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Household Characteristics and Poverty with Emphasis on Employment in Myanmar (2005 and 2010)

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Household Characteristics and Poverty with Emphasis on Employment in Myanmar (2005 and 2010)

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I hereby certify that the content of this thesis is wholly my own work unless otherwise referenced or acknowledged. Information from sources is referenced with original comments and ideas from writer him/her herself.

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4-Ph. D. Ah-2

Abstract

This study analyses empirically the employment poverty nexus in Myanmar between 2005 and 2010. For this purpose, micro-level relation between employment and poverty is investigated focusing on the poverty risk of households based on the household characteristics and employment at two time points 2005 and 2010. Probit model has been used to investigate the influence of industry, employment status and education level and household charateristics on poverty. And then, probit model has been also used to invesigate the influence of household characteristics on poverty. The analysis is carried out for rural and urban separately. In resulting the influence of household characteristics on poverty, although remittance variable can be used on urban poverty reduction, it cannot be used to reduce rural poverty as a factor. The results also confirm that education is the prime factor in both rural and urban household poverty in agriculature sector of Myanmar. Among the educational levels, the marginal effect of illiteracy on poverty is the largest for each employment status. The multiple rounds allow the comparison of poverty determinants at two time points. In studying the effect of employment status and educational level on poverty risk of household by sectors, it has been noticed the effects of change in 2005 was smaller than that of 2010.

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LIST OF ABBREVIATIONS

CBN	Cost of Basic Needs
DHS	Demographic and Health Survey
DOGEV	Dogit Ordered Generalized Extreme Value
FPL	Food Poverty Line
FSU	First Stage sampling Unit
GDP	Gross Domestic Product
GMM	Generalized Method of Moments
HCR	Head Count Ratio
HIES	Household Income and Expenditure Survey
IHLCA	Integrated Household Living Conditions Assessment
IID	Independent and Identically Distributed
ISIC	International Standard Industrial Classification
LSMS	Living Standard Measurement Survey
MDGs	Millennium Development Goals
MNPED	Ministry of National Planning and Economic Department
NGO	Non-Government Organization
OLS	Ordinary Least Squares
PDR	Peoples Democratic Republic
PL	Poverty Line
PPES	Probability Proportional to Estimated Sampling
SES	Social Economic Status
Sida	Swedish International Development Cooperation Agency
SSU	Second Stage sampling Unit
UN	United Nations
UNDP	United Nation Development Programme

CHAPTER I

INTRODUCTION

1.1 Rationale of the Study

Poverty makes people vulnerable to economic shocks, national disaster, violence, and crime. People in poverty are often denied access to education, adequate health services, and clean water and sanitation. Poverty has multiple dimensions, namely, income poverty, education and health poverty, tenure insecurity, personal insecurity, financial insecurity and social and political exclusion/disempowerment.

According to the World Bank (2000), poverty is pronounced as deprivation in "well-being". One approach is to think of one's well-being as the command over commodities in general. People are better off if they have a greater command over resources. In this view, the main focus is on whether households or individuals have enough resources to meet their needs.

A second approach to well-being is to ask whether people are able to obtain a specific type of consumption goods. Perhaps the effective approach to well-being (and poverty) is the labour market that is central in poverty reduction because labour is the major asset the poor possess (World Bank; 1999). The importance of labour market for poverty has long been recognized in the development theories, which were based on the assumption that industrialization would absorb the surplus labour from the traditional sectors and lead therefore to higher wages and positive effects on welfare (Lewis, 1954). However, it has become clear that development and employment generation is much less structured than the early theories predicted. For instance, the services sector has expanded much stronger than manufacturing in many developing countries, including Myanmar.

In 2001, the Ministry of National Planning and Economic Development (MNPED) conducted the Household Income and Expenditure Survey (HIES). The survey followed the national nutrition norms adopted by the Ministry of Health. According to the survey, the estimates of the poverty rate were 20.7 percent for urban, 28.4 percent for rural and the Union rate was 26.6 percent.

Since 2005, the government of Myanmar has been striving hard to carry out poverty reduction activities with high momentum. Concerted efforts were made to fulfill the targets of Millennium Development Goals (MDGs), namely (1) to eraticate extreme poverty and hunger, (2) to achieve universal primary education, (3) to promote gender equality and empower women, (4) to reduce child mortality, (5) to improve maternal health, (6) to combat HIV/AIDS, malaria and other diseases, (7) to ensure environmental sustainability and (8) to develop a global partnership for developmant. There exists poverty in some remote and border areas that lagged far behind in the past due to difficultly in transportation and multi-coloured insurgents. The government laid down comprehensive programs which aimed to achieve social development and poverty reduction in Myanmar.

To reduce poverty in Myanmar, the government took the following four initiations:

First, in order to implement poverty reduction, the government investigated who these poor people were, what was the situation was, what their needs were and desires and what they felt. In addition, the government also investigated to get a better understanding of the situation of the poor people and to improve their well-being. Based upon the vast experiences of many of the compatriots in civil society organizations, Non-Government Organizations (NGOs), government officials, business people, scholars, academics and foreign experts and organizations, a lot of work related to poverty alleviation in the country, especially in rural and border areas and also with respect to meeting special needs of disadvantaged ethnic nationalities and other distressed communities, has to be done.

Second, to reduce poverty in a systematic and an effective way, the government adopted poverty alleviation strategy. Useful inputs for the strategy were obtained from the experiences of Myanmar's neighbors and other countries both developed and developing throughout the world that embarked on poverty alleviation measures and programmes during 2005-2010. The United Nations has embarked on a major international initiative on poverty alleviation through its (MDGs) to which Myanmar has given its commitment. In the light of all these, Myanmar has adopted a new strategy

that made a significant contribution to uplift the living standard of the poor people in the country.

Third, the next step is to come up with what activities were to be done, that is, alleviation strategy needed to be put into operation by drawing up an implementation programme. The action programme had numerous projects that dealt with specific issues and recommendations set out in the strategy. The project has clearly defined objectives and targets which were time bound, that was measurable or gave clear indication that the poor people were indeed made better off. Time bound means the target had to be met within a specified time period. For example, a target can be set up such as the number of school-age children not attending school in a certain village must be reduced by half within a certain period.

Finally, there had to be monitoring and review of the implementation of the action programme. This was to make sure that the programme would achieve its objectives, and if not, then why not, what had be done so that the objectives were achieved. Hence, the implementation of the action programme was monitored and kept under constant review and immediate steps were taken to determine the underlying causes if divergences occur between planned targets and outcomes. Those undertaking the review reported their findings and recommendations to the appropriate authorities of Myanmar for corrective action as required.

It is obvious that every country has a set of development indicators for the poverty assessment at the district level. For example, Seila Program of Cambodia, focal site strategy in Lao PDR (Peoples Democratic Republic), and participatory district program in Nepal had done comprehensive poverty assessment studies. In Myanmar, poverty reduction plan has been initiated.

Inadequate income or consumption is the most widely used measure of poverty in the developing countries. It tends to be favored by economists who view it as a proxy for the inability to satisfy basic preferences. When using this approach, two questions immediately arise and must be addressed in one way or another. They are how to draw the poverty line and how to 'add up' those who fall below the poverty line.

There are many methods of drawing the poverty line using nutritional norm based on minimal dietary energy intake or actual consumption pattern.

One method for deriving a poverty line used in the developing countries is the cost-of-basic needs approach which is utilized by Integrated Household Living Conditions Assessment (IHLCA) survey. The IHLCA survey provides data on key dimensions of living conditions and well-being in Myanmar. The first IHLCA survey was conducted in 2004-2005 with the support of the United Nations Development Programme and national partners including the Ministry of National Planning and Economic Development. This survey represented IHLCA I with a nationally representative sample of 18660 households in both rural and urban areas across Myanmar. It allowed for the estimation of poverty levels drawing on a detailed consumption module, using modern, 'industry-standard' techniques to set the poverty line. The second IHLCA survey was conducted in 2009-2010 which was a follow-up survey to the original IHLCA I. The core objective was to update the 2004-2005 data, shedding, new light on levels and trends in living condition. As it is, the best that can be done is to adjust total household expenditure by some measure of the number of peoples in the household, and to assign the resulting welfare measure to each household member as an individual.

Moreover, the labour market is central in poverty reduction. Because of this, labour is the major asset the poor possess (World Bank, 1990). The importance of labour markets for poverty has long been recognised in the development theories, which were based on the assumption that industrialization would absorb the surplus labour from the traditional sectors and lead therefore to higher wages and positive effects on welfare (Lewis, 1954). However, it has become clear that development and employment generation is much less structured than the early theories predict. For instance, the service sector has expanded much stronger than manufacturing in many developing countries, including Myanmar. As a result, the expansion of the industrial sector did not necessarily lead to reduction in poverty in India (Ravallion and Datt, 1996). The productivity and the welfare effects of the employment opportunities that are generated in the course of economic expansion are not always clear. A substantial share of these occupations is as self-employed, including many petty activities of extremely low productivity. The relationship between employment and poverty can be investigated at macro and micro-economic levels. At the micro-level the interplay between economic development, labour markets and poverty has been studied using

these IHLCA household expenditure surveys, wherein poverty profiles are constructed for a variety of household characteristics. With the idea behind, this study explores empirically the employment-poverty nexus in Myanmar. For this purpose, this study analyses the interplay between household characteristics, the labour market and poverty in Myanmar between 2005 and 2010.

1.2 Objectives of the Study

The objectives of the study are:

- to investigate micro-level relationship between employment, household characteristics and poverty by industrial sectors in Myanmar at two rounds corresponding to the years 2005 and 2010.
- to detect the influencing factors in micro-level context and
- to point out the determinants of poverty for households in Myanmar based on household surveys in 2005 and 2010. In this study, the influence of such factors as employment status and education level on poverty of households, etc. in Myanmar are also investigated by using probit model.

1.3 Method of Study

It is known that poverty level of household is influenced by the household members working in various sectors across the industry at different employment status and educational levels. Probit model is used to study the effect of socio- economic variables, both direction and degree, on the poverty of households. In estimating this model, SPSS (version 22) which provides the probit estimates for the parameters is used. Pearson Chi-square values are observed as goodness of fit of the model from the computer package. The type of data is secondary which was obtained from IHLCA household expenditure survey in 2005 and 2010 in Myanmar (MNPED, 2005, 2010).

