionnaire (Faße and Hoffmann, 2011). In addition, a questionnaire section on production covers topics like agricultural and livestock production, tenure security and conditions of soil (Faße and Hoffmann, 2011). Issues like energy types used, agroforestry, extension access and time preference are comprised in the questionnaire, too (Faße and Hoffmann, 2011). Besides, data regarding tree cultivation as a way to counteract soil erosion and produce firewood was collected (Faße and Hoffmann, 2011). Overall the objective was to capture the whole village economy as well as the interdependence of the households (Faße and Hoffmann, 2011). Particularly the data collected with respect to tree growing are valuable for the scope of this paper. With the aid of this data the benefits accruing to the smallholders' of Tandai from tree planting can be examined.

Furthermore, information on the smallholders' time preference has been collected by the poll. Since benefits from growing trees accrue several years after planting trees, the information on the time preference of a person is vital for analyzing the factors of influence of tree planting. The information on the time preference was elicited by asking the respondent the hypothetical question, which amount of money he prefers to obtain today instead of TZS 100,000 in one year (Faße and Hoffmann, 2011). To the 100,000 TZS is referred as future value, whereas the value stated by the respondents is named present value. The question was asked stepwise beginning with a present value of TZS 90,000 which could be obtained immediately instead of TZS 100,000 in one year. If the respondent was not willing to accept TZS 90,000, a present value of TZS 100,000 was noted for that household and no additional question on the time preference was asked. If the respondent agreed on receiving TZS 90,000 today instead of TZS 100,000 in one year the interviewer proceeded with asking for the next lower present value. This kind of questioning was continued until the respondent denied accepting the next lower present value instead of the future value of TZS 100,000. The lowest present value, the respondent accepted to obtain today instead of the future value, was noted as the present value for that household. The intention of asking for the present value in this manner is to ensure data quality, since this kind of questioning is assumed to facilitate the respondents thought processes and may encourage them to consider their response carefully (Bolt et al., 2005).

After several training workshops for the interviewers, sampling and pre-testing, the household survey was conducted within six weeks from April to June 2010 (Faße and Hoffmann, 2011). During the whole period of time the research team, consisting out of five interviewers and two researchers, stayed in the village (Faße and Hoffmann, 2011). The respondents were interviewed at their homesteads. Through this the interviewers were able to collect additional information and could carry out counter-checks on the statements of the respondent (Faße and Hoffmann, 2011). After the two hour lasting interview, the respondent received the wage of a half working day as compensation for the time (Faße and Hoffmann, 2011).

5 Econometric Analysis on the Application of Agroforestry

5.1 Methodology

5.1.1 Analysing Methods and their Principles

The influencing factors on the smallholders' decision to apply agroforestry are examined in four steps. At first, descriptive statistics are provided for the variables which are identified in section 3.1 as being possibly relevant for smallholders' to decide whether to grow trees or not. Secondly, equivalence tests for unrelated samples are performed on subsamples of the whole sample (Wellek, 2010). In order to do this, the observed households are subdivided into subsamples according to dummy variables that are assumed to possibly influence smallholders' decision to apply agroforestry. These subsamples exhibit a characteristic which is common within the subsample but differs among the two subsamples. For instance, subsamples can be generated according to the gender of the household head. In the following, the continuously distributed variables, which may be vital to the smallholders' decision to use agroforestry, are examined on statistical significant differences in the means among the subsamples. The statistical significance is either detected by employing a two-sample t-test for equivalence or a Wilcoxon rank-sum test for equivalence. The t-test is applied if the variable, which is tested on equality of the means within the two subsamples, follows the Gauss distribution for both subsamples (Wellek, 2010). If the examined variable does not follow the Gauss distribution in both subsamples the non-parametric Wilcoxon rank-sum test can still be applied to test for equal means in both subsamples (Wellek, 2010).

Subsequently, the correlation coefficients with respect to the number of trees as well as the tree density per acre (=4.046 m^2) are computed and examined on their statistical significance. With the aid of correlation coefficients the degree of association of the variables *tree density* and *tree number* with other variables can be measured (Gujarati, 2004). The correlation coefficients with respect both variables *tree density* and *tree number* are of particular interest since each of these variables is theoretical suitable as a proxy variable for the smallholders' decision to apply agroforestry. The statistical significance of a correlation coefficient for two variables, which both follow the Gauss distribution, can be determined by a Pearson correlation coefficient (Lehman, 2005). In contrast, a Spearman correlation coefficient has to be used if only one or none of both variables follow the Gauss distribution (Lehman, 2005).

Finally, a regression model is run to determine the dependency of the smallholders' decision to apply agroforestry on specific criteria given by the explanatory variables. In Tandai tree planting is already spread and trees are grown by the majority of the inhabitants. This is caused by the previously conducted PRESA project. Indeed, within study sample only 10 out of 314 households do not grow any tree. In five out of these ten households the lack of tree planting is due to the fact that no household member works on the farm at all. In those households at least one of the household members has a full employment off the farm, for instance as a teacher, house-builder or shopkeeper. Therefore, a logistic regression on a binary variable that becomes 1 if trees are grown and 0 if not would not deliver meaningful results on the factors, which influence the smallholders' decision to grow trees. Instead, a classical linear regression model, solved by the method of ordinary least squares (OLS), is performed on the *tree density* as a proxy variable for the acceptance of agroforestry. Compared to the tree number the tree density is more suitable to capture the acceptance of agroforestry. Using just the tree number does not take into account that a higher tree number may be due to a larger land size and not due to a stronger acceptance of agroforestry. By putting the tree number in relation to the land size, as done in the variable *tree density*, this case is excluded.

In section 3.1 variables are identified which may have an impact on the farmers' decision to apply agroforestry. Each of these variables is included in a regression on the *tree density* without any other explanatory variable. All Variables, which were identified by this procedure to contain explanatory contents for *tree density*, are included in a stepwise regression on *tree density*. When conducting a stepwise regression the variables that show explanatory power for the dependent variable are added to a regression model sequentially, while the change in the parameter estimates and the R^2 is compared (Dobson, 2002). The model, which shows the highest R^2 and the maximum amount of significant parameter estimates, is chosen to explain the influencing factors on the decision whether to apply agroforestry or not.

In order to determine the regression coefficients the method of ordinary least squares is applied. Graphically, OLS minimizes the sum of squared deviations of the observation points from the regression line. The deviations are called residuals. The OLS method is applied since, according to the Gauss-Markov Theorem, the OLS estimators are best linear unbiased estimators (BLUE) in a linear regression model (Gujarati, 2004). Linear means that the estimated parameter $\hat{\beta}_i$ is a linear function of the mean predicted for the dependent variable (Gujarati, 2004). In addition, the OLS estimators are unbiased which implies that the expected value of the OLS estimator $E(\hat{\beta}_i)$ is equal to the true value β_i (Gujarati, 2004). Finally, the OLS estimators are efficient since they feature the smallest variance in the class of all linear unbiased estimators (Gujarati, 2004).

In addition to the parameters estimated by the regression, the BETA coefficients are listed. BETA coefficients result from a regression approach where all variables included in the model are standardized by deducting the mean from each observation and dividing this difference by the standard deviation of the respective variable (Hübler, 2005). Through BETA coefficients the influence of variables measured in different units is comparable (Hübler, 2005). BETA coefficients are limited in their extent to the range of -1 to 1. The value -1 indicates a perfect negative relation between the dependent variable and the independent variable. A BETA coefficient of 1, on the contrary, indicates a perfect positive relation. BETA coefficients can be either determined by estimating a standardized model or by computing the BETA coefficients based on the parameter estimates resulting from a not standardized model.

The BETA coefficient $\hat{\beta}_k^*$ for the independent variable k and its regression coefficient $\hat{\beta}_k$ are related as follows:

$$\hat{\beta}_k^* = \hat{\beta}_k \frac{\sigma_k}{\sigma_y}. \qquad (6)$$

The BETA coefficient equals the original coefficient times the relation of the standard deviation of the independent variable k (σ_k) and the standard deviation of the dependent variable y (σ_y). For the parameter estimate $\hat{\beta}_0$ no BETA coefficient is computable. The parameter estimate $\hat{\beta}_0$ yields the value for the dependent variable if all other variables take on the value 0. Thus $\hat{\beta}_0$ is not based on a variable, which features different observations and a mean, based on which a BETA coefficient could be computed. That is why the intercept is never included in the estimation of a standardized regression model (Hübler, 2005).

BETA regression coefficients are not only invalid for the intercept but also for dichotomous variables (Hübler, 2005). The standard deviation of dichotomous variables is a function of their skewness – the more skew a dichotomous variable is, the smaller is the standard deviation (Hübler, 2005). Therefore, standardized regression coefficients of dichotomous variables become the lower the more skew the variable is (see equation (6)).

5.1.2 Regression Diagnostic for OLS Regression

In general, the following assumptions are made for the classical linear model, which is intended to be solved by an OLS regression (Greene, 2002):

i. The available data have to be a random sample of the population.
ii. The expected value of the disturbances equals 0 ($E(u_i)=0$).
iii. The disturbances have same variance ($V(u_i)=\sigma^2$).
iv. The disturbances follow the normal distribution ($u_i \sim N(\mu,\sigma^2)$).
v. The model has to specify a relationship which is linear in the parameters.
vi. The endogenous variables are linear independent.
vii. The disturbances associated with different observations are independent from each other ($E(u_i u_{i'})=0$).

The assumptions ii to iv can be summed up to:

$$u_i \sim N(\mu,\sigma^2) = N(0, \sigma^2). \qquad (7)$$

The first assumption is fulfilled due to the data collection process employing a stratified random sample described in section 4. In addition, the issue of autocorrelation arising from a violation of assumption vii is in the first place relevant for time series data. Since the available data are cross sectional, the regression diagnostic will be focused on assumptions ii-vi. Outcomes resulting from the regression as well as the regression diagnostic are presented in section 5.3. The procedures utilized in the regression diagnostic are characterized in the following.

Goodness of fit

The goodness of fit (R^2) of a statistical model describes how well the model fits the data and is defined as $R^2 = SSE/SST = 1-SSR/SST$ (Woolridge, 2005). Where SSE represents the explained sum of squares, SST stands for the total sum of squares and SSR for the residual sum of squares. Hence, R^2 is the ratio of the explained variation compared to the total variation (Woolridge, 2005). In other words, R^2 gives the fraction of sample variation in the dependent variable that is explained by the independent variables. The R^2 can range between 0 and 1 where the value 0 stands for no explanation of the examined relation by the model and 1 indicates that the model explains the relation perfectly. Additionally, the regression specification error test (RESET) for omitted variables is applied. The null hypothesis of that test is "H_0= the model has no omitted variables". If the test statistic is statistically significant on the 5%-level H_0 has to be rejected. This indicates that additional variables exist which are not yet included in the model.

Expected value of the disturbances equals 0

Assumption ii states that the expected value of all error terms is zero. This implies that the deviations of the predicted values from the actual values of the dependent variable should sum up to zero. To put it another way: all factors of influence which are not observed within the model neutralize each other on average. If this assumption is not fulfilled the regression parameters are biased (Kohler and Kreuter, 2008). Since the disturbances are unobservable, reasons for $E(u)\neq 0$ have to be examined (Hübler, 2005). A breach of the assumption that the expected value amounts averagely to zero can emerge for three reasons (Kohler and Kreuter, 2008):

1. The relation of the parameters and the independent variable is not linear.
2. Unnoticed influential observations have an excessive influence on the results of the regression.
3. Other influencing factors which are correlated with already in the model included independent variables are missed out.

The dependency of the endogenous variable on the exogenous variables in a linear manner is one of the most important assumptions for applying linear regressions (Kohler and Kreuter, 2008). The assumption of linearity must not be understood as narrow as it might appear at the first glance. Solely the parameters and the disturbances have to enter the regression in a linear way (Greene, 2002). That is why each independent variable is plotted against the dependent variable to examine whether the relation captured by the estimated parameter is linear or not. In addition, the regression specification error test for omitted variables is employed. Originally this test was developed to test for missing independent variables but it turned out to be also powerful to detect nonlinearities (Kennedy, 2003). So if the null hypothesis "H_0= the model has no omitted variables" cannot be rejected, the linear relation between the dependent variable and the parameters cannot be rejected, too.

To check for influential observations the measure Cook's distance (Cook's D) is employed. By this measure the influence of a single observation on all regression coefficients simultaneously is estimated (Kohler and Kreuter, 2008). The influence of an observation on the regression model is composed of two aspects, the value of the dependent variable and the combination of the independent variables. An influential observation has an extraordinary value of the dependent variable – called discrepancy – and at once an exceptional combination for the independent variables – called leverage (Kohler and Kreuter, 2008). Such an outlier affects the estimation of all coefficients only strongly if both aspects appear at one observation (Kohler and Kreuter, 2008). The impact of an observation on the whole regression is determined by multiplying the value for the discrepancy with the value for the leverage of an observation. Due to the multiplication the impact of an observation on the regression is 0 if only leverage or only discrepancy is present. Observations that might have a strong impact on the regression model as a whole are identified by having a Cook's D of 4/n and above, where n determines the number of observations included in the regression (Kohler and Kreuter, 2008). Subsequently to the regression on *tree density* the Cook's D is determined for all observations. If there are no observations featuring a Cook's D larger than 4/n the parameters are likely to be unbiased due to influential observations.