1.4 Scope of the Study

A major interest in this study has been that of the relationship of household characteristics, labour market and poverty in Myanmar at two points in time: 2005 and

2010. The required data are obtained from the IHLCA I and II surveys, where the household questionnaire forms the basis of most of the information presented in the Poverty Profile. For each individual, a binary response variable is obtained within the context of a household. There are many methods on modeling binary response variables and the study has to focus on the area of probit analysis with application on household characteristics and labour market. Similar to the result identified by different researchers, among various factors of poverty, the dependent variable considered in this application is the level of poverty of households in both rural and urban areas in Myanmar in years 2005 and 2010.

1.5 Organization of the Study

This study is divided into five chapters. Out of which Chapter I is concerned with the introduction. It presents objectives, method, scope and organization of the study. Definitions, measures and different ways of measuring poverty identified from IHLCA household surveys are given in Chapter II. Moreover, literature reviews on poverty analysis in other countries based on household surveys are also discussed in the same chapter. Chapter III deals with the probit estimation and the statistical properties of conditional probit model. There, how to calculate the marginal effects of explanatory variables on poverty and how the adequacy of the model is measured are also explained. The theoretical aspect on bivariate and multivariate cases for probit model for the sake of completeness has been presented. Empirical results on the calculation of marginal effects of explanatory variables, such as industrial sector, employment status and educational level and the findings of the results are described in Chapter IV in detail. Finally, findings of the study and suggestions are made for further research on the basis of the results in Chapter V.

CHAPTER II
LITERATURE REVIEW

In this chapter, different views on poverty are presented. To help poor people in Myanmar move out of their poverty, it will be necessary to realize who these people are, depending on definition of poverty taken into consideration. Although there are different definitions of poverty for certain situations, the one which is suitable for people in Myanmar is presented in this study.

2.1 Definition of Poverty

Many definitions of poverty exist. For most developing countries including Myanmar, there are two ways to define poverty. The first is to find out if a household or a person has enough resources (money) to meet its basic needs. To do that the income or consumption of the household or the person is compared with some defined poverty threshold (or poverty line) below which they are considered to be poor. In this case, poverty is measured in money terms. The second approach is to go beyond the money measure and to think of poverty in terms of specific goods and services that are considered necessary to meet basic needs. The following questions should be asked to investigate needs of people in Myanmar. Do households or individuals in the country have enough food? Do households or individuals in the country have enough shelter? Do households or individuals in the country have enough clothing? Do households or individuals in the country have enough safe drinking water? Do households or individuals in the country have enough health care? Do households or individuals in the country have enough education?

Then some measures or indicators can be adopted to determine what is meant by enough. For food it could be for each person to have at least 2100 calories from food consumed per day the intake necessary to sustain life. With regard to shelter some people say it will not be enough for four people to live in a small room, in a hut with a thatched roof and a dirt floor. So a more appropriate dwelling is defined for a family depending on conditions prevailing in the country, likewise with respect to clothing. Obviously, clothing appropriate for the tropics will not be appropriate for someone living in Alaska or the North Pole. A shirt on the back, a sarong or a longyi and a pair of sandals may perhaps be adequate for a person in Southeast Asia. As for drinking water, it is often recommended that the source of water should not be more than 15

minutes walking distance from the house to be considered adequate. On health, there are many indicators- percentage of underweight or malnourished children, infant mortality rate, access to clinics, hospital and medical facilities, availability of doctors, nurses and midwives, incidence of major diseases such as HIV/AIDS, Malaria, TB, etc. The same is true of education; many indicators can be set up as well- percentage of children dropping out after completing primary school, education level of head of household, whether schools and teachers are available in the village, and so on.

According to UN statement of 1998, the UN definition of poverty is stated as follow:"Fundamentally, poverty is a denial of choices and opportunities, a violation of human dignity. It means lack of basic capacity to participate effectively in society. It means not having enough to feed and clothe a family, not having a school or clinic to go to, not having the land on which to grow ones' food or a job to earn one's living, not having access to credit. It means insecurity, powerlessness and exclusion of individuals, households and communities. It means susceptibility to violence, and it often implies living on marginal and fragile environments, without access to clean water or sanitation".

Gordon and Townsend (2005) suggested to define poverty as severe deprivation of seven operational indicators, namely (1) food, (2) water, (3) sanitation facilities, (4) health, (5) shelter, (6) education and (7) information. They also classified deprivation into five levels, namely, no deprivation, mild, moderate, severe and extreme deprivation. As an example, if we consider information as the indicator, having no access to radio or television (i.e. broadcast media) at home would fall into deprivation of information. But having no access to newspapers, radio, television, computers or phones at home (i.e. no information sources) would be considered as falling into the category of severe deprivation. Then any person living under conditions that are not able to satisfy any two or more of the indicators is considered to be poor. In other words the poverty threshold is equal to two more deprivation of seven indicators or basic human needs.

2.2 Poverty Measuring Process

There are three steps in the poverty measuring process.

The first step is to undertake a household survey, as all measures of poverty rely on the results of such a survey. In addition to adopting appropriate statistical techniques in conducting the survey,the World Bank has a Living Standards Measurement Survey (LSMS) method that is widely used. The LSMS has three components: household questionnaire, community questionnaire and price questionnaire.

The household questionnaire asks about the household composition, consumption patterns, ownership of assets, landholding, income and employment, education and health status, etc. The community questionnaire asks community leaders (village elders and officials, teachers, health workers) for information about the whole community such as number of health clinics, access to schools, taxes collected, agricultural patterns, and so on. Finally, the price questionnaire collects information on prices of the relevant commodities and services.

The next step is to construct a poverty line. Such a poverty line can be obtained by specifying a bundle or basket of food and non- food items that are considered necessary to meet the basic consumption needs and to estimate their cost. This cost estimate gives the poverty line. There are five methods in deriving a poverty line used in the developing countries. They are

(1) the relative poverty line method

(2) purchasing power poverty method

(3) the cost-of-basic needs method

(4) the food-share method and

(5) the food-energy method.

The relative poverty line method sets the poverty line at some share of the income or consumption distribution. The bottom 30 or 40 percent of the population may be designated as poor. This method is not based on a nutritional norm nor does it attempt to construct a basket of need goods on the basis of consumer's preferences.

Purchasing power poverty method was proposed in the World Bank's World Development Report 1990 (Ravallion, M., et,at. (1990)) to facilitate poverty comparisons across countries and over time. The two poverty lines selected, $US 275 and $US 370 per person a year, represent a range of poverty lines estimated in a number of low income countries, adjusted using purchasing power parity techniques. The

method is based, in part, on nutritional norms because it extrapolates from need adequacy levels estimated in a small number of countries (though not to other countries to which it is applied). It does not rely on consumer preferences because the poverty line is not derived on the basis of actual consumption patterns in all countries to which it is applied.

The cost-of-basic needs method relies on the judgment of a poverty analyst to construct and price a basic needs basket. The basket is usually composed of a basic diet in addition to other 'necessary' non-food items. The poor are those whose income/consumption expenditure falls below the price of this basket. In most cases, this method does not rely on a nutritional norm though (see the food-share method below) nor does it rely on actual consumer preferences.

The food-share method starts by choosing a reference population subgroup, say the bottom 30% of the income/consumption distribution. It uses the actual consumption patterns of this group to cost out a diet which satisfies a minimal level of caloric intake (e.g. 2100 kcals/day per adult). The non-food expenditure of this reference group is then used to calculate the cost of non-food needs. The food-share method is really a variation of the cost-of-basic need method, but uses both nutritional norms as well as actual consumer preferences to draw the poverty line.

The food-energy method sets the poverty line at a point on the income or consumption distribution where the average household is expected to meet minimal dietary energy requirements per household member. The poverty line may be set by regressing dietary energy intake against income or consumption expenditure. This method uses both a nutritional norm as well as consumer preferences. It does not require the arbitrary choice of a reference group (as the food-share method does) and as much, is a more pure example of the use of consumer preferences for setting the poverty line.

Two criteria are used to distinguish among them: whether or not basic nutritional requirements (dietary energy intake) are used to draw line; and whether or not people's preferences are used to identify the basket of needs in question. The question of adding up, or aggregation, of those below the poverty line is solved by using standard Foster, Greer, Thorbecke (FGT) (to be discussed in detail in section 2.3.3)

class of poverty measures. These measures permit the distinction between the incidence, intensity and inequality of poverty.

There can be several poverty lines. Commonly it is more costly to live in the cities and towns than in the villages, so most countries have one poverty line for urban areas and another for rural areas. Since food forms the major component in the consumption expenditure for the poor, a food poverty line is often calculated in addition to the overall poverty line that includes both food and non-food items. The poverty line will have to be adjusted as time passes. Also inflation is one reason to be considerated in poverty measurement. The second reason is that as a country develops the standard of living of the average person rises, and consequently the composition of goods and services in the basket to determine the poverty line should also be adjusted to reflect the changes.

Finally, after the poverty line is established, the extent of poverty in the country can be obtained by finding out the percentage of population with incomes or consumption expenditures below the poverty line. This is referred to as the headcount poverty index or headcount poverty rate and is a commonly used measure because it is easy to understand and to calculate. The result of measuring poverty in this way is also referred to as giving an indicator of absolute poverty in the country.

However, the poor can also be defined by comparing their income with a certain income level prevailing in society. For example, in the European Union, a household below 50 percent of the median (or average) income in a country is considered to be poor. This is referred to as relative poverty.

For completeness, a brief mention of inequality a concept that is often referred to in discussing the poverty issue should be made. However, inequality is a broader concept than poverty as it is defined over the entire population, and does not only focus on poverty.

According to UNDP's Poverty Profile (2009-2010) Report, the simplest and most common way to look at inequality is by sorting out the population from the poorest to the richest to show the percentage of expenditure or income that can be attributed to each fifth (quintile) or each tenth (decile) of the population. Usually, the poorest quintile

accounts for 6 to 10 percentage of all expenditure, while the top quintile accounts for 35 to 50 percent.

A popular measure of inequality is the Gini coefficient, which measures the inequality of income distribution in a country. The Gini coefficient is derived from the Lorenze curve, which sorts the population from poorest to richest, and shows the cumulative proportion of the population on the horizontal axis and the cumulative proportion of expenditure (or income) on the vertical axis.