If observations which feature a Cook's D larger than 4/n exist, they are temporarily deleted and the regression is re-estimated with the remaining observations. The estimated coefficients and the BETA coefficients of the regression including the observations with a high Cook's D are compared to the regression coefficients and BETA coefficients estimated if these observations are excluded. If no or only slight differences in the coefficients can be observed, the estimated parameters are not biased due to unnoticed influential observations. In case the estimated parameters or the BETA coefficients differ from the initial estimation parameters or BETA coefficients, the observations with a high Cook's D have to be checked for input errors (Kohler and Kreuter, 2008). If no input errors can be detected either the independent variables have to be transformed or the influential observations may be deleted (Kohler and Kreuter, 2008). The results obtained after deleting the identified influential observations and re-estimating the model are similar to the results of a robust method since many robust methods give no influence to outliers (Leroy and Rousseeuw, 2003). Transforming the independent variables is appropriate if the identified influential observations result from extreme values for any independent variable (Kohler and Kreuter, 2008). Common transformations are the application of the natural logarithm on the independent variables or squaring them.

Finally the expected value of the residuals can deviate from 0 because factors of influence are missed out. Missing out factors of influence is an issue which is not easy to detect since data on the influencing factor maybe was not even collected. Furthermore the aim to include all important factors of influence may lead to including that many variables that multicollinearity is established (Kohler and Kreuter, 2008). Hence, theoretical considerations on variables, which might have large explanatory power for the model, have to be made in the first place in order to counteract the problem of missing out relevant variables (Kohler and Kreuter, 2008).

Homoskedasticity

A violation of assumption iii by the fact that the variances of the disturbances are not constant leads to heteroskedasticity among the disturbances. The implications of heteroskedasticity are inefficient parameter estimates and biased standard errors (Hübler, 2005). As already mentioned the OLS estimators have the lowest variance of all unbiased estimators that are linear functions for the observations of the dependent variable. Inefficiency resulting from the presence of heteroskedasticity means that in principle other estimators can be found which exhibit a smaller variance and are still unbiased (Dougherty, 2007). As a result of Var(u) = Var(y) the range in which an observation for the dependent variable y_i may be located is small if the variance of the disturbance u_i is small (Woolridge, 2005). Hence, if a u_i has a small variance the range of the corresponding observation for the dependent variable y_i is small, which leads to a small residual for the observation y_i. A small residual, in turn, implies that this observation is a good guide to the location of the regression line (Dougherty, 2007). By contrast, if u_j exhibits a large variance the range in which the corresponding y_j is located is large. Thus y_j is a rather bad guide to the location of the regression line, because this observation is likely to feature a larger residual than the observation y_i, which has a smaller variance (Dougherty, 2007). If the variances of the disturbances are equal every observation of y is an equally good indicator for the location of the regression line. This is vital since the observations are not weighed according to their variance or their residuals when performing an OLS regression (Dougherty, 2007). Moreover, if homoskedasticity is present, fewer manifestations show a large distance to the regression line and the variance of the parameter estimates is low.

The second issue arising from heteroskedasticity are biased standard errors. Standard errors are statistical measures of the precision of a measurement or an estimation (Woolridge, 2005). The standard error of a parameter estimate is an estimator for the standard deviation of the respective parameter estimate (Woolridge, 2005). Since standard errors are computed based on the assumption of homoskedasticity, biased standard errors result if heteroskedasticity is present (Dougherty, 2007). Implications of biased standard errors are invalidity of the t-test for the coefficients as well as invalidity of the RESET or F-test on misspecification of the model (Dougherty, 2007). If hetersoskedasticity exists, the standard errors are likely to be underestimated (Dougherty, 2007). As a result of the t-value being the parameter estimate divided by the standard error, the t-values for the parameters are likely to be too large (Dougherty, 2007). To approve a higher level of significance a higher t-value is required when using the t-test statistic. Therefore, too high t-values may lead to the misbelief that parameters are different from 0 with respect to a certain significance-level although they are not (Dougherty, 2007). To check for heteroskedasticity the Breusch-Pagan test is applied. The null hypothesis “H_0=constant variance of the residuals” has to be rejected if the result of the Breusch-Pegan test is statistical significant on the 5%-level. This implies that the maximum probability of rejecting H_0 by mistake amounts to 5%.

Normally distributed disturbances

The normal distribution of the error term is not necessarily needed for applying an OLS regression (Hübler, 2005). Normality of residuals is only required for the validity of hypothesis testing, since the normality assumption assures that the p-values for the t-test and RESET are valid (Hübler, 2005). The normal distribution of the residuals refers to the fact that small deviations in the proximity of the mean are more likely than large deviations occurring close to the margin of all observations (Hübler, 2005). Since the disturbances are not observable, also their distribution is not observable. Therefore, the residuals resulting from the OLS regression have to be utilized to estimate the disturbances. The residuals are examined with respect to their distribution by normal probability plots. In a normal probability plot the true standardized residuals are plotted versus their expected values if they were normally distributed (Dobson, 2002). The expected value of the standardized residuals is depicted in a normal probability plot through a straight line featuring an angle of 45°. Systematic deviations from that angle bisector or outlying observations indicate that the standardized residuals are not normally distributed (Dobson, 2002). Furthermore, the Skewness-Kurtosis-test is performed on the presence of skewness respectively kurtosis among the residuals. Since the Gauss distribution is a symmetrical distribution neither skewness nor kurtosis must be present. If the null hypothesis of the Skewness-Kurtosis-test "H_0=No skewness or kurtosis" cannot be rejected and the normal probability plot indicates only slight deviations of the residuals from the Gauss distribution, the Gauss distribution of the disturbances can be assumed.

Absence of multicollinearity

Multicollinearity indicates a high correlation among two or more endogenous variables. Hence, the endogenous variables depend statistically upon each other (Gujarati, 2004). To perfect multicollinearity is referred if an independent variable can be expressed as a linear combination of other independent variables (Gujarati, 2004). Perfect multicollinearity occurs in particular if m categories of a categorical variable are captured by m dummy variables and all m dummy variables are included in a regression model (Gujarati, 2004). This is also known as the dummy variable trap and can be avoided by including solely (m-1) dummy variables into the model (Gujarati, 2004). The problems arising from multicollinearity are large standard errors and low levels of significance for the parameters estimates of the model, because the correlated independent variables explain at least partly the same circumstance (Greene, 2002). Moreover, the regression coefficients may have implausible signs or magnitudes, but the coefficients themselves are still unbiased (Greene, 2002). For the problem of multicollinearity can be controlled after the regression by employing the variance inflation factor (VIF). The VIF is defined as $1/(1-R_k^2)$ – where R_k^2 is the R^2 of the regression of a variable x_k on all other variables. R_k^2 equals one if the variable x_k can be expressed as a linear combination of other variables (Greene, 2002). The VIF ranges between 1 and infinity and becomes the larger the stronger the correlation among the independent variables becomes.

Values for the VIF above 10 point to multicollinearity being present among the independent variables (Demaris, 2004).

5.2 Household Survey Results with respect to Agroforestry

5.2.1 Vital Household Characteristics for the Application of Agroforestry

In the study village Tandai the average size of a household amounts to 6.25 persons, whereas the median household has six members. The smallest household has solely one member and the largest household comprises 17 persons. Within a household live averagely 2.82 children, which are identified by being aged 14 or younger, as well as 3.64 persons aged 15 or above. The latter are therefore considered as grown-ups. The average age of the children amounts to 7 years compared to an average age of the grown-ups of 35 years. The household head has an average age of 46 years and attended school for averagely 4.68 years. In 81.67% of all households, the household head is male.

Overall the education of adults amounts averagely to 5.15 years of schooling. Considering the duration of education differences between the sexes occur. While women attended school averagely for 4.63 years, men were on average schooled for even 5.68 years. This difference is according to the Wilcoxon rank-sum test statistically significant on the 1%-level.

The average land size available to a household for cultivation amounts 6.99 acres. But the cultivable area ranges from households having no arable land at all up to 90 acres of arable area possessed by one household. The smallholders had to indicate for every plot they cultivate, whether they perceive the tenure for that plot to be secure or insecure. Rather secure land tenure arises from purchasing or inheriting land. In contrast, if the land is leased the tenure is insecure because the smallholder does not know whether the plot may be available for him in the next year, too. The variable *tenure security* gives the percentage of how many of their plots the smallholders perceive as secure. On average 82% of the plots are perceived as secure, which represents that the smallholders of Tandai feel very secure about the land tenure, in general.

The presence of yield losses may be a problem, which induces tree planting, in order to mitigate the yield losses. On average the smallholders face on 47 % of their total land size yield losses, which is equal to 3.05 acres. Smallholders plant on their total land size averagely 239.74 trees and the tree density amounts on average to 33.15 trees per acre.

The slightly positive mean for the variable *firewood sufficiency* indicates the households' firewood production being on average sufficient. To recall from section 3.1.2 the variable firewood sufficiency is determined by deducting the weekly consumed amount of firewood from the weekly collected amount of firewood. The firewood consumption and the collected firewood are measured in head-lots. One head-lot contains roughly 15 kg of firewood (Faße and Winter, 2009). Nevertheless, there are households which consume by far more firewood than they collect. This is for instance the case for the household with the minimum value for firewood sufficiency. For this household the firewood consumption exceeds the firewood production by 14 head lots per week. Overall 20% of the households of Tandai show an insufficient firewood production.

Out of the 224 households which replied to the question on having access to extension 74% stated to have access to extension. The average number of visits by extension officers amounts to 1.5 visits per year.

Concerning the question, which amount of money the respondent wants to obtain today instead of TZS 100,000 in one year, the average answer was TZS 34,788.27. The equivalent discount rate to the average present value of TZS 34,788.27 amounts to 973%. Since such high figures for the rate of time preference are hard to grasp, the present value is chosen as a proxy variable for the pure rate of time preference within the regression model on the application of agroforestry.

The just described household characteristics as well as additional factors, which might have an impact on the smallholders' decision to plant trees, are summarized in table 2. The unit of the examined variables is written in squared brackets following the name of each variable. The fact that the variable wealth is an index without any unit is indicated by [-] following the variable name.

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
family size [members]	6.25	2.65	1.00	17.00	314
gender HH head [%; 0=female, 1=male]	0.82	0.39	0.00	1.00	311
age HH head [years]	46.15	16.15	18.00	92.00	312
education HH head [school years]	4.68	3.16	0.00	12.00	273
land size [acres]	6.99	7.76	0.00	90.00	307
tenure security [% of plots secure]	0.82	0.31	0.00	1.00	311
area yield loss [acres]	3.05	4.85	0.00	48.00	307
ratio of land with yield losses [%]	0.47	0.40	0.00	1.00	307
tree number[no.]	239.74	568.73	1.00	4600.00	304
tree density[trees/acre]	33.15	52.32	0.33	406.50	299
firewood sufficiency [headlots]	0.23	4.14	-14.00	46.00	303
extension access [%; 0=no, 1=yes]	0.74	0.44	0.00	1.00	224
extension Visits [no. of visits]	1.49	8.12	0.00	104.00	221
market distance [minutes by foot]	35.72	37.44	0.50	180.00	311
forest distance [minutes by foot]	135.52	68.49	0.00	480.00	281
mean plot distance[minutes by foot]	51.68	39.03	0.00	240.00	310
wealth [-]	18.89	88.23	0.00	1149.11	314
credit access [%; 0=no, 1=yes]	0.38	0.49	0.00	1.00	312
off-farm employment [%; 0=no, 1=yes]	0.67	0.47	0.00	1.00	314
present value [TZS]	34788.27	35072.81	5000.00	100000.00	307
hiring labour [%; 0=no, 1=yes]	0.64	0.48	0.00	1.00	312
scarcity family labour [%; 0=no, 1=yes]	0.72	0.45	0.00	1.00	311

Table 2: Relevant household characteristics for the application of agroforestry by smallholders of Tandai[1]
Source: Own table

[1] The number of observations does not amount for each variable to the sample size of 314 households due to missing values.

Also economic factors like access to credit and the wealth of a household are examined. The access to credit is determined through a dummy variable that takes the value 1 if the respondent states to have access and 0 otherwise. 37.82% of all surveyed respondents stated to have credit access. The wealth of the polled households is determined by computing the wealth score of Carletto et al. (2000) introduced in section 3.1.4 for each household. The average wealth score of a household in the study village Tandai adds up to 18.89. Again, there is a wide range among the households from a wealth score of 0 to a wealth score of 1149.11. In the wealth score are all assets included a household owns apart from land, which is considered separately, and the homestead. The latter one is not included because nearly every household possesses a house. Therefore, including the homestead in the wealth score did not seem to deliver much additional information.

When economic features of households are discussed, the presence or absence of off-farm employment has to be considered, too. In Tandai the households without off-farm employment show averagely a wealth score of 6.16, whereas households with off-farm employment have on average a wealth score of 25.28. This difference is statistical significant to the 1%-level and is obtained by applying the Wilcoxon rank-sum test. This suggests that off-farm employment has a positive impact on the wealth of a household. A vast number of empirical studies conducted in rural Africa as for instance the one from Barrett et al. (2001) obtain such a result. Besides a positive impact of off-farm employment on the households' wealth, Barrett et al. (2001) find barrier to entry off-farm employment for less wealthy and less educated households. Consequently, rather already relatively well-endowed and well-educated households have the ability to participate in off-farm employment (Barrett et al., 2001). This seems to be valid in Tandai, too, because the household head attended school on average 0.8 years longer if a household shows off-farm employment.

Out of the 311 households, which provided information on the presence of scarcity of family labour, 72% households face a scarcity labour to cultivate their arable land. Although it may seem counterintuitive, it is likely that this strikingly high number is caused by the limited arable area in Tandai. The limitation of arable area, in turn, results from the location of Tandai adjacent to the mountains and the protected forest. In addition, since the population growth rates were very high for Tanzania over a long period of time the population density in the Ulugurus increased, too. For the year 2010 the population growth rate of Tanzania amounted e.g. to 2.04% (IndexMundi, 2010). Since no arable land is left for the younger generation many people of the younger generation migrate to the cities to look for off-farm employment. As a result of this their parents have less family labour on hand

5.2.2 Effects of the Firewood Sufficiency on the Use of Agroforestry

The two main reasons for tree planting are assumed to be firewood production and soil conservation – respectively both may go hand in hand. The household's need to generate firewood is captured by the household's sufficiency in firewood production. The household's sufficiency in firewood production is determined by deducting the weekly firewood consumption of a household from the households' weekly firewood production. If the variable *firewood sufficiency* takes on values above 0 or equal to 0 a household has a sufficient firewood production. A negative value for the variable firewood sufficiency stands for an insufficient production. To be able to examine differences in the household characteristics for households with a sufficient or insufficient firewood production a dummy variable is generated. An insufficient firewood production is represented by the value 0, whereas 1 stands for a sufficient firewood production. The analysis of statistical significant differences in the mean of continuously distributed variables for households with a sufficient firewood production compared to firewood insufficient households is conducted by employing either the t-test or the Wilcoxon rank-sum test. The t-test is used if the examined variable is normally distributed. If the normal distribution is not present for an examined variable the Wilcoxon rank-sum test is employed. By examining the histogram for each variable was checked whether a variable is normally distributed or not.

Several statistical significant differences for households with a sufficient firewood production, compared to households with an insufficient firewood production, are summed up in table 3. A (t) indicates that an outcome is obtained by the t-test and (w) indicates the application of the Wilcoxon rank-sum test. The unit of the examined variable is written in squared brackets behind the respective variable.

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
family size [members] (t)					
firewood sufficient households	6.49***	2.72	2.00	17.00	235
firewood insufficient households	5.51***	2.40	1.00	12.00	79
forest distance [minutes afoot] (w)					
firewood sufficient households	130.69***	71.39	0.00	480.00	215
firewood insufficient households	150.45***	56.31	0.00	240.00	66
extension visits [no. of visits] (w)					
firewood sufficient households	1.81*	9.29	0.00	104.00	165
firewood insufficient households	0.54*	1.81	0.00	11.00	56
tree number[no.] (w)					
firewood sufficient households	270.40***	611.53	2.00	4600.00	234
firewood insufficient households	137.26***	379.112	1.00	3022.00	70
tree density [trees/acre] (w)					
firewood sufficient households	35.55**	55.99	0.50	406.50	232
firewood insufficient households	24.82**	36.00	0.33	183.15	67
land size [acres] (w)					
firewood sufficient households	7.61***	8.47	0.70	90.00	233
firewood insufficient households	5.02***	4.35	0.25	20.50	74

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 3: Statistical significant differences for households with and without a sufficient firewood production[1]

Source: Own table

[1] The number of observations does not add up for each variable to the sample size of n=314 due to missing values.

From table 3 becomes apparent that households whose firewood production is sufficient comprise on average one family member more than households with an insufficient firewood production. A larger family does not only imply more people, who have to be nourished and for whom firewood has to be collected, but also more people who can help to collect firewood. On grounds of this, the finding by Cavatassi and Lipper (2004) of a rising family size leading to less tree planting, due to the smallholder's fear of food insecurity seems to be invalid in Tandai. Since many younger people leave Tandai to look for off-farm employment, the number of people, which have to be nourished by the yields of the self-grown crops, may decrease for the households. This circumstance might lead to a lower fear of the smallholders of experiencing a consumption short-fall due to planting trees on part of the plots instead of cash crops.

Furthermore, table 3reveals that households who are self-sufficient in their firewood production live on average twenty walking minutes closer to the forest than those whose production is insufficient. That result is statistical significant on the 1%-level and has been derived by the Wilcoxon rank-sum test. It confirms the hypothesis that smallholders, who live closer to the forest, meet at least part of their firewood consumption by collecting firewood within or in the proximity of the forest and therefore grow fewer trees.

The extension access is not easy to capture in Tandai. On one side only 46 respondents, out of 314 polled households, stated to be visited by the extension officers, 175 respondents answered that they receive no visits by extension service and the remaining 93 households did not respond at all to this question. On the other side many respondents replied to have contact to extension during village meetings. When asking for extension access in general, 165 of the respondents answered to have access to extension, although only the already mentioned 46 households are visited by extension officers at all. The 165 smallholders, who state to have access to extension in general, grow averagely 46 trees more than smallholders, who do not have access to extension. This result is obtained with the aid of the Wilcoxon rank-sum test and is statistical significant on the 10%-level. Moreover, in table 3 is depicted that firewood sufficient households are on average three times more often visited by extension officers than households whose firewood production is insufficient. Consequently, the firewood sufficiency of households who are visited by extension officers may result from more tree planting induced by the extension officers. Therefore, the argumentation by Adesina et al. (2000) that contact to extension service makes smallholders more open minded to new technologies and thus enhances tree planting seems to be valid for Tandai, too.

A to the 1%-level statistical significant difference exists in the mean for the variable *tree number* between firewood sufficient and firewood insufficient households. Households with a sufficient firewood production grow on average 133 trees more, than households with an insufficient firewood production. This is equal to a by 97% higher tree number for the firewood sufficient households. That result is straight forward because households who possess a larger number of trees can generate more firewood from their trees, unless all trees grown by a household are very young.

Another result that confirms the positive relation between tree planting and firewood sufficiency is that the tree density for firewood sufficient households is by 45% higher, than for households with an insufficient firewood production. The tree density amounts in the first case to 35.55 trees per acre compared to 24.82 trees per acre in the latter case. This result is according to the Wilcoxon rank-sum test statistical significant to the 5%-level. Although households with a sufficient firewood production plant significantly more trees, the tree density is with 35.55 trees per acre even for these households moderate. This suggests that smallholders still grow mainly food and cash crops on their plots instead of trees.

Finally, the land size of households producing sufficient firewood is on average by 2.6 acres bigger than the land size of households with an insufficient firewood production. This may result from the fact that for growing more trees also more land is needed, if the production of cash and food crops should still be self-sufficient. The connection of the tree number and the land size becomes obvious, when plotting the variable *tree number* against the *land size*. Furthermore, a connection of *tree number* and *land size* is also documented by the correlation coefficient for these variables of r=0.27. The Spearman correlation coefficient for the not normally distributed variables *tree number* and *land size* reveals this result being statistical significant on the 1% level. Consequently, the total land size seems to have a positive impact on tree planting, which is also found in a study of Emtage and Suh (2004) conducted in the Philippines.

5.2.3 Effects of the Sex of the Household Head on the Use of Agroforestry

If female headed households are compared to male headed households several significant differences can be identified. An overview of these differences is provided in the following table. A (t) following the name of the examined variable indicates that the outcome results from the application of the t-test respectively a (w) indicates the application of the Wilcoxon rank-sum test. The unit of the examined variable is written in squared brackets behind the respective variable.

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
education HH head [school years] (w)					
male household head	4.85**	3.08	0.00	12.00	231
female household head	3.76**	3.53	0.00	12.00	42
tree number [no.] (w)					
male household head	272.93***	612.28	1.00	4600.00	247
female household head	98.19***	239.10	1.00	1518.00	54
land size [acres] (t)					
male household head	7.52***	8.25	0.25	90.00	253
female household head	4.06***	2.74	0.50	12.00	51
tree density [trees/acre] (w)					
male household head	35.33**	53.69	.56	406.5	247
female household head	22.68**	44.93406	0.33	303.6	49
wealth [-] (w)					
male household head	14.67***	44.39	0.00	481.12	254
female household head	38.60***	184.36	0.00	1149.11	57

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 4: Statistical significant differences for households with male and female household heads [1]
Source: Own table

[1] The number of observations does not add up to for each variable the sample size of n=314 due to missing values.

On average the total tree number for male headed households amounts to 272.93 in comparison to averagely 98.19 trees, which are grown in female headed households. In addition, the tree density is in male headed households by approximately 13 trees per acre or 56% higher than in female headed households. This matches with the findings by Scherr (1995) and Adesina (1996), mentioned in section 3.1.1, of more trees being planted in male headed households compared to female headed households.

The previous results can be added by the fact that female household heads have an average duration of education of 3.76 years compared to male household heads who attend school on average 4.85 years. Hence, the result for the whole sample that men are averagely educated one year longer than women remains valid for the subsample of the household heads, too. Due to this, the difference in the total number of trees and in the tree density could be caused by the difference in education of male and female household heads. The latter case would support the hypothesis of Ervin and Ervin (1982), who stated that more education goes along with a more intense application of soil conserving measures like tree planting. However, it remains for the regression analysis to examine whether the factor gender or the factor education has a bigger impact on planting trees.

Although female household heads are on average one year less educated than men, the female headed households show a more than three times higher wealth score. This result is counterintuitive but explainable by the fact that the largest two manifestations of *wealth* are observed for female headed households. These exceptionally large manifestations can be identified as outliers. Outliers are observations that feature a manifestation which is at least by three standard deviations larger or smaller than the mean (Gujarati, 2004). Since the standard deviation for the variable *wealth* is larger than the mean, outliers can only be detected by adding three times the standard deviation to the mean. All in all four outliers can be detected for the wealth score – two for female headed households and two for male headed households. When these outliers are temporarily excluded male headed households show on average a wealth score of 9.87 compared to an average wealth score for female headed households of 4.34. This result is still statistical significant to the 1%-level according to the Wilcoxon rank-sum test and points to better opportunities for male headed households to acquire wealth. This might be due to the longer education of men as well as to a male oriented culture, which is for instance indicated by 82% of the household heads being men.

5.2.4 Effects of the Access to Credit on the Use of Agroforestry

Also the access to credit seems to play an important role in the decision to plant trees. At least the difference in the average of *tree number* is statistical significant on the 1% level. Households with access to credit plant on average 263 trees more than households without credit access. Moreover, the wealth score differs on the 10% significance-level. Households with access to credit have a wealth score of 38.02 compared to a wealth score of 7.43 for households without credit access. This suggests that tree seedlings, which are sold for TZS 200 (= € 0.11), may be rather expensive for households without credit access and thus a lower level of wealth. Another reason for the strikingly higher tree number for households with credit access, compared to households without credit access, may result from the land size. Households with credit access have averagely a by 3.2 acres larger land size than households without credit access. This difference is also statistical significant to the 1%-level. Consequently, many households without credit access may tend to grow rather food and cash crops on their limited arable area to meet their own consumption needs than growing trees.

Another reason why households with credit access grow nearly three times more trees, than households without credit access, might be that the first ones are visited on average three times more often by extension officers, than the latter ones. This distinction in extension visits is statistical significant on the 5%-level. The households with credit access may be more sensitive to tree planting and the benefits from tree planting due to the better extension access. The difference in extension visits might be due to the larger land size of households with credit access. As a consequence of the larger land size, households with credit access could perceive a greater need for support of how to cultivate their arable area and, thus ask more often for extension visits. The described significant differences are summed up in table 5.

Variable	Mean	Std. Dev.	Min.	Max.	Obs.
tree number[no.](w)					
no access to credit	139.73***	271.11	1.00	2170.00	186
access to credit	402.29***	831.11	2.00	4600.00	116
land size [acres] (w)					
no access to credit	5.75***	4.89	0.25	29.00	187
access to credit	8.95***	10.60	0.50	90.00	118
extension visits [no. of visits] (w)					
no access to credit	0.85**	4.61	0.00	52.00	138
access to credit	2.63**	11.95	0.00	104.00	81
wealth [-] (w)					
no access to credit	7.43*	20.05	0.00	225.44	194
access to credit	38.02*	139.89	0.00	1149.11	118

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 5: Statistical significant differences for households with and without access to credit[1]
Source: Own table

[1] The number of observations does not add up for each variable to the sample size of n=314 due to missing values.