It can be calculated after obtaining the percentage of income or expenditure attributed to each quintiles or deciles. The Gini coefficient can vary from zero, indicating perfect equality with every household earning exactly the same income, to one, where there is perfect inequality with a single household earning the entire income of the country. Regions in the world with the most uneven income distributions have Gini coefficient of round 0.5. In rich countries the coefficient is about 0.3.

In Myanmar, effort and money are required to get a reasonably good and credible measure of poverty. Many difficult conceptual and statistical problems will have to be dealt with in the process. So, there are four reasons to measure poverty.
First, a poverty measure helps focus attention of policy makers on the conditions of the poor and thereby keep these poor people on the development agenda. For instance, saying "18 million people which form 21% of the population are in abject poverty and are having great difficulty in making ends meet" will send a powerful signal to the policy makers that something has to be done about them.

Second, a poverty measure helps to identify the poor that needs help. A poverty profile is useful in this regard. The profile provides information on the pattern of poverty and how it varies with respect to geographical location (such as rural/urban), community aspects (whether the community has a school or a clinic) and household characteristics (such as its size, and educational level of the head of household). Having such information enables better targeting of aid and especially to ensure aid is given to those who need it most.

Third, a poverty measure is needed to monitor and evaluate outcomes of projects and policy interventions undertaken to reduce poverty, which is an important measure

in assessing the policies. There must be a measure or an indicator to show, in what way, and to what extent actually improved the well-being of the poor.

Finally, a poverty measure is required to evaluate the effectiveness of initiatives undertaken by institutions to reduce poverty. For example, the cooperative ministry may set up farmer organizations to provide rural credit or the Ministry may help poor village people to form consumer societies to enable them to buy essential commodities at reasonable prices. Success of these ventures can be demonstrated by coming up with credible and believable evidence that rural credit provided by the farmer organizations and bringing cheaper food and other essentials by forming consumer societies have enabled a certain percentage of farm households to rise above the established poverty line. Such evidence will restore faith and confidence in the cooperative movement and enable it to play an important role in addressing the poverty issue in the country.

2.3 Poverty Analysis

In analyzing poverty in Myanmar, there are three core issues. The first concerns the appropriate well-being metric, to use and addresses the question 'poverty of what'. The second concerns the distinction between the 'poor and non-poor', and addresses the question 'how to set the poverty line'. The third issue, aggregation, concerns the poverty measures used and addresses the question 'how to add-up those who fall below the poverty line.'

In the poverty profile, the well-being metric used is consumption expenditure. There are two key advantages to using consumption expenditure, over say income. First, generally, consumption expenditure is measured with less error than income to capture the actual household consumption status. Second, it is subject to less fluctuation than income and as such, is a better medium-term gauge of well-being as households smooth consumption over time.

In order to make consumption expenditure comparable across households a number of adjustments must be made. Specifically, it is necessary to adjust for different household composition, for economies of scale in consumption and for price differences across sites. All of these adjustments have been made and are detailed in a

technical report accompanying Integrated Household Living Conditions Assessment (IHLCA) Survey in Myanmar.

One final complication to note when using consumption expenditure as a measure of well-being is the problem of 'necessary' expenditures which are wellbeing-reducing. Large expenditure on health care causes increase in household expenditure, as well as reduction in well-being (from both the illness and the expenditure burden). While the issue is complex, we address it by removing health expenditure from household expenditure estimates in calculating poverty measures.

There are two poverty lines in the poverty profile, namely, the food poverty and poverty lines. The food poverty line measures how much consumption expenditure is required to meet basic caloric needs only. The poverty line simply adds allowance for non-food expenditure.

There are different ways to set food poverty and poverty lines. In the poverty profile, the food share method has been used, relying on the actual expenditure patterns of the poor.

2.3.1 The Food Poverty Line

There are five basic steps which are required to set the food poverty line:

First, a poor reference group is selected, which, in the present case, is the second quartile (25%) of the normalized consumption, i.e. the bottom 25-50%.

Second, the number of calories consumed by this reference group is calculated. This step requires information on the quantities of food items consumed and the caloric content of these food items.

Third, the minimum required caloric intake is calculated for different population groups based on nutritional norms. In Myanmar, different caloric requirements have been set for males, females, children and rural/urban dwellers.

Fourth, the food actually consumed by reference group is 'scaled up or down' until it reaches the minimum required level of caloric intake. In practice, this means that the 'basket' of foods consumed stays the same but the level is increased or decreased.

Finally, the cost of this new scaled food basket is calculated, and represents the food poverty line.

It should be noted that the 'food poverty' line is very meager indeed. It represents the amount required to meet caloric requirements assuming that all household income is spent on food. As such, it represents a level of extreme.

2.3.2 The Poverty Line

The poverty line retains all of the above steps and simply adds an allowance of non-food expenditure. Three additional steps are required:

First, the non-food share in consumption expenditure of the reference group is calculated.

Second, a monetary value is assigned to this share (by multiplying it by the food poverty line).

Third, the monetary value is added to the food poverty line to arrive at the poverty line.

Calculated in this way, the poverty line represents a minimum of food and non-food expenditure based on the consumption patterns of the second quartile of the consumption distribution.

The actual (normal) values of the food-poverty and poverty lines per adult equivalent per year, in 2005 and 2010, are as follows;

Table (2.1)

The Actual (Nominal) Values of the Food-Poverty and Poverty Lines in Myanmar (2005 and 2010)

Type	Per Adult Equivalent per Year (Kyats)	
	2005	2010
Food Poverty Line	118,402	274,990
Poverty Line	162,136	376,151

Source: IHLCA survey 2009-2010

2.3.3 Poverty Measure

In the poverty profile, the standard Foster-Greer-Thorbecke (FGT) class of poverty measures is used 'add up' those who fall below the poverty line.

The Foster- Greer -Thorbecke (FGT) class of poverty measures may be represented as;

$$P_\alpha = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{g_i}{z}\right)^\alpha \quad (2.1)$$

where z is the poverty line;

$g_i = z - y_i$, the consumption shortfall from the poverty line of the i^{th} poor person,

q the number of poor persons and n the total population and y_i household expenditure per adult equivalent per year.

When α is assigned the value of 0, the index collapses to q/n, the proportion of poor individuals in the total population or poverty incidence. When α is assigned the value of 1, the index measure the normalized poverty gap, or population-weighted average shortfall from the poverty line. $P_{\alpha=1}$ provide a measure of the intensity of poverty. When α is assigned a value greater than 1, the index becomes distributional sensitive as greater weight is assigned larger individual poverty gaps. By convention,P_α is assigned the value of 2 to gauge the severity of poverty.

By convention, three FGT measures are widely used, represented as P_0, P_1 and P_2.

P_0 or poverty incidence is the proportion of individuals whose normalized consumption expenditures per adult equivalent are lower than the poverty line

P_1 or poverty intensity indicates the depth of poverty, it multiplies poverty incidence by the poverty gap, i.e., the average shortfall from the poverty line. As such, it is a combined measure of the extent and the depth of poverty.

P_2 or poverty severity is poverty incidence multiplied by the squared poverty gap. The effect is to give proportionally more weight to households which are further away from the poverty line. Accordingly, P_2 may be interpreted as a combined indicator of the extent of poverty and inequality among the poor.

While the value of P_0 has a clear intuitive interpretation the same cannot be said of P_1 and P_2. Their main values are to allow for a relative ranking of the poverty situation of different population groups in terms of poverty intensity and severity respectively.

Another useful feature of the FGT class measures is called 'additive decomposability'. Otherwise stated, it is possible to calculate the relative contribution of different population groups to overall poverty for the three FGT measures.

2.4 Review of Empirical Studies

Buvinic and Gupta (1997) considered if the female-headed households and female-maintained families were worth targeting to reduce poverty in developing countries. They suggested that female headship should not be used as the main targeting criterion because female headship was not correlated with poverty. There were practical difficulties in identifying de facto headship, and there might be perverse incentive effects as a result of targeting benefits or services to single mothers, that is, it might promote rather than discourage single motherhood. Moreover, they addressed two issues. The first issue was related to the definition and measurement of female headship and importance of the concept for development policy, and then a systematic review of the empirical evidence on the relation between female headship and poverty was undertaken. As the second issue, they examined potential costs and benefits of targeting female headship and reviewed the experience of Chile, one of the few countries that had targeted female headship though government intervention. They used the analysis of the project experience along with a review of the empirical evidence to answer the question of the desirability and efficiency of targeting female headship to reduce poverty in developing countries.

Demeke, Guta and Ferede (2003) observed that there was strong relationship between demographic characteristics and the probability of a household being poor in

Ethiopia. In other words, households with larger family size and older heads of households were more likely to fall into poverty than those households with smaller family size and younger heads of household. Moreover, education was important in bringing about sustained growth and reducing poverty in the country. The impact of education in alleviating poverty was significant in both rural and urban areas of the country.That is, households with higher levels of literacy were less likely to fall into poverty than those households with lower levels of literacy. Investing in education was found to be one of the key elements in reducing poverty in the country.

Fissuh and Harris (2005) considered modeling determinants of poverty in Eritrea by a new approach. They used Dogit Ordered Generalized Extreme Value (DOGEV) model for modeling determinants of poverty in Eritrea by employing Eritrean Household Income and Expenditure Survey 1996/97 data. It was found that education impacted welfare differently across poverty categories and there were pockets of poverty in the educated population sub group. Effect of household size was not the same across poverty categories. Contrary to the evidence in the literature, the relationship between age and probability of being poor was found to be convex to the origin. Regional unemployment was found to be positively associated with poverty. Remittances, house ownership and access to sewage and sanitation facilities were found to be highly negatively related to poverty. They also found out that there was captivity in poverty category and a significant correlation between poverty orderings which rendered usage of standard multinomial/ordered logit in poverty analysis less defensible.