5.2.5 Correlations regarding the Number of Trees and the Tree Density

One of the main reasons for planting trees is assumed to be soil conservation. The need for soil conservation is captured with the aid of the proxy variable *area yield loss*. This variable represents the total land size on which households face yield losses. By putting the variable *area yield loss* in relation to the total land size, the percentage of land is obtained on which smallholders face yield losses. The correlation coefficient for the variables *ratio of land with yield losses* and the *tree number* amounts to r = -0.07 and is statistical significant on the 5%-level according to the Spearman correlation coefficient. This negative correlation coefficient supports the reasoning that tree planting is used by the smallholders to lessen the problem of yield losses.

Besides the purpose of counteracting yield losses the firewood production was already identified to be an important reason for tree planting. Remember that the variable firewood sufficiency is defined as the difference of the consumption and the production of firewood. Values below 0 stand for a lack of firewood from the own production, whereas positive values including 0 represent that a household's firewood production is sufficient. The positive correlation coefficient of r = 0.04 for the variables *tree number* and *firewood sufficiency* reflects the expected result, of more trees going along with the firewood production of a household being more sufficient. The correlation coefficient of the variables *tree number* and *firewood sufficiency* is according to the Spearman correlation coefficient statistical significant on the 1%-level.

Apart from these two correlation coefficients several other statistical significant correlation coefficients can be identified with respect to the variable *tree number*. An overview of these correlation coefficients is presented in table 6. Since *tree number* is not normally distributed the Spearman correlation coefficient is employed to identify, whether a correlation coefficient is statistical significant or not.

Variable	*wealth*	*extension visits*	*present value*	*family size*	*land size*
<u>*tree number*</u>	0.05***	0.06**	0.10**	0.24***	0.27***

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 6: Statistical significant correlation coefficients for the variable *tree number*
Source: Own table

From table 6 becomes apparent that the variables *family size* and *land size* have high positive correlation coefficients with respect to the variable *tree number*. In addition, these correlation coefficients are statistical significant on the 1%-level. That points to an increase in the number of trees when either the family size or the land size rises. The positive correlation coefficient of the *tree number* and the *land size* is plausible, because on a larger *land size* more trees can be grown and also have to be grown to counteract soil erosion. The positive correlation coefficient with respect to the *family size* is unexpected, because in the conceptual framework was assumed that more family members require more food and, thus smallholders refuse to plant trees on the area where they could grow food crops instead. There are two possible reasons for the positive correlation coefficient of the *family size* and *tree number*. On one side a larger family needs more firewood and to generate the needed firewood more trees have to be grown. On the other side smallholders could have recognized the soil conserving features of tree planting so they even utilize tree planting to alleviate soil erosion and yield losses in order to ensure the larger amount of food required by a larger family.

The positive correlation coefficient between the variables *wealth* and *tree number* is statistical significant on the 1%-level. Thus wealthy households grow more trees, which may be caused by the fact that wealthy smallholders can afford more tree seedlings. That refers again to the argumentation of tree seedlings being rather expensive for the inhabitants of Tandai.

The positive correlation coefficients of the variables *tree number* and *extension visits* respectively *present value* are statistical significant to the 5%-level. Consequently, more visits by extension staff go along with more grown trees. This result is straight forward because the extension officers disseminate tree planting as a method to conserve soils. More interesting is the positive correlation coefficient of the variables *present value* and *tree number*. The variable *present value* comprises the value at which a surveyed person is indifferent between obtaining that value today and TZS 100,000 in one year. The higher the present value of a person, the lower is the emphasis that person puts on present consumption compared to consumption in the future. This becomes obvious when considering that a person with a high present value is not willing to abandon much money for receiving the present value today instead of the TZS 100,000 in one year. Hence, a high present value is equal to low rate of time preference by which future results are discounted. The circumstance of a higher present value being accompanied by a higher tree number suggests that smallholders are aware of the soil conserving features of planting trees. Moreover, by this connection is pointed out that smallholders may perceive tree planting as a long-term farm investment to ensure obtaining yields from their plots in the future.

Examining the correlation coefficients of the variable *tree density* similar outcomes are obtained like for the variable *tree number*. An overview of the statistical significant correlation coefficients with respect to *tree density* is delivered in table 7. Again all results on the statistical significance are obtained by using the Spearman correlation coefficient since *tree density* is, as *tree number*, not normally distributed.

Variable	*wealth*	*extension visits*	*present value*	*firewood sufficiency*
<u>*tree density*</u>	0.05**	0.06*	0.10**	0.05***

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 7: Statistical significant correlation coefficients for the variable *tree density*
Source: Own table

Contrary to the results obtained for the variable *tree number* no statistical significant correlation coefficient can be identified for the variables *tree density* and *family size*. This may result from the fact that when examining *tree density*, which is defined as trees per acres, a connection like growing more trees requires more land and more land requires more manpower to cultivate that land is ruled out. This indicates that the observed statistical significant correlation coefficient for *tree number* and *family size* is due to a larger land size, which goes along with more trees. The on the 1%-level statistical significant correlation coefficient r = 0.32 for the variables *land size* and *family size* also supports this reasoning. That statistical significance is identified by the Spearman correlation coefficient.

5.3 Results from the Econometric Model on Agroforestry

The dependent variable of the model, which is employed to estimate the influencing factors on the smallholders' decision to apply agroforestry, is the natural logarithm (ln) of *tree density*. A log-transformation of the variable *tree density* is indicated since heteroskedasticity can be detected for the model with a not log-transformed dependent variable. As a result of the log-transformation the dependent variable follows approximately the normal distribution, instead of being highly right skew as the not log-transformed *tree density* is. Moreover, the null hypothesis of the Breusch-Pagan test "H_0= Constant variance" cannot be rejected for the regression model with the log-transformed *tree density* as dependent variable. However, the log transformation of the dependent variable leads to a shift in the interpretation of the estimated regression parameters. The changes in the dependent variable, resulting from a change in an independent variable by the amount x must not to be interpreted as changes in absolute values but as changes in percentage.

Since the null hypothesis "H_0= No skewness or kurtosis" is rejected to the 10% significance-level when employing the Skewness-Kurtosis-test on the residuals, the assumption $u_i \sim N(\mu,\sigma^2) = N(0, \sigma^2)$ is likely to be violated. To counteract this issue observations which presumably influence the regression as a whole are identified by applying the measure Cook's D. Predicting the values for Cook's D and identifying observations, which feature values larger than 4/n and are therefore regarded as probably influential observations, results in 51 out of 314 observations. Prior to the econometric analysis was carefully considered whether input errors exist in the data. As a result of this, the presumably influential observations are not caused by input errors. Since the number of influential observations could not get reduced by transformations of the independent variables, the influential observations are deleted. Although 51 observations are deleted the number of observations included in the regression decreases solely from 279 to 263. As a quid pro quo the R^2 increases from 0.18 to 0.26. The fact that only 279 observations are included in the initial regression model is caused by missing values for the not included 35 observations. When the model is re-estimated after the influential observations are deleted, the parameter estimates nearly double for some variables. Just as the results of the Skewness-Kurtosis-test this points towards biased parameter estimates resulting from a violation of the assumption $u_i \sim N(\mu,\sigma^2) = N(0, \sigma^2)$, too. After dropping the influential observations, the Skewness-Kurtosis-Test does no longer indicate skewness or kurtosis for the distribution of the residuals. In Appendix A the normal distribution of the residuals, resulting from the model depicted in table 8 is illustrated by two normal probability plots. In order to detect deviations close to the mean of the residuals a p-norm plot is utilized, whereas a quantile plot against the normal distribution is employed to detect deviations at the margins.

The assumption of linearity is examined by plotting the independent variables against the dependent variable. For the main area of observations all explaining variables show a linear relation with respect to the dependent variable. This supports the assumption of OLS being an appropriate model to estimate the influencing factors on the smallholders' decision to plant trees. In addition, the regression specification error test is performed with the result that "H_0= model has no omitted variables" cannot be rejected. The regression specification error test is not only useful to test for omitted variables but also to test for nonlinearity of the characterized relation. Thus the fact that the null hypothesis cannot be rejected indicates that the model is correctly specified because neither variables are omitted nor a nonlinear relation is present.

For multicollinearity is checked with the Variance Inflation Factor. As mentioned before the VIF takes on the value one if no multicollinearity is present and values above 10 indicate multicollinearity among the independent variables. For all variables included in the regression on ln(*tree density*) the VIF ranges between 1.04 and 1.49. The average VIF for all variables included in the model amounts to 1.24. Thus multicollinearity can be excluded for that model.

The results for the econometric model, which determines the influencing factors on the logarithm of *tree density*, are presented in table 8. As a result of the improvement in the Skewness-Kurtosis-Test and in the R^2 by deleting the observations which feature a Cook's D larger than 4/N only the observations with a Cook's D lower than 4/N are included in the OLS regression. The R^2 of that model amounts to 0.26. The BETA coefficients listed in the last column of the table are standardized coefficients as described in section 5.1.2. By comparing the BETA coefficients the impact of non-dichotomous variables which have different units can be compared because the BETA coefficients are normalized to the range between -1 and 1.

Independent Variables	Parameter Estimate	Standard Error.	t-Value	BETA coefficient
family size	0.07	0.02	3.09***	0.18
gender HH head	0.36	0.17	2.13**	.
area yield loss	-0.07	0.01	-5.40***	-0.32
firewood sufficiency	0.05	0.01	3.68***	0.21
credit access	0.36	0.13	2.72***	.
present value	0.000006	0.00	3.38***	0.19
Doga	0.09	0.21	0.42	.
Kisambwa	0.32	0.19	1.65*	.
Lukenge	0.30	0.22	1.38	.
Lusegwa	0.38	0.20	1.91*	.
Nyange	-0.58	0.24	-2.45**	.
Tonya	-0.46	0.23	-2.02**	.
Intercept	1.81	0.24	7.43***	.

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 8: Variables influencing the application of agroforestry by smallholders of Tandai, dependent variable: ln(*tree density*), n(=263)

Source: Own table

The coefficient for *family size* is positive and statistical significant on the 1%-level. The extent of that regression coefficient amounting to 0.07 implies that the predicted mean of *tree density* increases by 7% if the family size increases by one member while all other variables remain unaltered. The positive sign for the independent variable family size is contradictory to the hypothesis formulated in section 3.1.1. Thus the hypothesis that the smallholders refuse to grow trees instead of food or cash crops, because they might fear a shortage of consumption when they have a large family, does not hold in Tandai. This might be due to a still relatively low tree density of averagely 33.15 trees per acre indicating that the competition for cultivable land amongst trees and food crops is not that strong (see section 5.2.2). By contrast, the positive relation could also result from positive experiences of trees mitigating soil erosion and thereby reducing yield losses. Accordingly, the smallholders would even employ trees to ensure the required food consumption of a larger family, because they expect lower yield losses going along with a higher tree density. Taking into account that the PRESA project created incentives to plant trees the latter explanation for the positive parameter estimate with respect to the family size appears even more likely.

The independent variable *gender HH head* exhibits a positive parameter estimate that is statistical significant on the 5%-level. If the household head is male the variable *gender of household head* takes on the value 1 and 0 otherwise. Hence, the parameter estimate of 0.36 implies that the predicted mean of *tree density* increases by 36%, if the household head is male instead of female. This result confirms on one hand the hypothesis constructed in section 3.1 of men headed households having a higher tree density. On the other hand the parameter estimate of 0.36 for the variable *gender HH head* matches with the finding of men headed households featuring a tree density which is 56% higher compared to female headed households (see section 5.2.3). In section 5.2.3 remained the question, whether the higher tree density for households headed by men simply results from differing preferences for men and women or from a better education of men. Since education does not show a statistical significant parameter estimate, whereas the variable *gender HH head* features according to the parameter estimate quite a bit explanatory power, the impact of the difference in education of men and women on the tree density appears limited.

From the BETA coefficients depicted in table 8 becomes obvious, that the variables *area yield loss* and *firewood sufficiency* exhibit the largest BETA coefficients in absolute values. That is why these two variables have the largest impact on the smallholders' decision to plant trees among the non-dichotomous variables. This supports the initial hypothesis that the two main reasons to apply agroforestry are soil conservation – and therewith counteracting yield losses – as well as the generation of firewood.

The parameter estimate for *area yield loss* is statistically significant to the 1%-level. The variable *area yield loss* is employed as a proxy variable for the area on which smallholders face problems with soil degradation. This is particularly suitable because yield losses result, due to the partly quite steep plots, very likely from soil erosion. Since tree planting was already promoted by the PRESA project carried out prior to the project Better-iS, the positive effects of planting trees to alleviate yield losses can be already detected in the data. The parameter estimate of -0.07 for the variable *area yield loss* implies that the predicted mean of *tree density* increases by 7% if the area on which a smallholder faces yield losses declines by one acre. This relation supports the argumentation that the intention to conserve the soil and thereby to counteract yield losses is a vital determinant for the smallholder's decision to plant trees.

The positive parameter estimation for the variable *firewood sufficiency* is statistical significant to the 1%-level, too. Positive values including 0 for the variable firewood sufficiency indicate that the household can generate sufficient firewood. As a result of this the parameter estimate for *firewood sufficiency* of 0.05 implies a rise in the predicted mean of *tree density* by 5% if the firewood sufficiency increases by one head-lot. In contrast to the regression coefficients, the BETA coefficients are interpreted in terms of standard deviations. The BETA coefficient of 0.21 for *firewood sufficiency* means that the natural logarithm of *tree density* increases by 0.21 standard deviations if the firewood sufficiency increases by one standard deviation. Regardless of whether the BETA coefficients or the parameter estimates are examined, the positive sign for both coefficients indicates that the intention to generate firewood is vital to the smallholders for applying tree planting.

Just as for the variable *gender HH head* the variable *credit access* has parameter estimate of 0.36. That regression coefficient is statistical significant on the 1%-level and implies if a household gains access to credit the predicted mean of *tree density* increases by 36%. In addition, the large positive regression coefficient for *credit access* indicates that a liquidity constraint is often present which hinders the smallholders' of Tandai from tree planting.

For the variable *present value* the regression coefficient is very small amounting to just 0.000006. Nevertheless, this coefficient is statistical significant on the 1%-level and according to the BETA coefficient the impact on a change in *tree density* is approximately as high as the impact of the firewood sufficiency or the family size. The parameter estimate for the present value implies that the predicted mean of *tree density* increases by 0.0006% if the present value increases by TZS 1. Hence, when the present value increases by TZS 1889 (= €1) the *tree density* increases by 1.13%. Remember that a higher present value implies a lower rate of time preference by which future benefits arising from agroforestry are discounted. Due to this, the positive sign of the parameter estimate for the variable present value indicates that the acceptance of agroforestry is higher if the rate of discount is lower.

The dummy variables *Doga, Kisambwa, Lukenge, Lusegwa* and *Tonya* result from a categorical variable by which the belonging of a household to a sub-village is captured. As previously mentioned, if the information of a qualitative variable with m different manifestations is captured by m dummy variables, including all dummy variables in a regression would lead to perfect multicollinearity (Gujarati, 2004). Therefore, the dummy variable which has the most observations is not included in the regression. In the present regression this is true for the dummy variable *Tandai*. The left out variable constitutes the reference category with respect to which a change in the sub-village dummy variables from 0 to 1 has to be interpreted.

Out of six included dummy variables for the sub-villages the estimated regression coefficients are statistical significant for four dummy variables. The regression coefficients for the variables *Lusegwa* and *Kisambwa* are statistical significant on the 10%-level. The positive parameter estimate of 0.32 for *Lusegwa* and 0.38 for *Kisambwa* implies that the predicted mean of the *tree density* increases by 32% respectively 38% if a household is located in Lusegwa or in Kisambwa instead of in Tandai. This is particularly plausible since the sub-villages Lusegwa and Kisambwa are most far away from the community forest as well as the protected forest. The households, which are situated in these sub-villages, have fewer opportunities to collect firewood in the forest and are therefore more dependent on tree planting to generate firewood.

The parameter estimates for the dummy variable *Tonya* amounts to -0.46 and is statistical significant on the 5%-level. Hence, the predicted mean of *tree density* is by 46% lower if a household is located in Tonya instead of in Tandai. The large negative impact on *tree density* arising from the location of a household in Tonya, may be explained by the perception of the interviewers that the households from Tonya and Doga generate a relatively low income compared to households from other sub-villages. That is why these households may merely be able to afford few quantities of tree seedlings so the tree density is rather low compared to Tandai. Since the income is not yet available to validate this perception, the wealth score for households from Tonya is compared to the wealth score for the households located in Tandai. However, a comparison of the mean of *wealth* subdivided for the seven sub-villages does not validate the perception of the interviewers. Although the households from Tandai show on average a six times higher value for *wealth* than the households from Tonya, the mean of *wealth* for the households from Doga, Lukenge and Nyange is even lower than for the households from Tonya. The fact that the households from Doga feature a slightly lower mean for the variable *wealth* is not remarkable, because Doga was also perceived by the interviewers as rather poor. In contrast, Lukenge and Nyange feature fairly fertile plots due to the location close to the forest and due to this the households from these sub-villages are expected to be wealthy. For that reason, the households from Lukenge and Nyange are also supposed to show a higher mean for *wealth* than households from Tonya. But the averagely higher wealth score for the sub-village Tonya could be explained by three households from Tonya, who own particular valuable assets like motorcycles and efficient stoves. Nevertheless, the question whether Tonya and Doga are indeed the sub-villages with the lowest average income remains for a future analysis.

The dummy variable *Nyange* shows even a regression coefficient of -0.58. Therefore, the *tree density* decreases by 58% if a household is located in Nyange instead of being located in Tandai. This coefficient is statistical significant on the 5%-level. Nyange and Lukenge are the sub-villages which are nearest to the protected forest and the community forest. This suggests in conjunction with the large negative parameter estimate for *Nyange*, that households from Nyange cover at least part of their consumption needs for tree products by extracting these products from the forest.

6 Econometric Analysis on the Rate of Time Preference

6.1 Methodology

6.1.1 Analyzing Methods and their Principles

The available data allows an estimation of the influencing factors on the smallholders' rate of time preference solely for a time span of one year and not for several different time spans. Consequently, an estimation of the rate of time preference based on a hyperbolical discounting model is impossible. Along the lines of Holden et al. (1998) the approach of Samuelson's discounted utility model is chosen to circumvent this issue. With the aid of that model the factors of influence on the pure rate of time preference of the smallholders of Tandai are estimated. According to Holden et al. (1998) the following functional form is assumed for the individual's discount function:

$$PV = \frac{FV}{(1+\delta)^t} \tag{8}$$

Where the present value (PV) stands for the value a person needs to receive today, to be indifferent of obtaining that monetary value today or a given amount of money at a certain point in the future. The amount of money which can be obtained in the future is represented by FV.

Solving equation (8) for the rate of time preference δ yields the following expression for an individual's pure rate of time preference:

$$\delta = \left(\frac{FV}{PV} \right)^{\frac{1}{t}} - 1 \tag{9}$$

Employing the survey data and the expression of equation (9), the pure rate of time preference of each respondent can be determined. However, many respondents replied to accept a present value of TZS 50,000 or less instead of obtaining TZS 100,000 in one year. If a respondent states a present value which is lower than TZS 50,000 equation (9) yields an individual discount rate of more than 100%. If a present value of TZS 5,000 is put into equation (9) and the future value of TZS 100,000 is maintained, equation (9) yields even an individual discount rate of 1,900%. Since these figures are hard to grasp referring to the rate of time preference, the variable *present value* is selected as a proxy variable for *rate of time preference*. The present value and the rate of time preference feature an inverse relation. Due to this the signs for the possibly influencing factors on the rate of time preference assumed in section 3.2 are opposite to the signs these factors are supposed to show with respect to the present value.

The factors of influence on the present value are analyzed in four steps. First of all, descriptive statistics are provided for the variables that were identified in section 3.2 of possibly influencing the smallholders' rate of time preference. Secondly, the degree of association of the variable *present value* with respect to possibly influential continuously distributed variables is measured by correlation coefficients (Gujarati, 2004). Since *present value* does not follow the Gauss distribution the Spearman correlation coefficient is preferred instead of the Pearson correlation coefficient. Thirdly, equivalence tests for unrelated samples are performed again on subsamples of the whole sample (Wellek, 2010). In order to do so subsamples are made out through dummy variables, which are identified in section 3.2 to possibly influence the smallholders' rate of time preference. These subsamples are examined with respect to statistical significant differences in the mean of the variable present value. This analysis is performed employing the Wilcoxon rank-sum test since *present value* is not normally distributed. Finally, a regression is conducted to determine the factors that influence the extent of the smallholders' present value.

An OLS regression is not applicable with *present value* as dependent variable, because *present value* does not show linear relations with the variables, which possibly have an impact on *present value*. In addition neither a log-transformation nor squaring *present value* leads to linear relations of *present value* and the independent variables. Due to this a fundamental assumption of the OLS regression is violated. A solution is the application of a generalized linear model (GLM). This category of models allows working with data, for which the predicted mean of the dependent variable is a nonlinear function of the regression parameters (Dunteman and Ho, 2006).

GLMs consist out of two components. The first component is a probability distribution of the dependent variable belonging to the exponential family (Dunteman and Ho, 2006). To the exponential family belong continuous distributions as well as discrete distributions. For instance, the normal distribution and the gamma distribution represent continuous distributions belonging to the exponential family. In contrast, the Poisson, the binomial and the negative binomial distribution are examples for discrete distributions out of the exponential family. The choice of a specific probability distribution for the dependent variable grounds on the assumption that this probability distribution with its particularities characterizes the data well (Dunteman and Ho, 2006).

The second component of a GLM is a link function, which transforms the mean of the predicted variable such that this is usually a linear function of the regression parameters (Dunteman and Ho, 2006). For each distribution of the dependent variable belonging to the exponential family a particular canonical link function $\theta(\mu)$ is defined. By selecting the canonical link function for a GLM the mentioned linear relation of the regression parameters and the dependent variables is established. The canonical link function for the normal distribution is e.g. $\theta(\mu)= \mu$, whereas the canonical link function for the gamma distribution is $\theta(\mu)= (\mu)^{-1}$. Nevertheless, deviations from the canonical link function are possible, if a non-canonical link function fits the data better (Dunteman and Ho, 2006). Of course, a deviation from the canonical link implies that the relation of the predicted mean of the dependent variable and the parameter estimates is non-linear.

To determine the regression parameters of a GLM the method of maximum likelihood estimation is applied. Through maximum likelihood estimation the parameter values, which are most likely to generate the sample observations, are determined conditional on the sample data (Dunteman and Ho, 2006). The probability distribution assumed for the dependent variable determines the likelihood function based on which the maximum likelihood estimation is conducted (Dunteman and Ho, 2006). In principle the likelihood function is identical to a probability density function for a given distribution (Dunteman and Ho, 2006). The only difference is that the density function regards the parameters of a distribution as fixed and the data as varying, whereas the likelihood function regards the data as fixed and the distribution parameters as varying (Dunteman and Ho, 2006). Thus the parameters values generating most likely the sample observations can be obtained by varying the parameters until the likelihood function is maximised. The parameter estimates result from numerical optimization since the solutions to the likelihood function are often not analytically tractable (Dunteman and Ho, 2006). The model estimation is terminated when the value of the likelihood function changes only very little between successive iterations (Henson et al., 2010). Small changes in the value of the likelihood function indicate that the current specification of the parameters is close to the parameter specification that generates most likely the sample observations.

Probability distributions belonging to the exponential family have in common that their variance is a function of their mean (Crawley, 2010). The only exception is the normal distribution featuring a constant variance of σ^2. Due to this the relation of the mean and the variance for the dependent variable has to be nearly identical to the relation of the mean and the variance for the assumed probability distribution. As a result of this the choice of the probability distribution for the dependent variable depends on whether the dependent variable is discretely or continuously distributed, the shape of its distribution as well as on how the mean and the variance of the dependent variable are linked. For instance the connection of the variance and the mean of the gamma distribution is $Var(\mu)=\mu^2$ (Hardin and Hilbe, 2007). In contrast, for the Poisson distribution $Var(\mu)=\mu$ is true. Choosing the probability distribution of the dependent variable affects also the probability distribution of the error term since Var(u) = Var(y) (Woolridge, 2005).

Whether the correct link function has been chosen and the model is thus properly specified or not can be examined by performing a link-test. When the command link-test is conducted two new variables are generated; the variable of the predictions (*_hat*) and the variable of the squared predictions (*_hatsq*). Subsequently, the model is estimated again with the two newly generated variables as explaining variables whereby the dependent variable remains unchanged (Hardin and Hilbe, 2007). The regression coefficient of the variable *_hat* should be statistically significant since these are the predicted values resulting from the initial model (Hardin and Hilbe, 2007). By contrast, the estimated parameter of the variable *_hatsq* should not be statistically significant, if the model is correctly specified (Hardin and Hilbe, 2007). When performing the link-test it is vital to specify the same probability distribution and the same link function as was specified for the model on which the link-test is performed. Otherwise the results from the link-test are meaningless.

In section 3.2 variables were identified, which may have an impact on the smallholders' rate of time preference and therefore also on the present value stated by the respondents. Each of these variables is included in a GLM on *present value* without any other explanatory variable. These regressions are performed to receive indications on which variables may contain explanatory power for the smallholders' present value and which not. Furthermore, a regression model is run in which all variables showing explanatory power for *present value* are included. In a stepwise procedure variables are sequentially deleted from the GLM on the present value. During this procedure the Akaike information criterion (AIC) and the Schwarz' Bayesian information criterion (BIC) are considered for competing models. Both measures, AIC and BIC, are employed for model selection and aim at selecting the model with the maximum information (Bhatti et al., 2006). Moreover, the AIC and BIC are useful fit statistics to compare the fit of competing models (Hardin and Hilbe, 2007).The AIC respectively BIC are defined as (Bhatti et al., 2006 , Kaplan, 2004):

$$AIC = -2\ln(L(\hat{\theta})) + 2k. \tag{10}$$

$$BIC = -2\ln(L(\hat{\theta})) + k\ln(N). \tag{11}$$

Where $L(\hat{\theta})$ is the maximum of the likelihood function of the regression model, k is the number of parameters included in the model and N is the sample size (Bhatti et al., 2006). Since the likelihood function is part of the AIC and the BIC both measures are only applicable if the method of maximum likelihood estimation is applied.