Aassve, Kedir and Woldegebriel (2006) studied State dependence and casual feedback of poverty and fertility in Ethiopia in three waves (1994, 1995 and 1997) for both rural and urban areas. They implemented simultaneous random effect models as a means to analyze causality issues related to poverty and fertility in Ethiopia, a country which is plagued by high and persistent poverty and very high fertility rates in rural areas. Using longitudinal data from both urban and rural areas of Ethiopia, they analyzed the relationship between childbearing and poverty. In addition to identifying State dependence in poverty and fertility, they investigated to what extent fertility act as a feedback mechanism leading to higher poverty and vice versa. They found that

poverty itself had little effect on fertility, whereas there was evidence of State dependence in poverty and important feedback from fertility on future poverty. Not unexpected, they found substantial differences between rural and urban areas.

Andersson, Engvall and Kokko (2006) tried to determine the determinants of poverty for Lao PDR (Peoples Democratic Republic) through econometric modeling of household level consumption based on comprehensive primary data from the Lao expenditure and consumption survey 2002/2003. Their study also provided a unique mapping of poverty broken down by regions as well as on main ethnic groups. Their analysis identified five crucial areas for reducing poverty:

(1) Reducing the number of dependents in households
(2) Investment in education, not at least for girls
(3) Promotion of entrepreneurship
(4) Raising agricultural productivity, and
(5) Improvement of the infrastructure.

Banerjee and Duflo (2006) studied the economic lives of the poor using the survey data of 13 countries (Cote d'Ivoire, Guatemala, India, Indonesia, Mexico, Nicaragua, Pakistan, Panama, Papua New Guinea, Peru, South Africa, Tanzania, and Timor Leste), under six topics, namely (1) the living arrangement of the poor, (2) how the poor spend their money, (3) how they earn their money, (4) markets and the economic environment of the poor, (5) infrastructure and the economic environment of the poor and (6) understanding the economic lives of the poor. They found that there were many important issues with the identification of the poor. First, purchasing power parity exchange rates, which were essential to compute a "uniform" poverty line, had been criticized as inadequate, infrequently updated, and inapplicable to the consumption of the extremely poor. Prices were typically higher in urban than in rural areas, and even in rural areas, the poor might have to pay different prices than everyone else. Also, reporting periods varied significantly from survey to survey and the report would have been affected significantly.

They stated that in describing what the lives of poor look like, misclassifying a number of households would not change anything very important about the averages, unless the number affected are very large, and those artificially moved into or out of poverty are very different than the other poor. They also claimed that most of their

conclusions would not change if the interested group was the poor rather than the extremely poor. Nevertheless they admitted that one could not obviously entirely rule out the possibility that the results might have been different with a different poverty line.

Bruck and Broeck (2006) stated that there were three important issues in employment and poverty. Firstly, the determinants of individual employment status could be estimated. Secondly, different groups shared, in the reduction of poverty to varying degrees. Poorer households benefited less from growth than better-off households, raising the issue of widening inequality. So, the determinants of household consumption, demonstrating for the new data set that education had positive effects on consumption in aggregate could be estimated. Finally, instrumental variable techniques to control for the joint determination of employment status (aggregated to the household level) and household consumption could be used. Summary of these suggested that no single nation strategy which could strengthen the pro-poor growth affects employment across the country. Instead, three sets of policies aimed at overcoming the new challenges could be discussed. They include policies dealing with (i) regional and pectoral divergences, (ii) agricultural development, and (iii) education and gender.

Rani and Schmid (2006) investigated macro and micro-economic relations between employment and poverty. The focus was on the household and employment determinants of poverty for households in both rural and urban areas at three time points, 1983, 1993/94, 1999/2000. They used probit model to investigate the influence of industry, employment status and education level on poverty. They used the concept of possible channel in the relationship between poverty and GDP growth through the labour market and GDP was translated into demand for labour with different characteristics in terms of skill. The relations could be formalized in the following way.

$$\text{Poverty}_t = f[\text{Employment}\{\text{GDP(t)}, \text{Skill}\},\text{Skill}] \tag{2.2}$$

This equation defines poverty as a function of employment, which is a function of GDP and skill. The exact relation of poverty with employment and of employment with GDP depends on the skill of the worker. Ignoring the skill and focusing on the changes over time they got

$$\frac{\mathrm{dP(t)}}{\mathrm{dt}} = \left\{\frac{df(.)}{dEmp}\right\}\left\{\frac{dEmp}{dGDP}\right\}\left\{\frac{dGDP}{dt}\right\} \tag{2.3}$$

They used the idea of the relationship to measure in change of poverty over time as the product of three elasticities, the elasticity of poverty with respect to employment, the elasticity of employment with respect to growth and the elasticity of GDP with the respect to time (i.e, GDP growth rate). The results confirmed the important role of employment for poverty reduction. Nevertheless, having employment in certain industry groups did not help the poor to reduce their poverty risks. Low educational levels of the workforce were the major impediment for more substantial poverty reduction. So, they found that employment status of a worker was also an important determining factor in poverty reduction.

Kyaw and Routray (2006) did a micro level study on gender and rural poverty in Myanmar in the dry zone. They investigated the poverty incidence, access to resources, and the factors influencing income of both male and female-headed households in the dry zone of Myanmar. A household survey was conducted in six villages with a sample of 220 households in 2003. The Cost of Basic Needs (CBN) method was applied in constructing the absolute poverty line. By applying the absolute poverty line of 252 Kyats per person per day, the female-headed households were more likely to be poorer than the male-headed households with or without household size adjustment. Results of the regression analysis revealed that average per capita income of rural households was significantly influenced by 8 independent variables. They are gender of household head, household size, land holding size, degraded land size, cattle heads, labour force, sources of income, and irrigation water. Moreover, the separate regressions were run for male and female-headed households. In addition to some common significant variables (land, labour, cattle, degraded land, and household size), female-headed households' income was significantly influenced by training attendance and schooling years of household head. In male-headed households, age of household head, number of income sources and irrigation water were highly linked with the average per capita income. They suggested that the gender focus rural development strategies should be adopted for promoting the welfare status of both male and female headed households in the dry zone.

Arranz and Canto (2007) tried to measure the effect of spell recurrence on poverty dynamics in Spain. According to the analysis of poverty dynamics, yielded important insights about the nature of poverty and the expected effectiveness of alternative social policies in order to fight against it. They carried out the estimation of

a hazard regression model where the individual probability of leaving and entering poverty was affected by the length of the current poverty spell, the fact that the individual experiences repeated spells which accumulated in time. Their study indicated that poverty transitions still showed some negative duration dependence even if they introduced control for unobserved heterogeneity and lagged durations. The duration of previous poverty spells reduced the exit and increased the re-entry hazard. Finally, estimating separate hazards by spell order allowed for some control for the relevant impact of left-truncation on results and showed the significant differences in the covariates that turn out to promote transitions for individuals that often fluctuate into and out of poverty (transitory poor) in comparisons with those that suffered a rather more persistent poverty experience (chronic poor).

Benhabib, Ziani, Bettahar and Maliki (2007) analyzed poverty dynamics in Algeria by multidimensional approach. First approach was one dimensional or monetary approach conventionally splitting the population into two groups: poor and non-poor according to some hypothetical poverty line. However, Cerioli and Zani (1990) pointed out that a strict division of the population into poor and non-poor is unrealistic as one dimension cannot capture all factors of poverty. To avoid this shortcoming, many researchers have used multidimensional approach increasingly. In multidimensional approach it is assumed that all the individual different dimensions can be aggregated into a single welfare index. Then individuals are classified as poor if their welfare index is below an estimated poverty line. There are many models and they have used logit,probit and fuzzy set method. Their results showed that the fuzzy set approach was more pertinent than the others in capturing different graded attributes of poverty. Therefore, the study revealed that income is not the sole indicator of well-being and should be supplemented by other attributes, mainly, housing, level of comfort and social capital. Moreover, the main finding highlighted that rural areas were the most hit by deprivation and poverty. Their analysis served as a basis for a better targeting as far as policy options for poverty reduction are concerned.

Bokosi (2007) studied to indentify the sources of expenditure and poverty dynamics among Malawian households between 1998 and 2002 and to model poverty transitions in Malawi using a bivariate probit model with endogenous selection to address the initial conditions' problem. The exogeneity of the initial state is strongly rejected and could result in considerable overstatement of the effects of the explanatory

factors. The results of the bivariate probit model do indicate that education of the household head, per capita average cultivated and changes in household size are related to the probability of being poor in 2002 irrespective of the poverty status in 1998. For those households who were poor in 1998, the probability of being poor in 2002 was significantly influenced by household size, value of livestock owned and mean time to services, while residence in the Northern region was a significant variable in determining the poverty of being poor in 2002 for households that were not in 1998.

Bruck, Danzer Muravyev and Weisshaar (2008) studied the determinants of poverty during transition in Ukraine using household survey. They analyzed the incidence, the severity and the determinants of household poverty in Ukraine during transition using two comparable surveys of 1996 and 2004. They measured poverty using income and consumption and they did the sensitivity analysis of the poverty estimates for the choice of welfare indicator and poverty line, the effects of various poverty lines. Poverty in both periods followed some of the determinants commonly identified in the literature, including greater poverty among households with children and with less education. They also identified specific features of poverty in transition, including the relatively low importance of unemployment and the existence of poverty even among households with employment. Poverty determinants changed over time in line with the experience of transition and restructuring. In their study, they used empirical strategy to assess the incidence of poverty and its determinants over time which included (1) setting the poverty line, (2) analysis of determinants of welfare in a broad sense (OLS regressions), (3) analysis of poverty in a more narrow sense (probit regressions). (4) investigation of differences in the determinants across the welfare distribution (quantile regressions) and (5) test for ethnic discrimination.

Litchfield and Mcgregor (2008)'s paper on the "Poverty in Kagera, Tanzania: Characteristics, Causes and Constraints", analyzed the determinants of household welfare in the northwest region of Tanzania using micro level cross section data. Despite having gone through a series of structural adjustment programs in the late-1980s, Tanzania was still considered to be one of the poorest countries in Sub-Saharan Africa. They argued that the determinants of household welfare were numerous and complex, ranging from individual and household to community and social characteristics, but that the relative importance of these factors varied across the welfare distribution. Using quantile regressions, they found that human, social and physical capital all play a significant role in improving households' living standards, but that the

relatively poor were harmed more by weather shocks because they face more constraints in diversifying out of agriculture. Their results also revealed subtle insights into the relationships between gender and poverty.