Considering the AIC or BIC solely for one model does not comprise much information. The information arises by comparing the AIC and BIC values among different competing models. No matter whether AIC or BIC is employed, a model featuring a smaller value for these information criteria is preferable to a model that shows a higher AIC or BIC value (Kaplan, 2004). Both measures impose a penalty for model complexity because a term, which comprises the number of included parameters, is added within both measures (Bhatti et al., 2006). Nevertheless, the BIC puts a higher emphasis on parsimony due to multiplying the number of included parameters by the natural logarithm of the sample size (Bhatti et al., 2006). Starting with the figure e = 2.718… the natural logarithm of a figure takes a value larger than one. Thus the penalty for adding additional parameters is larger for the BIC compared to the AIC if the sample size $n \geq 3$. With an increasing sample size the penalty for adding additional parameters becomes even larger if the BIC is utilized.

Raftery (1995) suggests rules for the model selection employing the difference in the BIC between two competing models (BIC_1-BIC_2). Weak evidence for preferring model two is provided if the BIC for model two is by 0-2 lower than for model 1 or the BIC difference amounts to 0-2 (Raftery, 1995). A BIC difference of 2-6 provides positive evidence for favouring model two, whereas BIC differences of 6-10 indicate strong evidence for the preference of model two to model one (Raftery, 1995). Finally BIC differences larger than 10 indicate a very strong evidence for favouring model two (Raftery, 1995).

On one hand the tendency to over-fit the data is present when the AIC is employed for model selection (Bhatti et al., 2006). This is caused by the lower penalty for adding parameters to the model if the AIC is employed instead of the BIC. On the other hand the BIC makes strong assumptions about the prior distribution of the parameters, which may be problematic in some situations (Bhatti et al., 2006). As a result of this both measures are used to select the final regression model. The model, which shows lower values for the AIC and the BIC than other-models, good results for the link-test and many statistical significant parameter estimates is selected as the final model.

6.1.2 Regression Diagnostic for Generalized Linear Models

The selected GLM has to be examined on whether the assumptions for GLMs are fulfilled or not. The issues examined by a regression diagnostic for a GLM are similar to the issues checked for when conducting a regression diagnostic for an OLS regression. Again the disturbances are of particular interest, because the disturbances should not contain much explanatory power if the model is well specified (Dobson, 2002). More precisely the presence of the following assumptions are examined (Dobson, 2002):

i. The expected value of the disturbance equals 0 ($E(u_i)=0$).
ii. The disturbances have the same variance ($V(u_i)=\sigma^2$).
iii. The disturbances follow the normal distribution ($u_i \sim N(\mu,\sigma^2)$).
iv. The independent variables and the disturbances do not depend upon each other ($E(x_i u_i)=0$).
v. The disturbances associated with different observations are independent from each other ($E(u_i u_{i'})=0$).

The assumption about the disturbances not being autocorrelated is again in the first place vital when dealing with time series data. Since the available data is cross-sectional the regression diagnostic of the GLM is focused on assumptions i to iv.

As mentioned above the assumed distribution of the dependent variable and its implications for the connection of the mean and the variance are valid for the disturbances, too. Since the disturbances are unobservable, the residuals – as an estimator for the unobservable disturbances – have to be employed to examine whether assumptions i-iv are fulfilled (Dobson, 2002). However, using standardised residuals is necessary because with error distributions like the binomial, Poisson or gamma distribution, the variance changes with the mean (Crawley, 2010). The standardised residuals are computed as follows (Crawley, 2010):

$$r_{is} = \frac{y_i - \hat{\mu}_i}{\sqrt{V(\hat{\mu}_i)}} \quad . \tag{12}$$

Where y_i are the observed values of the dependent variable and $\hat{\mu}_i$ are the fitted values resulting from the GLM (Crawley, 2010). As a result of this, the difference of y_i and $\hat{\mu}_i$is equal to the non-standardized residuals. $V(\hat{\mu}_i)$ is the function that describes the relation among the variance and the mean for the residuals, which results from the assumed probability distribution (Crawley, 2010).

With respect to the regression diagnostic of a generalized linear model not as many tests are available as for the regression diagnostic of an OLS regression. Hence, graphical methods have to be employed in the first place to validate whether the distributional assumptions are fulfilled or not.

Examining the variance and the mean of the standardised residuals gives first evidence concerning the fulfilment of the assumptions about the probability distribution and the link function. Since the specific connection of the variance and the mean resulting from a supposed distribution is considered by using the standardized residuals, they are comparable to the normal distribution to assess the adequacy of the distributional assumptions (Dobson, 2002). That is why the mean of the standardized residuals is supposed to be equal to 0 and the standard deviation should amount to 1. In addition, less than 5% of the standardized residuals should be outside the range of ±1.96 and not more than 1% of the standardized residuals should be outside the range of ±2.58 (Dobson, 2002). These values coincide with the properties of the Gauss distribution, which features 95% of its density within the range of ±1.96 and 99% of its density within the range of ±2.58. For the assumption of the residuals being normally distributed can be checked through normal probability plots. In a normal probability plot the true standardized residuals are plotted versus their expected values if they were normally distributed (Dobson, 2002). The expected value of the standardized residuals is depicted in a normal probability plot through a straight line featuring an angle of 45° (Dobson, 2002). Systematic deviations from that angle bisector or outlying observations indicate that the standardized residuals are not normally distributed. Again deviations close to the mean of the residuals are detected by a p-norm plot, whereas a quantile plot against the normal distribution is employed to detect deviations close to the margins.

Since the standardised residuals are supposed to exhibit the characteristics of the normal distribution no large variations in the variance should exist. Changes in the variance can be detected by plotting the residuals versus the fitted values (Dobson, 2002). An increase in the spread of the residuals somewhere in the residual versus fitted plot indicates a departure from the assumption of homoskedasticity (Dobson, 2002).

Moreover, the standardized residuals are plotted against each of the explanatory variables included in the model (Dobson, 2002). If the model does not describe the examined relation well there will be a systematic pattern in the plot, which would suggest that additional or alternative variables exist which are not yet included in the model (Dobson, 2002).

In addition, to the already introduced analysing methods for GLMs the absence of multicollinearity is examined through the VIF – an OLS post-estimation test. Thus subsequently to estimating the GLM the same model is re-estimated employing an OLS regression and the VIF is determined for the independent variables. To check for multicollinearity in this way is viable since the VIF examines only linear dependencies among the independent. Finally, the measure of Cook's D is applied to detect influential observations, which may have an impact on the regression parameters. If the parameter estimates change largely after dropping the observations featuring a high Cook's D the parameters were probably biased prior to the deletion of outliers. Again either the independent variables can be transformed if the identified influential observations result from extreme values for any independent variable or the influential observations may be dropped (Kohler and Kreuter, 2008). Remember from section 5.1.2 that the results obtained by re-estimating the model after the influential observations are deleted, are similar to using a robust method (Leroy and Rousseeuw, 2003). This is due to the fact that many robust methods give no influence to outliers (Leroy and Rousseeuw, 2003).

6.2 Household Survey Results with respect to Time preference

6.2.1 Vital Household Characteristics for the Rate of Time Preference

For the analysis on the present value three outliers are dropped. These outliers had a remarkable combination of the lowest present value that could be stated by the respondents, although they have at the same time an exceptional high wealth score. This is noticeable since being wealthy is expected to go along with a higher present value and accordingly a lower rate of time preference. Moreover, the deleted observations were already identified as outliers with respect to the variable *wealth* because their manifestations of the wealth score are larger than the mean plus three times the standard deviation. De facto, these outliers have a highly distorting impact because the correlation coefficient for the variables *present value* and *wealth* would show a negative sign if these outliers were not deleted. By contrast, that correlation coefficient shows a positive sign and is statistical significant on the 5%-level after dropping the outliers. Therefore the descriptive statistics for variables which may have an impact on *present value* do not include the deleted observations. An overview of these variables is depicted in table 9. The unit of the examined variables is written in squared brackets behind the name of each variable.

Variable	Mean	Std. Dev.	Min	Max	Obs
gender HH head [%; 0=female, 1=male]	0.82	0.38	0.00	1.00	308
age HH head [years]	46.02	16.04	18.00	92.00	309
education HH head [years]	4.17	3.38	0.00	14.00	306
credit access [%; 0=no, 1=yes]	0.37	0.48	0.00	1.00	309
wealth [-]	11.66	36.32	0.00	481.12	311
child parent ratio [children-no./adult-no.]	1.00	0.70	0.09	5.00	276
time since shock [years]	1.02	0.69	0.00	5.00	150

Table 9: Relevant household characteristics for the extent of the rate of tme preference of the smallholders of Tandai[1]
Source: Own table

[1] The number of observations does not amount for each variable to the sample size of n=311 due to missing values.

The variable *child parent ratio* puts the number of children and the number of adults living in one household in relation. The fact that the mean of the variable *child parent ratio* amounts to one implies that the number of children and the number of adults living averagely in a household are equal. The minimum and maximum for the variable *child parent ratio* reveal that there is a wide range from 0.09 children living in one household per adult to 5 children, which live per adult in a household.

Moreover, table 9 comprises information on when a household exhibited an idiosyncratic shock for the last time. The variable *time since shock* comprises solely 150 observations, because it features only manifestations for households which ever exhibited a shock. Thus nearly half of all sample households exhibited a shock and the average time span since the occurrence of the last shock amounts approximately to one year.

Finally, information on the age, gender and the education of the household head as well as on the households' wealth and credit access is depicted in table 9. Nevertheless, due to dropping three outliers the descriptive statistics differ slightly from the ones provided in section 5.2.1. The deviations are fairly small for the variables *gender HH head, age HH head, education HH head* and *credit access*. Since the dropped observations are outliers with respect to the variable *wealth* the mean for *wealth* decreases from 18.88 to 11.66, which is equal to a decrease by 38%. However, the change in the mean of *wealth* is justifiable with respect to the distortional influence on the correlation coefficient for the variables *present value* and *wealth*.

6.2.2 Correlations regarding the Present Value

An overview of the statistical significant correlation coefficients for the variable *present value* with respect to other continuous variables is given in the following table. Since *present value* does not follow the normal distribution the analysis on statistical significant correlation coefficients is conducted by applying the Spearman correlation coefficient.

Variable	*tree density*	*tree number*	*wealth*	*child parent ratio*
present value	0.10**	0.10**	0.13**	0.08**

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 10: Statistical significant correlation coefficients for the variable *present value*
Source: Own table

As already brought up in section 5.2.5 the correlation coefficient of the variable *present value* with respect to both variables *tree number* and *tree density* amounts to 0.10 and is statistically significant on the 5%-level. Due to this, a higher present value and therefore a lower rate of time preference are accompanied by more trees in total as well as by more trees per acre. This supports the significance of the rate of time preference for the smallholders' decision to make long-term investments, which was already revealed by the regression on ln(*tree density*).

Among all statistical significant correlation coefficients the one with respect to the variable *wealth* shows the largest magnitude. The positive sign indicates that the argumentation of wealthy people stating higher present values and thus having lower rates of time preference holds in Tandai, too. This result is statistical significant on the 5%-level.

Finally, the correlation coefficient for *present value* and *child parent ratio* is also statistical significant on the 5%-level. The variable *child parent ratio* becomes larger when more children live in a household while the number of adults remains constantly. Hence, the positive relation of the variables *present value* and *child parent ratio* indicates that the rate of time preference is lower when smallholders' have more children. This maintains the reasoning from section 3.2.1 that having children makes the respondents more sensitive for the future.

As mentioned before the Wilcoxon rank-sum test is employed to detect significant differences in the mean of *present value* among two groups, because *present value* is not normally distributed. Employing the Wilcoxon rank-sum test detects a statistical significant difference in the mean of *present value* solely for households which have access to extension compared to those which state not to have extension access. Averagely households which have access to extension (n=163) prefer to receive a value of TZS 40,276 today instead of TZS 100,000 in one year. In contrast, households with no extension access (n=56) prefer on average obtaining an amount of TZS 28,214 today instead of TZS 100,000 in one year. The remaining 88 households did not respond to the question whether they have access to extension. The mean for *present value* for these households amounts to TZS 28,806. This result is statistical significant on the 1%-level. It underpins that respondents who state a higher present value may be more interested in receiving information from the extension service on how to improve the cultivation of their arable area. This is reasonable since a higher present value implies a lower rate of time preference and therefore reflects more awareness about the future.