Mcgregor (2008) analysed the determinants of household welfare in the Northwest region of Tanzania using micro-level cross section data (1991 to 2004), for a brief analysis of the change in poverty over the period, and then exploited the 2004 data to examinants of household welfare. He found that the data on consumption do record a rise in living standards over the period but that this is well below that which is suggested by national accounts, and then accounting for lower calorie requirements of female members, having a larger share of female member increases welfare, finally, households with women that were relatively healthy, as measured by their weight-for-age z-score, were better off and interestingly that among the very poor the effect of the alpha female's weight was as important as that of the alpha male. So, this paper attempted to show that the fortunes of households in sub-Saharan Africa, even those that take steps to spread their risk, are still at the mercy of good and bad luck.

Neilson, Contreras, Cooper and Hermann (2008) studied the dynamics of poverty in Chile using the 1996-2001 National Socio-Economic Survey on panel data base. In their analysis of poverty dynamics in Chile, they drew a distinction between chronic and transient poverty and found that while 20 percent of the population were living below the official poverty line both in 1996 and 2001, only 9 percent of the population were poor at both years. It was found that when the poverty line was raised, the amount of households which could be considered chronically poor rose steadily, whereas the transitory component of poverty remained more or less stable. Moreover, in analysis of the direct reasons for changes in household poverty status, they concluded that labour dynamics were far more relevant than demographic changes. Household heads who suffered health problems were significantly less likely to leave poverty. Household human and physical capital was also relevant, as well as the sector to which the household head worked. Simulation study using different poverty lines revealed that some variables were not robust to changes in the definition of poverty, while others which originally appeared to be insignificant became so for most other possible poverty lines.

Ayllón (2009) tried to model state dependence and feedback effects between poverty, employment and parental home emancipation among European youth. She

studied the interrelationship between employment, residential emancipation and poverty amongst young people in eight European countries for the period 1994 to 2000. She proposed the estimation of a trivariate multinomial probit model for poverty status, employment and leaving home decisions with feedback effects between the three processes that allowed the measurement of state dependence, accounts for the initial condition problem and controls for unobserved heterogeneity and non-random selection of the sample. Her results showed that youth poverty genuine state dependence was positive and highly significant in all analyzed countries. There was evidence of a strong casual effect between poverty and leaving home in Scandinavian countries, although, time in economic hardship did not last long. In Southern Europe, instead, youth tended to leave their parental home much later in order to avoid falling into a poverty state that is more persistent. Past poverty had negative consequences on the likelihood of employment ever where.

Achia, Wangombe and Khadioli (2010) examined the determinants of poverty in Kenya. While most of the studies done on poverty determinants rely on the income, expenditure and consumption data, data used in their study came from the Demographic and Health Surveys (DHS). The principal component analysis was used to create an asset index which gave the social economic status of each household. A logistic regression was estimated based on the data with the Social Economic Status (SES) (that is poor and non-poor) as the dependent variable and a set of demographic variables as the explanatory variables. They suggested that the DHS data can be used to determine poverty from many different aspects.

Beccaria, Fernandez, Maurizio and Alvarez (2010) studied the dynamic of poverty in Latin America. Because, Latin America has traditionally registered very high levels of absolute poverty due in part to a very unequal income distribution and to scare growth and high macroeconomic instability. However, the response of poverty to change in those variables differed between countries. The main objective of that paper was to study the dynamics in different Latin American countries, emphasizing a comparative point of view. In particular, that study aimed at analyzing to what extent countries with different or similar poverty incidences might show exist and entry rates from and to poverty of different intensity, identifying the importance of diverse events associated to poverty transitions and analyzing the effect of those events on households of different structures and characteristics. They studied to attain that objective; a dynamic analysis of panel data from regular household surveys was used in order to

assess the importance of poverty entry and exist rate in changes in poverty incidence. The focus was set on the identification of factors associated to poverty mobility, especially those related to labour market instability, demographic changes and public policy.

Runsinarith (2011) tried to find determinants of poverty in Cambodia. The researcher attempted to examine the determinants of poverty for a panel data of 827 households surveyed in 2001, 2004 and 2008. Panel data analysis with fixed effect estimation was applied to investigate factors influencing household's consumption and food consumption. Multinomial logistic regression was utilized to explore the factors that affected chronic and transient poverty. The primary result suggested that assets, agricultural land size, irrigated land and access to microfinance institutions yielded positive and significant impact on consumption while shock exerted a negative one. Further, it was suggested that an increase in agricultural land size decreased the possibility of being transient poor while an increase in irrigated land ratio decreased the possibility of being chronic poor.

Bogale (2011) analyzed the extent and determinants of rural household poverty in the eastern highlands of Ethiopia, based on 216 households using a household consumption expenditure approach. The particular interest was on the effects of location-specific and institutional factors (networks) in determining the probability of being poor by using ordered probit model. The findings suggested that poverty was location specific, depended on access to irrigated land (not land per se) and access to non-farm income. Results also indicated that household wellbeing was negatively affected by household size, and positively affected by age of household head. Involvement in governance, social and production related networks were also found to be strongly associated with the probability of a household being poor.

Chattopadhyay (2011) explored the causes of the differential levels of economic well-being in two parts of West Bengal, an eastern state of India in terms of incidences of poverty and various socio economic explanatory variables. Using a regression based technique, the incidences of poverty were found separately for these two parts, North Bengal and South Bengal. The disparity in poverty was estimated (in particular, the Head Count Ratio (HCR) between rural North and South Bengal is studied). The difference between the poverty estimates was then decomposed into a characteristics effect, showing the effects of the regional characteristics and a coefficients effect, showing the effects of the differential impact of the characteristics over the regions

using the familiar Oaxaca decomposition method. The outcome of the above analysis was that specific policy measures could be identified for lowering the poverty gap between the two parts of West Bengal. As the results suggested, there was disparity in the availability of the characteristics (resources) as well as in utilization of resources (efficiency) in the two parts and the latter effect was found to be more prominent in terms of the share in explaining the poverty gap. While the baseline consumption was lower in North Bengal, in terms of both availability of resources and utilization of resources North Bengal lagged behind South Bengal. Thus he claimed that attention needed to be paid to North Bengal with respect to enhancement of important policy variables liked education level, government aid and employment opportunities. Also, the causes of low resource utilization were needed to be investigated.

Giles and Murtazashvili (2012) considered a control function approach to estimating dynamic probit models with endogenous regressors, with an application to the study of poverty persistence in China. They used a parametric approach to estimating a dynamic binary response panel data model that allowed for endogenous contemporaneous repressors. Their approach was of particular value for settings in which one wanted to estimate the effects of an endogenous treatment on a binary outcome. The model was used to estimate the impact of rural-urban migration on the likelihood that households in rural China fall below the poverty line. It showed that migration was important for reducing the likelihood that poor households remain in poverty and that non-poor households fall into poverty. Furthermore, they demonstrated that failure to control for unobserved heterogeneity would lead the researcher to underestimate the impact of migrant labor markets on reducing the probability of falling into poverty.

Alem (2013), in the paper on "Poverty Persistence and Intra-Household Heterogeneity in Occupations: Evidence from Urban Ethiopia" used five rounds of panel data to investigate the persistence of poverty in urban Ethiopia with a particular focus on the role of intra-household heterogeneity in occupations. He used dynamic probit and system Generalized Methods of Moments (GMM) regression approaches and the results suggested that international remittances and labor market status of non-head household members were important determinants of households' poverty status. The results also showed that controlling for the above mentioned variables and the initial conditions problem encountered in non-linear dynamic probit models reduced

the magnitude of estimated poverty persistence significantly for urban Ethiopia. His findings had important implications for identifying the poor and formulating effective poverty reduction and targeting strategies.

Thapa, Dhungana, Tripathi and Aryal (2014) intended to analyze the major determinants of rural poverty in Nepal. A two-stage sampling method was applied to generate cross sectional data by randomly selecting 279 households from one village Development Committees of six districts of Western Development Region of Nepal. In their study area thirty- three percent of households were lying below poverty line as per the poverty scoring method. By applying binary logistic regression, the study identified age of household head, size of land holding, and female's involvement in service, family occupation and caste as major determinants of rural poverty. Contrary to general view, remittance did not show any significant effect on rural poverty as per their study. So, it could be inferred that poverty in rural parts of Nepal was entangled in structural and cultural web, and the remittance sent by migrant family members to rural households might have been siphoned off to urban pocket areas. With large chunk of young rural population engulfed by international labor market and existing socio-economic structures, the policy makers needed to address the rural poverty via social and cultural aspects.

CHAPTER III
METHODOLOGY

It is intended to present methodology of probit model which will be used to analyze the poverty in Myanmar (2005-2010) in this chapter.

According to many poverty researchers, such a regression would be in the form of

$$y_i = \beta x_i + \varepsilon_i \quad (3.1)$$

where y_i is the per capita household expenditure of individual i, x_i are household characteristics and ε_i is the error term. This equation can be estimated by the Ordinary Least Squares (OLS) method under the condition that the error term and the regressors are not correlated.

An alternative approach is to define a binary variable

$$p_i = \begin{cases} 1 & \text{if } y_i|z < 1 \\ 0 & \text{otherwise,} \end{cases} \tag{3.2}$$

where z is the poverty line, and hence the binary variable measures whether a household is poor or not. The probability that a household will be poor is

$$\begin{aligned} P &= \text{Prob}\,[y|z<1\,|x] \\ &= \text{Prob}[\varepsilon< (1 - \beta)|\, x] \\ &= F\,(1-\beta) \end{aligned} \tag{3.3}$$

where F is the cumulative distribution function specified for the error term in the regression. This model can be estimated by probit or logit, depending on the assumption of the error term.

It is not clear which of the two approaches is preferable, as both have their respective advantages. The main advantage of the regression is that it uses more information. The probit model pretends not to observe the dependent variable, but only the probabilities and the vector characteristics x_i. But in reality this is redundant as there is no latent variable that is measured in binary form. The regression should be preferred is that it depends on weaker assumption about the error term than the binary model. Other authors who have used regressions based on similar arguments.

In spite of the advantages of the simple linear regression, the binary model has been widely used. An important disadvantage of the regression is that it imposes constant parameters over the entire distribution. The constant parameters bias the estimates if the poor face different constraints than the rich. In this case the effects of specific characteristics differ between poor and rich (Grootaert, 1997) used a multinomial logit model to predict probabilities for income quintiles, conditional on personal and household characteristics. He showed that for the US data the functional form restriction from level-estimates fitted poorly. The constant parameter restriction is not always a problem. Appleton (1995, 1996) found that in the case of Uganda the

poor were like the rich but without money, i.e, they have the same parameters in the regression. The conclusion is that the functional form depends on the specific case studied.