6.3 Results of the Econometric Model on the Present Value

For the present value is asked by means of a stepwise hypothetical question. Beginning with a present value of TZS 90.000 the respondent is offered to obtain the next lower present value until the respondent denies accepting the next lower present value. The lowest accepted present value is noted as the present value, which a respondent would be willing to accept today instead of TZS 100,000 in one year. This kind of questioning leads to manifestations for the variable *present value* only for certain monetary values. Precisely, the categories for the present value are TZS 5,000, TZS 10,000, TZS 20,000, TZS 30,000, … , TZS 100,000. The presence of *present value* in positive integer values may at first lead to the assumption that *present value* could be a count variable. Though, when considering the definition of count data as the number of events during a certain period of time, the assumption of *present value* being a count variable turns out to be wrong (Cameron and Trivedi, 1998).

The fact that the observed manifestations of *present value* are discrete does not imply that the values for the variable *present value* estimated by the GLM may only assume discrete categories. By contrast, due to *present value* being expressed in monetary terms, the true distribution of *present value* is continuous instead of discrete. The discrete categories for *present value* are rather owed to ensure data quality. Asking for the accepted present value until the respondent rejects the next lower present value is assumed to facilitate the respondents thought processes and to encourage them to consider their responses carefully (Bolt et al., 2005). Consequently, all discrete probability distributions belonging to the exponential family are inappropriate for the model on the dependent variable *present value*.

As already mentioned assuming the probability distribution for dependent variable requires considering how the variance and the mean of the dependent variable are related. For the variable present value the relation $Var(\mu)= \mu^2$ is nearly fulfilled with μ=35,082.24 and σ=35,119.92. Since the mean and the variance of the gamma distribution feature the relation $Var(\mu)= \mu^2$ the gamma distribution is assumed for the dependent variable and the disturbances. The canonical link for the gamma distribution is the inverse. Remember that the canonical link transforms the mean of the predicted variable such that a linear relation with respect to the regression parameters exists. However, deviations from the canonical link are according to Duntemann and Ho (2006) possible if another link function fits the data better.

The quality of model specification of a respective GLM is examined through the link-test. If the gamma distribution is assumed as probability distribution and the inverse as link function, none of the variables generated by the link-test shows a statistical significant parameter estimates when the link-test is carried out. As mentioned previously the variables *_hat* and *_hatsq* are generated when the link-test is performed. The variable *_hat* contains the predicted values from the previously estimated GLM, whereas the variable *_hatsq* comprises the square of the predicted values. By performing the link-test these variables are employed as independent variable in a GLM on the dependent variable *present value* (Hardin and Hilbe, 2007). If the variable *_hat* reveals no statistical significant parameter estimate the previously estimated GLM does not comprise much explanatory power for the dependent variable. By selecting the link function identity instead of the canonical link and maintaining the gamma distribution, the link-test reveals a statistical significant parameter estimate for the variable *_hat*. In contrast, the parameter estimate for the variable *_hatsq* remains statistical insignificant. Since choosing the canonical link results in a worse model specification than the link function identity, the latter is selected for the GLM on the *present value*.

The results of the GLM on *present value* are presented in table 11. The variables included in that GLM lead to lower values for the AIC and BIC compared to competing models. In addition, a good model specification measured by the link-test. As mentioned in section 6.1.1 the model is selected by dropping sequentially variables in the order that the biggest improvement in the AIC and the BIC is achieved but the link-test still indicates a proper model specification. For instance, the BIC value could be improved by dropping the sub-village dummy variables, but this causes according to the link-test a strong decrease in the quality of model specification. Furthermore, there would be no improvement in the AIC. For dropping any other of the variables from the model on the present value the trade-off would be the same. Therefore the model including the variables depicted in table 11 is maintained.

By applying the measure of Cook's D after estimating a GLM including the same variables as presented in table 11, 59 presumably influential observations are detected within the sample. Nevertheless, dropping these observations reduces the number of observations included in the regression only from n=265 to n=252. This is due to the fact that observations, which feature missing values for in the regression included variables, do not enter the regression model. As a quid pro quo the properties of the parameter estimates and of the residuals following the normal distribution as well as the model specification improve. On one side for two variables a 1.5 times increase respectively a 2.5 times increase in the parameter estimates appears after dropping the observations with a Cook's D larger than 4/N. On the other side without deleting the influential observations 20% of the residuals are larger than 1.96 and 19% of the residuals are larger than 2.58. Both facts indicate that the assumption of the normal distribution for the standardized residuals is violated if the observations featuring a high Cook's D are included in the regression. After dropping these observations 3% of the standardized residuals are larger than 1.96 and 1% of the standardized residuals are larger than 2.58. That is why the regression model comprising solely n=252 observations is selected as the final model. This model is depicted in table 11.

Independent Variables	Parameter Estimate.	Standard Error.	z-Value
age HH head	-265.74	102.79	-2.59***
gender HH head	6430.41	2850.66	2.26**
wealth	173.21	132.29	1.31
child parent ratio	8743.60	3132.46	2.79***
Doga	-12468.99	6009.76	-2.07**
Kisambwa	-21582.55	4674.49	-4.62***
Lukenge	-6704.37	6958.84	-0.96
Lusegwa	-1237.75	7071.80	-0.18
Nyange	5580.61	9607.89	0.58
Tonya	-16605.47	5466.18	-3.04***
Intercept	35639.18	7446.51	4.79***

*Significant at 10%. **Significant at 5%. ***Significant at 1%.

Table 11: Variables influencing the rate of time preference of the smallholders of Tandai, dependent variable: *present value*, (n=252)
Source: Own table

The VIF for the model presented in table 11 is excellent and amounts averagely to 1.19. As can be seen in a normal probability plot, which is depicted in Appendix B, some deviations of the standardized residuals from the normal distribution still exist. In addition, a residual versus fitted plot indicates that the variances of the standardized residuals are not completely homoskedastic. Nevertheless, the outcome of the link-test indicates an excellent model specification for the GLM presented in table 11. The parameter estimate for the variable *_hat* amounts to 0.00 respectively the parameter estimate for the variable *_hatsq* amounts to 0.94. Due to this, the results can still be regarded as fairly good. This is all the more true given that many respondents reflected for the first time which present value they would require to be as well-off as with obtaining TZS 100,000 in one year.

The negative parameter estimate for the variable *age HH head* is statistical significant on the 1%-level. The regression coefficient of -265.74 implies that the predicted mean of *present value* decreases by TZS 265.74, if the household head grows one year older. This result coincides with the hypothesis constructed in section 3.2.1 that a lower present value and accordingly a higher rate of time preference goes along with becoming older. Ervin and Ervin (1982) explained this circumstance by a shortening of the planning horizon when a person grows older.

With respect to the impact of gender differences on the rate of time preference no assumptions were made in the conceptual framework. However, the inclusion of the variable *gender HH head* resulted in a BIC being by 14 lower than the inclusion of the variable *education HH head*. Since a BIC difference larger than 10 provides strong evidence for preferring one model to a competing model, the variable *gender HH head* is included in the GLM on *present value*. In addition, the parameter estimate for the dummy variable *gender HH head* being statistical significant to the 5%-level, supports the inclusion of this variable. The dummy variable takes the value 1 if the household head is male and 0 otherwise. Hence, the parameter estimate for the variable *gender HH head* indicates that the predicted mean of *present value* increases by TZS 6,430.41 if the household head is a man. This may be caused by the averagely better social situation of male household heads. Men attend school on average one year longer than women and male headed households have on average three more acres on hand to cultivate. Finally, if the outlying observations for the variable *wealth* are excluded, as temporarily done in section 5.2.3, male headed households are averagely wealthier. Since each of these features bears already the potential to increase a person's present value, it is not remarkable that *present value* increases by such a large amount if the household head is a man.

Although the parameter estimate for the variable *wealth* is statistical insignificant the variable *wealth* is maintained in the model on *present value*. This decision rests upon the statistical significant correlation coefficient for the variables *present value* and *wealth*, which indicates that the variable *wealth* contains explanatory power for the variable *present value*. The positive parameter estimate for the variable *wealth* coincides with the positive correlation coefficient for *present value* and *wealth* as well as with the expectations formulated in the conceptual framework. Overall, the results underpin the assumed relation of the variables *wealth* and *present value*. If the well-being in the present is ensured, the smallholders' present value is probably higher and accordingly their rate of time preference is lower. This implies they are less willing to abdicate consumption merely to consume now instead of in the future. Consequently, smallholders who are wealthy and thus state a higher present value, put a higher emphasis on benefits accruing in the future than less wealthy smallholders who state a lower present value. However, because rather a sufficient income than assets ensure essential consumption today the smallholders' income may deliver more explanatory power with respect to *present value* than *wealth*. Since the information on the income is not available, examining whether the income features a statistical significant parameter estimate in a model on *present value* remains for a future analysis.

The variable *child parent ratio* is an indicator for the importance of generations within a household. If the variable *child parent ratio* takes on the value 1 as many children as adults live in a household. By contrast, a manifestation larger than 1 means that more children compared to adults live in a household. The parameter estimate of 8743.60 for *child parent ratio* implies that the predicted mean of *present value* increases by TZS 8,743.60 if the *child parent ratio* increases by one. This result is statistical significant on the 1%-level. For instance, the child parent ratio increases by one if the number of children rises by one, whereas the number of adults remains constantly. This implies that smallholders having a family with relatively many children take benefits accruing in the future more into account than smallholders with relatively fewer children.

This relation can be caused by two completely different reasons. On one side the adults of a household which comprises many children could be comparatively young and a lower present value would be due to the lower age. On the other side smallholders who have more children might give more thoughts about the future, because they want their children to have a basis of life, too. The first circumstance might be the case, because children are defined as household members with an age of 14 or younger. If the children are younger than 14 the parents are probably not older than 50 and thus comparatively young. If this relation would be valid the variable *child parent ratio* would depend on the manifestations of the variable *age HH head*. To test whether the *child parent ratio* is independent of the *age of the HH head* the model presented in table 11 is also run including an interaction term for these variables (Gujarati, 2004). The interaction term showed neither previously to dropping the observations with a high Cook's D nor subsequently to the deletion a statistical significant parameter estimate. This result supports the second argumentation. As a result of this, smallholders who have more children may state a higher present value because they want to preserve a basis of life for their children.

Out of the six included sub-village dummy variables *Doga*, *Tonya* and *Kisambwa* show a statistical significant parameter estimate. The regression coefficients for *Tonya and Kisambwa* are statistical significant on the 1%-level, whereas the one for *Doga* is significant on the 5%-level. All three coefficients have in common to be negative. The parameter estimate for *Kisambwa* implies that if a household is located in Kisambwa instead of in Tandai the predicted mean of *present value* decreases by TZS 21,582.55. This effect with respect to the sub-village dummy variable *Kisambwa* can be explained by the fact that a relatively low plot size is observed for households from Kisambwa. De facto, the available arable area is for households from Kisambwa and Lusegwa with averagely 4.8 acres the lowest among all sub-villages. This raises the question why only the variable *Kisambwa* and not also the variable *Lusegwa* has such a strong negative impact on the predicted mean of *present value*? A reason can be that for households belonging to Kisambwa the off-farm employment is rather low in addition to the small plot size. Solely 68% of the households of Kisambwa show off-farm employment, whereas in the reference sub-village Tandai 74% of the households show off-farm employment. Furthermore, even 82% of the households from Lusegwa state to have off-farm employment. Due to this, the respondents of the households from Kisambwa might fear a shortfall of income and consumption, because they neither have much off-farm employment nor large cultivable areas to carry out agriculture. Consequently, the respondents of households from Kisambwa may state a low present value since they fear a consumption shortfall.

The negative parameter estimate with respect to *Doga* and *Tonya* may again be explained by perception of the interviewers that the households from these sub-villages are the ones with the lowest income. This seems plausible, because the present value is assumed to be the lower, the lower the income and therewith the consumption opportunities are. However, as mentioned examining the variable *wealth* subdivided for the sub-villages does not underpin the perception of Doga and Tonya being the poorer sub-villages. In fact, the households from Lukenge and Nyange feature a lower mean for *wealth* than the households from Tonya and Doga. This is remarkable because Lukenge and Nyange feature fairly fertile plots and the households from these sub-villages are thus presumed to be rather wealthy. As mentioned before the income was not yet available. That is why it remains for a future analysis to examine, whether the negative impact of the sub-village dummy variables *Doga* and *Tonya* may result from a comparatively low income for households belonging to these sub-villages.

7 Conclusion

The influencing factors on the decision of the smallholders of Tandai whether to apply agroforestry were determined out of a large number of possibly influencing factors. These factors were derived either by theoretical considerations or by drawing on the results of previous empirical studies. Since every site has its own particularities not all possibly influencing factors showed an impact on the application of agroforestry in the end. An empirical analysis resulted in the intention to alleviate yield losses and the intention to generate firewood being the most vital factors for using agroforestry in Tandai. In addition, the availability of credit enhances the application of agroforestry remarkably, which indicates that a lack of liquidity to buy tree seedlings may often restrain the smallholders from applying agroforesty. Moreover a rising family size is likely to induce to grow more trees, which points in the direction that the smallholders of Tandai utilize tree planting purposeful to mitigate yield losses and thus ensure the needed food consumption by subsistence agriculture. Besides, men utilize agroforestry more intensively than women as well as differing economic and environmental conditions among the sub-villages influence the intensity of the use of agroforestry, too. Finally the utilization of agroforestry is more intense if the present value stated by the respondents is higher and, thus their rate of time preference is lower. This implies that smallholders, who put compared to other smallholders a lower emphasis on consumption today instead of in the future plant more trees. As a result, the hypothesis that the smallholders' rate of time preference is vital for long-term investments like tree planting is confirmed.