A second reason for using the binary model is that income and expenditure distribution data typically contain non-negligible errors. This problem is especially severe as income accrues individually but expenses and poverty are measured on the household level. The use of per capita expenditure as the dependent variable therefore infers a precision, which cannot be taken as granted. In such cases, it can be safer to analyze the probability of expenditures falling within a specified interval. So, the probit model is chosen to investigate the importance of household and labour market characteristics for poverty.

3.1 Individual Binary Response Variables

In many areas of social science research, one encounters a dependent variable that assumes one of two possible values. For example, a youngster may graduate or fail to graduate from high school; a worker may be employed or unemployed; a patient in a clinical trial may respond or not respond to treatment during a period of observation, a household may be below or above the poverty line. Data of such kind-having two possible outcomes- are said to be binary. By convention, the outcomes are commonly described as success and failure. In general, the substantive outcome of interest is considered to be a success (y=1), whereas its complement is considered a failure (y=0). With this in mind, researchers in the social and biological sciences often consider as a success a qualitatively unsuccessful outcome and realize, such as failing to graduate from high school, being unemployed or dying during a clinical study. Binary variables are also referred to as (0,1) variables. With binary dependent variables, the researcher's goal is to estimate or predict the probability of success or failure, conditional on a set of independent variables.

At the most basic level, the units of analysis for a binary (0,1) variable are individuals. In this case, there is only one trial for each individual, and the outcome is either 1 (success) or 0 (failure). This type of trial is called a Bernoulli trial, which has one parameter (p), the probability of success. In such a case the random variable has

Bernoulli probability distribution function, with probability of success, Pr (y = 1) = p, and its complement, the probability of failure, Pr (y = 0) = 1- p. In principle, success probabilities can assume different values for each sampled individual, when modeled as functions of explanatory variables. For example, the likelihood of high school dropout for the i^{th} individual may depend on a number of individual characteristics and would be denoted as p_i. In practice, it is common that researchers group observations of binary (0,1) responses when explanatory variables are categorical. Such data are often represented in the form of contingency (or frequency) tables. For example, the record could be the number of high school dropouts by sex in each racial or ethnic group. Then, the data could be represented in the form of a 2× 2×R contingency table, with frequency counts cross-tabulated by the two possible outcomes, 2 sex categories, and R racial or ethnic categories. If all individuals within each cell are independent and identically distributed (iid) as bernoulli trials, the sum of the total number of successes (or failures) follows a binomial distribution with two parameters, p and n, where n is the number of total trials for each cell.

When each individual is considered household it can be poor or non-poor and hence it follows Bernoulli distribution. But, households in the sample are considered the random variable, number of poor households follow binominal distribution. By central limit theorem, for large samples, it can be approximated by normal distribution.

3.2 Binary Response Models

The transformational, or statistical, approach to modeling binary data is based on the one-to-one correspondence between the sample data and the population quantities being modeled. This idea is the most intuitive when data are grouped according to an array of categorical independent variables. With grouped data, frequency counts are transformed to proportions, which are estimates of the population-level conditional probabilities. In the case of linear probability models, the dependent variable is the sample proportion or empirical probability (i.e., an estimate of the population proportion) and is modeled using the classical regression model and estimated by Ordinary Least Squares (OLS). This technique does not guarantee that

predicted conditional probabilities lie in the range from zero to one. This shortcoming is avoided in logit and probit models in which transformations are used to ensure that the estimated conditional probabilities are constrained to be in the $[0,1]$ range.

Moreover, a binary response model is referred to as a probit model if F is the cumulative normal distribution function. The normal distribution is symmetrical around zero. The probit model can be estimated by maximum likelihood. This is because the maximum likelihood estimator has good properties in large samples. In particular, it is asymptotically efficient; that is, it is the most precise estimator in large samples. An advantage of maximum likelihood estimation is that it is feasible when there are few observations per cell, which includes the case of no observations in some cells.

Assuming that the binary response function is structural should be treated with caution. If it does not hold up in laboratory-controlled colonies, then there is reason to believe that it may not hold up in the real-world evidence studied by economists. However, binary response studies in economics are seldom repeated, so it is more difficult to detect if there is parameter constancy.

3.3 Binary Probit Model

The probit model is widely used in the social and biological sciences. This model is especially useful in epidemiological and demographic research in the assessment of the effects of explanatory factors on the relative risk of outcomes such as fertilities, mortality and the onset of disease or illness. The probit model is a nonlinear model in p and is transformed so that a monotonic function of p_i is linear with respect to explanatory variables. The probability in the i^{th} cell or the i^{th} observation, p_i, is given by the standard cumulative normal distribution function:

$$P_i = \int_{-\infty}^{\eta_i} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2} u^2\right) du \tag{3.4}$$

where, η_i is a constant.

The above equation is more conveniently written as $p_i = \phi(\eta_i)$, where $\phi(.)$ denotes the cumulative distribution function of the standard normal distribution. The probit transformation, or probit link, is given by the inverse of the standard cumulative normal distribution function. Solving equation (3.4) for η_i yield

$$\eta_i = \phi^{-1}(p_i) = \text{probit}(p_i) \tag{3.5}$$

Equation (3.5) defines the probit link. Thus, the probit model can be written as

$$\phi^{-1}(p_i) = \eta_i = \sum_{i=0}^{K} \beta_i x_{ij} \tag{3.6}$$

or

$$p_i = \phi\left(\sum_{i=0}^{K} \beta_i x_{ij}\right) \tag{3.7}$$

This function is symmetric around $p_i = 0.5$, where probit (p_i) is zero. As p_i approaches 1, probit (p_i) tends toward $+\infty$; as p_i approaches 0, probit (p_i) tends toward $-\infty$. Letting $F^{-1}(p_i)$ denote the inverse of the cumulative logistic or standard normal distribution functions (i.e., the link function), one finds that for ranges of p_i between 0.2 and 0.8 these transformations are essentially linear. For ranges of p_i outside this range, this function is highly nonlinear. This implies that if p_i is modeled as a function of continuous explanatory variable (x), the effect of *x* on p_i is not constant but varies with *x.*

3.3.1 Model Specification

The early origins of the probit model can be traced to the field of psycho-physics. Modern developments of the probit model, however, were developed in the field of dose-response methodology. Binominal response models can be motivated by considering an experiment in which different amounts of a drug or other chemical compound are applied to batches of experimental subjects. Suppose that a particular insecticide is applied to batches of insects at a given dosage level u_i. At low dosages, none of the sampled insects may succumb; at high doses, all may die. The purpose of the experiment is to determine the lethal dosage levels (or response rates) or levels at which we would expect a certain proportion of the population to respond (by dying) to a given dosage level. Whether or not an insect dies is assumed to depend on its *tolerance* to the insecticide. Let c_i be a random variable denoting the tolerance of a particular insect. The i^{th} insect dies ($y = 1$) if ($u_i > c_i$) and survives ($y = 0$) if ($u_i < c_i$). Thus, the probability of dying is

$$\Pr(y = 1) = \Pr(u_i > c_i) \tag{3.8}$$

Binary response model can be derived from a latent variable approach. A latent variable is a variable that is incompletely observed. Latent variables can be introduced into binary outcome models in two different ways. In the first the latent variable is an index of an unobserved propensity for the event of interest to occur. In the second the latent variable is the difference in utility that occurs if the event of interest occurs, which presumes that the binary outcome is a result of individual choice.

The latent variable approach essentially treats dichotomous variables as a problem of measurement. In effect, there exists a continuous underlying or latent variable but just haven't measured it. Instead, we have only a dichotomous indicator of the latent variable.

Suppose that there is some unobserved or unmeasured (latent) variable such that the regression can be written as follow:

$$y_i^* = \boldsymbol{x_i\beta} + \varepsilon_i \tag{3.9}$$

where, assume that ε has mean 0 and has either a standard logistic distribution with (known) variance $\frac{\pi^2}{3}$ or a standard normal distribution with (known) variance 1. The latent variable, y_i^*, itself.

$$y_i = \begin{cases} 1 & if\ y_i^* > t \\ 0 & if\ y_i^* \leq t \end{cases} \tag{3.10}$$

where, t is some threshold. For convenience, assume that t = 0. Thus, this can be written as

$$y_i = \begin{cases} 1 & if\ y_i^* > 0 \\ 0 & if\ y_i^* \leq 0 \end{cases} \tag{3.11}$$

This mean that probit or logit is just regression with less information all about the covariates but only the sign of the dependent variable- y_i indicates whether the latent variable y_i^* is positive or negative are known.

Assumptions:

1. Known variance of ε: This is an innocent assumption. Suppose that the variance of ε is scaled by an unrestricted parameter σ^2. The latent regression in this case would be $y^* = x\beta + \sigma\varepsilon$. However, this can be written as $\frac{y^*}{\sigma} = x\frac{\beta}{\sigma} + \varepsilon$. Note that this is the same model with the same data. The observed data will be unchanged: y is still 0

or 1, depending only on the sign of y^* and not on its scale. These particular assumptions about the variance of ε must be make this distribution is easier to handle.

2. Threshold is 0: This is an innocent assumption so long as the model contains a constant term. Let a be the supposed non-zero threshold and α be an unknown constant term. Let x not include the constant term for now. If this is the case, then

$$\begin{aligned} \Pr(y^* > \alpha) &= \Pr\{(\alpha + \mathbf{x\beta} + \varepsilon) > a\} \\ &= \Pr[\{(\alpha - a) + \mathbf{x\beta} + \varepsilon\} > 0] \end{aligned} \tag{3.12}$$

Since α is unknown, the difference (α-a) remains an unknown parameter. With these assumptions, for latent variable, probability distribution can be written as follow:

$$\begin{aligned} \Pr(y=1) &= \Pr(y^* > 0) \\ &= \Pr\{(\mathbf{x\beta} + \varepsilon) > 0\} \\ &= \Pr(\varepsilon > -\mathbf{x\beta}) \\ &= 1 - \Pr(\varepsilon \leq -\mathbf{x\beta}) \\ &= 1 - F(-\mathbf{x\beta}) \end{aligned} \tag{3.13}$$

where F is the cumulative distribution of ε i,e. either the standard logistic or the standard normal. If F is symmetric about 0 (as is the case with logit and probit), This can be written as follow:

$$\begin{aligned} \Pr(y=1) &= 1 - F(-\mathbf{x\beta}) \\ &= F(\mathbf{x\beta}) \end{aligned} \tag{3.14}$$

Thus, if F is a cumulative standard normal distribution, this model becomes probit model, where

$$\Pr(y=1) = F(\mathbf{x\beta}) = \Phi(\mathbf{x\beta}). \tag{3.15}$$

If F is a standard logistics model, this model becomes logit model, with

$$\Pr(y=1) = F(\mathbf{x\beta}) = \Lambda(\mathbf{x\beta}). \tag{3.16}$$

Extending the latent variable, it is commonly associated with the analysis of individual-level data. Suppose that a data set with data points x_{ik} and y_i (i=1,2,…,n), where y is a dichotomous dependent variable (y= 0,1), and x_{ik} is the value of the k^{th} covariate for the i^{th} individual (including the constant term). For the i^{th} individual, a continuous latent variable was defined y_i^* representing the latent propensity that y=1. Now express y_i^* as a linear function of x_{ik} and a residual ε_i:

$$y_i^* = \sum_{k=0}^{K} \beta_k x_{ik} + \varepsilon_i \tag{3.17}$$

The normalization of equation (3.17) simplifies equation (3.14) to

$$\Pr(y = 1) = \Pr(\varepsilon \leq \sum_{k=0}^{K} \beta_k x_k = F(\sum_{k=0}^{K} \beta_k x_k), \tag{3.18}$$

where F(.) denotes the cumulative distribution function of ε. Still, it is necessary to standardize the mean and the variance of ε to identify the magnitudes of the β parameters.

For simplicity, this individual-level model will be illustrated with the constant criterion normalization equation of (3.18), although other normalizations are statistically equivalent. Thus, the following "threshold-crossing" measurement model:

$$y_i = \begin{cases} 1 & \text{if } y_i^* > 0 \\ 0 & \text{otherwise,} \end{cases} \tag{3.19}$$

where, ε_i is assumed to be i.i.d., as a standard normal distribution on both equations (3.17) and (3.19).

Furthermore, assume that the individual observations (x_i, y_i) are i.i.d., that the explanatory variables are exogenous and that the error term is normally distributed and homoskedastsic.

$$u_i | x_i \sim N(0, \sigma^2)$$

The probability that individual i chooses $y_i = 1$ can now be derived from the latent variable and the decision rule, i.e.

$$\begin{aligned} \Pr(y_i=1|x_i) &= \Pr(y_i^* > 0|x_i) \\ &= \Pr(\boldsymbol{x_i'\beta} + u_i > 0|x_i) \\ &= \Pr(u_i > -\boldsymbol{x_i'\beta}|\, x_i) \\ &= 1 - \phi(-\boldsymbol{x_i'\beta}/\sigma) \end{aligned} \tag{3.20}$$

So the probit model can be defined as;

$$\begin{aligned} \Pr(y=1|x_i) &= F(\mathbf{x\beta}) \\ &= \phi(\boldsymbol{x_i'\beta}/\sigma) \end{aligned} \tag{3.21}$$

The observed values of y is only slightly different from the grouped data case, where the probabilities vary by groups, and the number of trials reflects the size of the group or the cell total n a contingency table.

3.3.2 Marginal Effect

Regression analysis usually aims at estimating the marginal effect of regressor on the outcome variable controlling for the influence of other regressors. In the linear regression model, the regression coefficients can be interpreted as marginal effects. In non-linear regression models, such as the probit model, coefficient cannot be interpreted as marginal effects. Moreover, the coefficients from the probit model are difficult to interpret because they measure the change in the unobservable y^* associated with a change in one of the explanatory variables. A more useful measure is the marginal effect. The marginal effect is the change in x_{ik} on the expected value of the observed variable y_i, i.e.

$$\frac{\partial E(y_i|x_i)}{\partial x_{ik}} = \frac{P(y_i|x_i)}{\partial x_{ik}} = \phi(\boldsymbol{x_i'\beta})\beta_k \tag{3.22}$$

This marginal effect depends on the characteristics of all x_{ik} for observation i. Therefore, any individual has a different marginal effect. There are several ways to summarize and report the information in the model. A first approach is to present the marginal effects for the "mean type", i.e. $x_i = \bar{x}$, the "median type", or some interesting extreme types. A first approach is to calculate the marginal effect for all observations in the sample and report the mean of the effects. The two measures can be constructed to the actual numbers. The first portion also allows comparing actual and predicted outcomes for any observation. It is also often interesting to report and construct predicted numbers for certain types of individuals.

Another, previously very often used alternative, it to use a translation formula. If the index function is 0, then we get Ø (0) ≈ 0.4.

3.3.3 Model Adequacy

The Pearson goodness of fit chi-square statistics is used to test the null hypothesis that the model adequately fit with the data. The Pearson χ^2 statistics can be

constructed by considering the observed frequencies (y_i) and those expected under a given model ($n_i\hat{p}_i$):

$$\chi^2 = \sum \frac{(y_i - n_i\hat{p}_i)^2}{n_i\hat{p}_i(1-\hat{p}_i)} \tag{3.23}$$

Small values of χ^2 indicate agreement or goodness-of-fit, between the observed and expected frequencies, whereas large values indicate disagreement, or lack of fit. The calculated statistics is compared to a χ^2 statistic with degrees of freedom equal to the number of cells minus the number of model parameters. The parallelism test checks to see whether the assumption of equal slops across factor levels is reasonable. If the null hypotheses of these tests are true, the statistics have chi-square distribution with the displayed degree of freedom. If the significance value of a given test is small (less than 0.05), then the model does not adequately fit the data. In this case, the data do not violate the model assumption.

3.3.4 Strengths and Weaknesses of Binary Probit Model

The strengths of binary probit model are as follows:

(1) The method is theoretically sound,

(2) The results generally can be interpreted directly as fault probabilities,

(3) The significance of the model and the individual coefficients can be tested.

Weaknesses of binary probit model are as follows:

(1) The interpretation of the coefficients is not straightforward,

(2) Binary dependent variables do not have inherent scales, because it is unlikely continuously measured variables,

(3) Assuming that residual utility or criterion is due to a large number of small and accidental causes, some scholars have appealed to the central limit theorem.

3.4 Multinomial Probit Model

The multinomial probit model is a generalization of the probit model when there are several possible categories that the dependent variable can fall into. As such, it is

alternative to the multinomial logit model as one method of of multiclass classification. It is not to be confused with multivariate probit model, which is used to model correlated binary outcomes for more than one independent variable.

It is assumed that there is a series of observations Y_i, for i = 1, 2, ...,n, of the outcomes of multi-way choices from a categorical distribution of size m (there are m possible choices). Along with each observation Y_i is a set of k observed values $x_{1,i}$, ..., $x_{k,i}$ of explanatory variables (also known as independent variables, predictor variables, features, etc.).

The multinomial probit model is a statistical model that can be used to predict the likely outcome of an unobserved multi-way trial given the associated explanatory variables. In the process, the model attempts to explain the relative effect of differing explanatory variables on the different outcomes.

Formally, the outcomes Y_i are described as being categorically-distributed data, where each outcome value h for observation i occurs with an unobserved probability $p_{i,h}$ that is specific to the observation i at hand because it is determined by the values of the explanatory variables associated with that observation. That is:

$Y_i|x_{1,i},x_{2,i},..,x_{k,i} \sim$ Categorical (p_i, ..., p_m), for i = 1,2,...,n or equivalently

$Pr[Y_i = h|x_{1,i}, ..., x_{k,i}] = p_{i,h}$, for i = 1, 2, ..., n for each of m possible values of h.

Multinomial probit is often written in term of a latent variable model:

$$Y_i^{1*} = \beta_1 x_i + \varepsilon_1$$

$$Y_i^{2*} = \beta_2 x_i + \varepsilon_2$$

.

.

.

$$Y_i^{m*} = \beta_m x_i + \varepsilon_m \qquad (3.24)$$

where $\boldsymbol{\varepsilon} \sim N(\mathbf{0}, \boldsymbol{\Sigma})$

Then

$$Y_i = \begin{cases} 1 & \text{if } Y_i^{1*} > Y_i^{2*}, \ldots, Y_i^{m*} \\ 2 & \text{if } Y_i^{2*} > Y_i^{1*}, Y_i^{3*} \ldots, Y_i^{m*} \\ . & \\ . & \\ m & \text{otherwise.} \end{cases} \tag{3.25}$$

That is,

$$Y_i = \arg \max_{h=1}^{m} Y_i^{h*} \tag{3.26}$$

3.5 Bivariate Probit Model

The multivariate probit model is a generalization of the probit model used to estimate several correlated binary outcomes jointly. For example, if it is believed that the decisions of sending at least one child to public school and that of voting in favor of a school budget are correlated (both decisions are binary), then the multivariate probit model would be appropriate for jointly predicting these two choices on an individual-specific basis.

In the ordinary probit model, there is only one binary dependent variable Y and so only one latent variable $Y^*$is used. In contrast, in the bivariate probit model there are two binary dependent variables Y_1 and Y_2, so there are two latent variables: Y_1^* and Y_2^*. It is assumed that each observed variable takes on the value 1 if and only if its underlying continuous latent variable takes on a positive value:

$$Y_1 = \begin{cases} 1 & \text{if } Y_1^* > 0 \\ 0 & \text{otherwise,} \end{cases} \tag{3.27}$$

$$Y_2 = \begin{cases} 1 & \text{if } Y_2^* > 0 \\ 0 & \text{otherwise,} \end{cases} \tag{3.28}$$

with

$$\begin{cases} Y_1^* = X_1\beta_1 + \varepsilon_1 \\ Y_2^* = X_2\beta_2 + \varepsilon_2 \end{cases} \tag{3.29}$$

and

$$\begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \end{bmatrix} \Big| \mathrm{X} \sim \mathrm{N}\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right)$$

Fitting the bivariate probit model involves estimating the values of β_1,β_2 and ρ . To do so, the likelihood of the model has to be maximized.