Beyond, the GLM on the present value yielded the following results: 1) if a person grows older the present value is likely to become lower; 2) wealthy smallholders may state a higher present value; 3) the present value is higher if the household head is male and 4) respondents probably state a higher present value if the households comprises more children. Furthermore, particular conditions of the sub-villages, like less off-farm employment compared to other sub-villages, have an impact on the present value, too. With respect to the rate of time preference the opposite relation is true, because the present value and the rate of time preference are related inversely.

The socio-demographic factors of influence on the use of agroforestry and the rate of time preferences cannot be affected. That is why the focus for inducing tree planting has to be put on economic factors like the wealth of a household and the household's credit access. Making credit more available to the smallholders could be a strategy to encourage tree planting. As a result of this the smallholders could afford to buy tree seedlings in spite of liquidity constraints. Furthermore the availability of credit would help smallholders to smooth their consumption over time so they exhibit less likely periods of consumption shortfall. This would in turn increase the present value and accordingly lower the rate of time preference. The latter is again vital for long-term investments like tree planting.

Nevertheless, future analysis is needed since data on the smallholders' income was not available for the econometric analysis. But in particular the income may have an impact on tree planting, because the smallholders can purchase tree seedlings only if they have sufficient income. Apart from that a sufficient income ensures consumption in the present which in turn leads to a higher present value and accordingly a lower rate of time preference. Thus the income would be also vital for the analysis of the rate of time preference.

Appendix

Appendix A: Distribution of the Residuals resulting from the OLS Regression on ln(*tree density*)

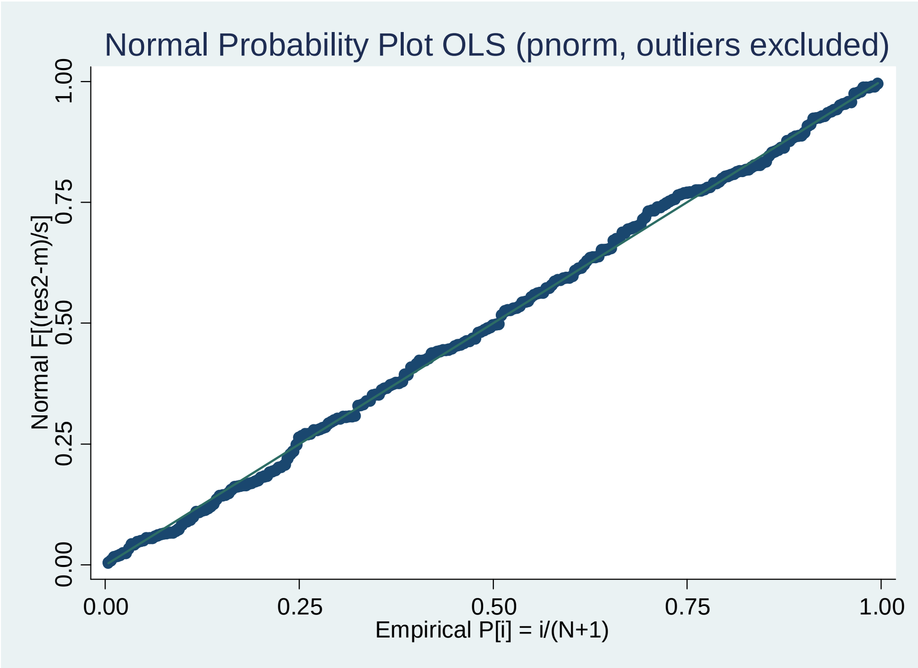

Figure A.1: Normal Probability Plot (p-norm) for the residuals resulting from the OLS regression on ln(*tree density*) (except observations with a large Cook's D)

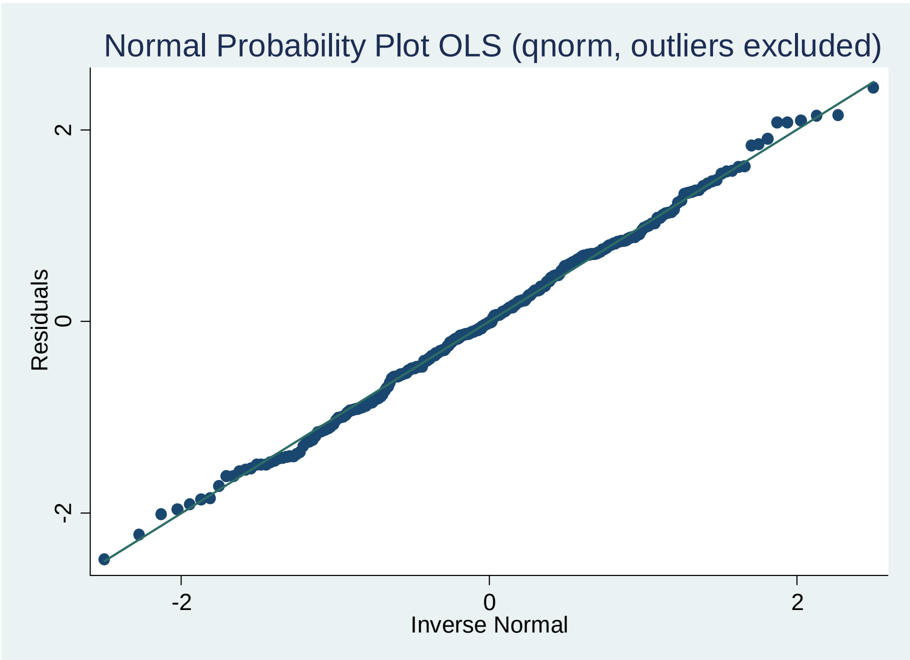

Figure A.2: Quantile plot against the normal distribution for the residuals resulting from the OLS regression on ln(*tree density*) (except observations with a large Cook's D)

Appendix B: Distribution of the Residuals resulting from the GLM on *present value*

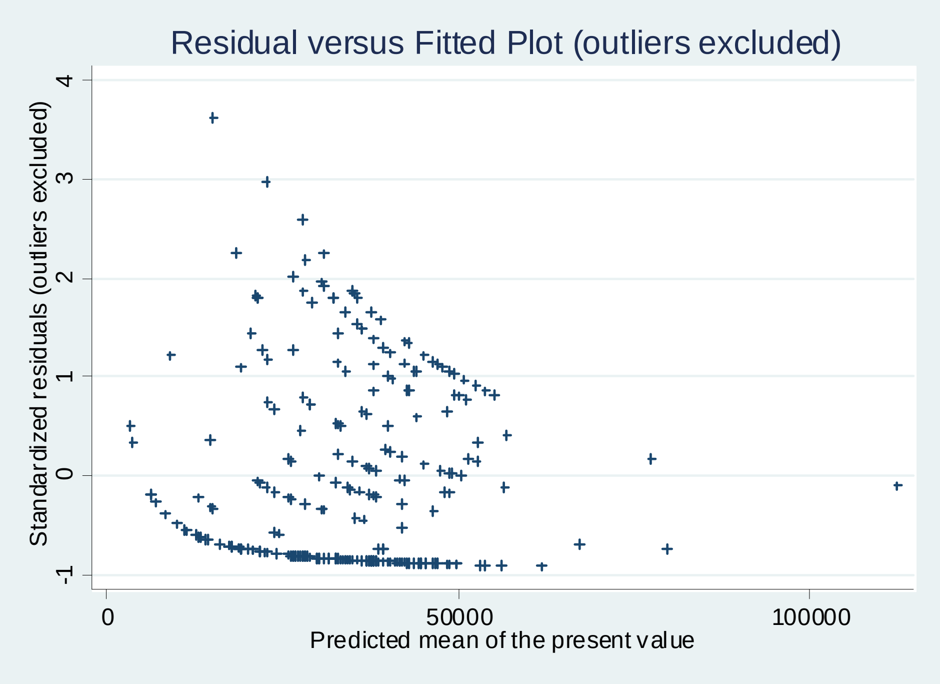

Figure B.1: Residual versus Fitted Plot for the GLM on *present value* (except observations with a large Cook's D)

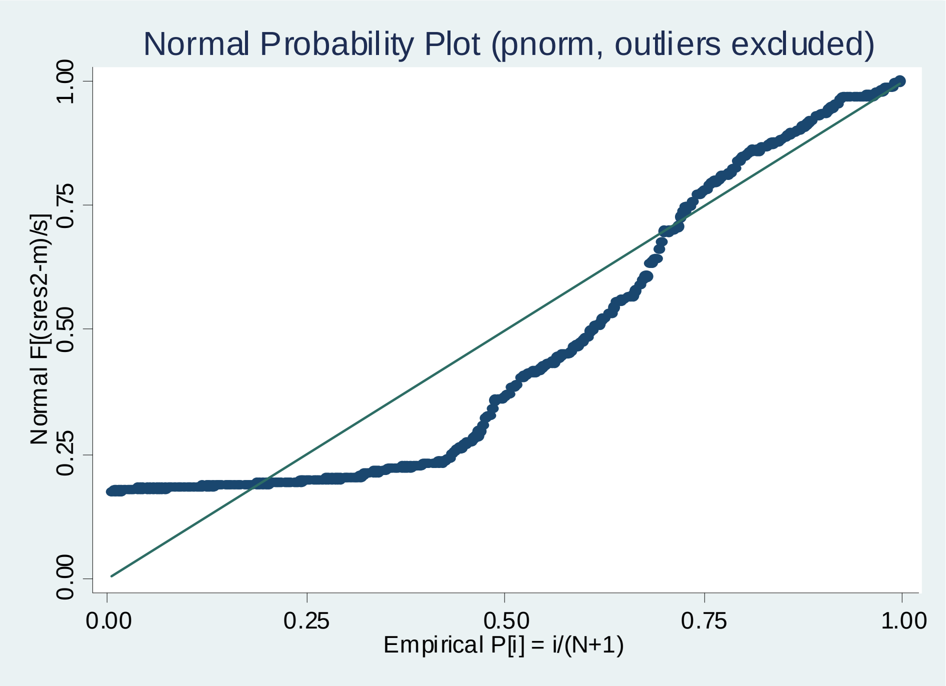

Figure B.2: Normal Probability Plot (p-norm) for the residuals resulting from the GLM on *present value* (except observations with a large Cook's D)

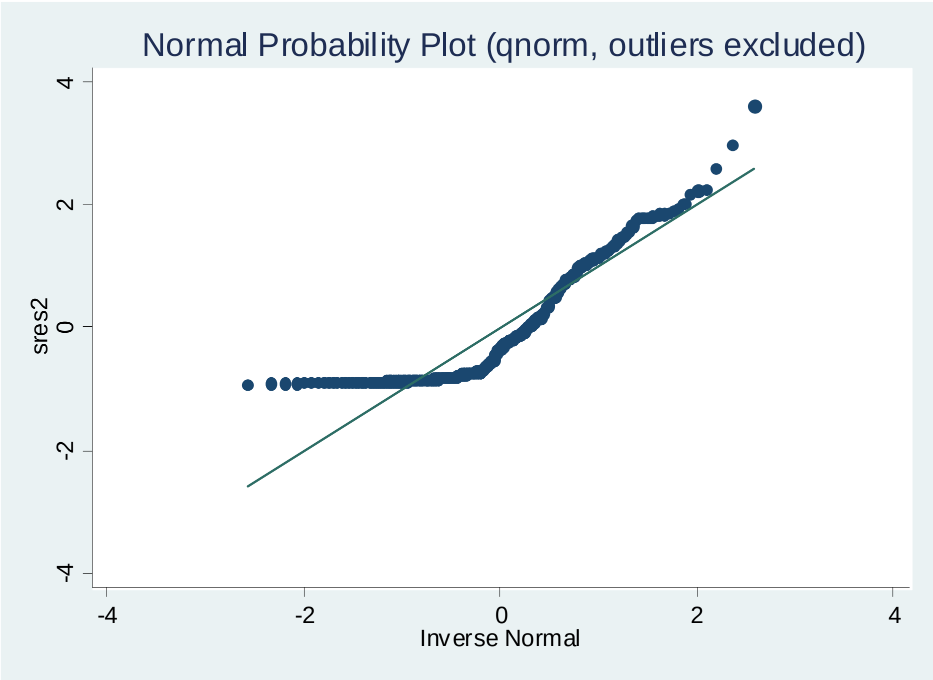

Figure B.3: Quantile plot against the normal distribution for the residuals resulting from the GLM on *present value* (except observations with a large Cook’s D)

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