3.6 Oaxaca Decomposition

Poverty is affected by many factors and poverty is defined by using income or expenditure. There is a method of developing inequality in income or expenditure into contributing factors, known as Oaxaca decomposition.

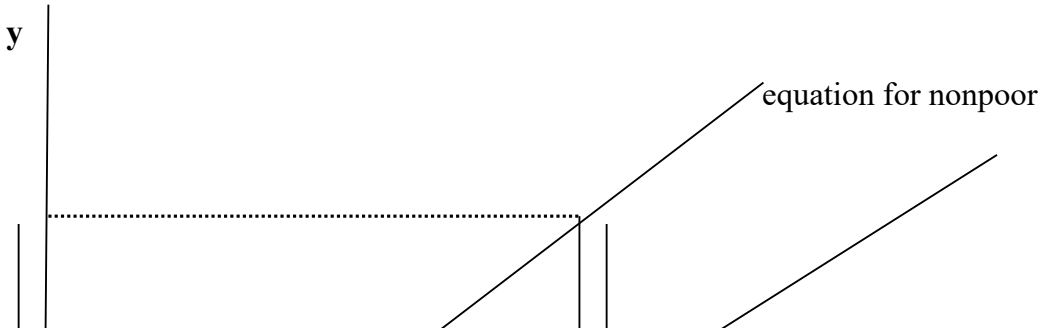
The Oaxaca decomposition (Oaxaca 1973), explains the gap in the means of an outcome variable between two groups (e.g., between the poor and the non-poor). The gap is decompositions of the outcome in question, on the other hand, and group differences in the effects of these determinants, on the other. Two groups are called the poor and non-poor. Assuming that y is explained by a vector of determinants, **x**, according to the regression model:

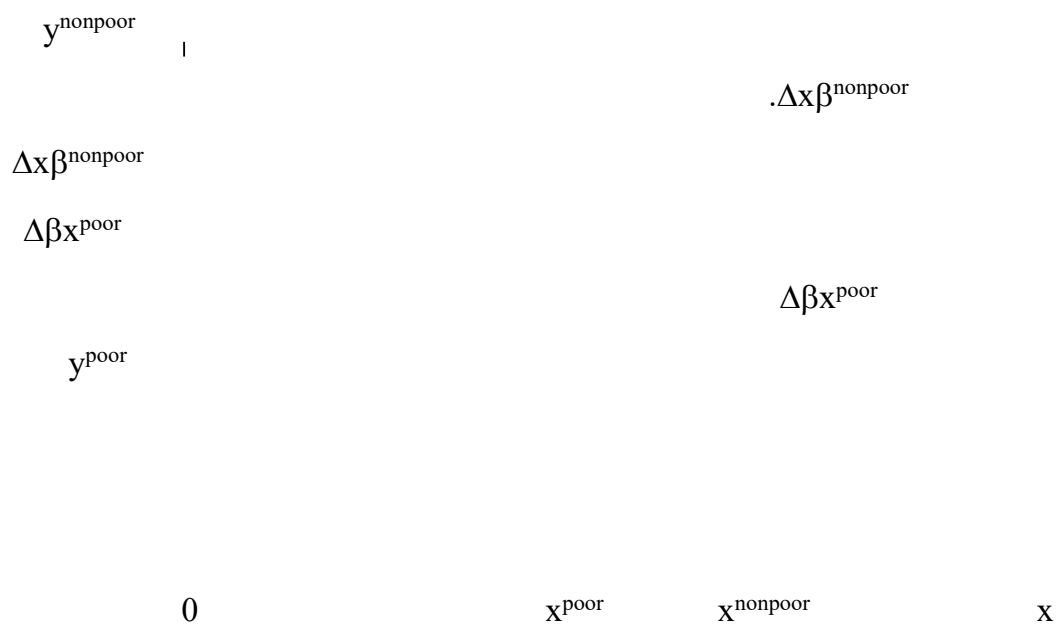
$$y_i = \begin{cases} \beta^{\text{poor}} x_i + \varepsilon_{\text{i}}^{\text{poor}} & if \ \text{poor} \\ \beta^{\text{nonpoor}} x_i + \varepsilon_{\text{i}}^{\text{nonpoor}} & if \ \text{nonpoor} \end{cases} \tag{3.30}$$

where the vectors of β parameters include intercepts. In the case of a single regressor, down in figure (3.1), the non-poor are assumed to have a more advantageous regression line than the poor. At each value of x, the outcome, y_i, is better. In addition, the non-poor are assumed to have a higher mean of x. The result is that the poor have a lower mean value of y than do the non-poor.

Figure (3.1)

Oaxaca Decomposition





Source: Oaxaca (1973)

The gap between the mean outcomes,

$$y^{nonpoor} - y^{poor} = \beta^{nonpoor}\mathbf{x}^{nonpoor} - \beta^{poor}\mathbf{x}^{poor}$$

where $\mathbf{x}^{nonpoor}$ and $\mathbf{x}^{poor}$ are vectors of explanatory variables evaluated at the means for the non-poor and the poor, respectively. As an example x's, x_1 and x_2 can be written the following:

$$y^{nonpoor} - y^{poor} = (\beta_0^{nonpoor} - \beta_0^{poor}) + (\beta_1^{non-poor}x_1^{nonpoor} - \beta_1^{poor}x_1^{poor}) + (\beta_2^{nonpoor}x_2^{nonpoor} - \beta_2^{poor}x_2^{poor})$$

$$= D_0 + D_1 + D_2 \qquad (3.31)$$

So that the gap in y between the poor and the non-poor can be decompored as

(i) differences in the intercepts (D_0),

(ii) differences in x_1 and β_1 (D_1) and

(iii) differences in x_2 and β_2 (D_2).

In problem, D_1 might measure the part of the gap in poverty status (y) due to differences in location, urban or rural (x_1) and the effect of location (β_1). D_2 might

measure the part of the gap due to differences in attainment in education (x_2) and the effect of attainment in education (β_2).

CHAPTER IV
EMPIRICAL ANALYSIS

This chapter presents the analysis of the status of poverty in Myanmar as observed in the IHLCA household survey conducted by Ministry of National Planning and Economic Department (MNPED) in 2005 and 2010. Efforts have been made to test the effect of household characteristics on labour market by using probit model.

4.1 Empirical Data

The results are based on two rounds of the household expenditure survey in connection with IHLCA survey, the first round in 2005 and the next in 2010, covering the whole country. Because of this, a stratified multi-stage sample design was used for the IHLCA survey with 62 districts as the strata. Given their special importance, Yangon City and Mandalay City were treated as separate strata. In carrying out the sampling design, townships across all districts were used as first stage sampling units (FSU). The sampling frame for the first stage was an official list of townships with their estimated number of households in each district.The second stage sampling unit (SSU) was the ward (urban) or village tract (rural) within the selected townships. The sampling frame for the second stage was the list of wards and villages in the selected townships along with their estimated numbers of households. All wards and village tracts in each selected township within a particular district were grouped into urban/rural substrata. A predetermined number of wards/village tracts were then drawn with Probability Proportional to Estimated Sampling (PPES) method using systematic random selection from those township frames. In selecting wards and village tracts, the main issue for estimation was to compute the sampling weight. The third stage was the combined weight for the third and fourth stages of selection (selection of one street segment or village per ward/ village tract and selection of 12 households per street segment or village). The two weights were combined into one because only one street segment or village per ward/village tract was selected. The selected sample townships from big cities namely Yangon, Mandalay and other smaller townships are presented in Appendix table (1). The detailed information on sex, age, religion, marital status and

relationship to the head of the household, education level, employment status, occupation, industry category etc; for all household members were included in the household expenditure survey. Information on remittances, if any, from family members were working away from home, within the country or overseas was also included. Based on monthly per capita consumption expenditure that was used to classify the households into below and above poverty line was obtained for the households from these surveys.

In Myanmar, industries are classified into three categories, namely primary, secondary and tertiary. However, there are five categories by International Standard Industrial Classification (ISIC), namely, primary, secondary, tertiary, quaternary and quinary sectors.

The primary sector of the economy extracts or harvests products from the earth. This sector includes the production of raw material and basic foods. Activities associated with this sector include agriculture (both subsistence and commercial), mining, forestry, farming, grazing and gathering, fishing, and quarrying. The packing and processing of the raw material associated with this sector is also considered to be part of this sector.

The secondary sector of the economy manufactures finished goods. All of manufacturing, processing, and construction lies within the secondary. Activities associated with the secondary sector include metal working and smelting, automobile production, textile production, chemical and engineering industries, aerospace manufacturing, energy utilities, engineering, breweries and bottlers, construction, and shipbuilding.

The tertiary sector of the economy is the service industry. This sector provides services to the general population and to businesses. Activities associated with this sector include retail and wholesale sales, transportation and distribution, entertainment (movies, television, radio, music, etc.), restaurants, clerical services, media, tourism, insurance, banking, healthcare, and law.

The quaternary sector of the economy consists of intellectual activities which associated with this sector include government, culture, libraries, scientific research, education, and information technology.

Some consider there to be a branch of the quaternary sector called the quinary sector, which includes the highest levels of decision making in a society or economy. This sector would include the top executives or officials in such fields as government, science, universities, nonprofit, healthcare, culture, and the media.

There were 17 industries in IHLCA survey. For the sake of simplicity in classification, in this study, the industries are grouped into five, namely

(1) Agriculture (comprising agriculture, hunting, forestry and fishing),

(2) Manufacturing (including mining and quarrying, manufacturing, electricity and gas and water supply),

(3) Construction,

(4) Services I (including wholesale and retail trade including repairs, hotels and restaurants, transport, storage and communication and other community, social and personal services) and

(5) Services II (including financial intermediation, real estate, renting and business activities, public administration, education, health and social work, activities of private household head as employers and extra-territorial organization and bodies).

The categorization of the service sector into two groups is justified on the basis of skill and capital requirements. Services I is related to largely low productive services, whereas services II consists of more modern, skill and capital-intensive services.

Moreover, the countries divided into 4 national geographic regions with similar qualitative characteristics as follows:

(1) Coastal region (including Mon State, Tanintharyi Division, Rakhine State),

(2) Delta region (including Ayeyarwaddy, Yangon and Bago Division),

(3) Dry region (including Magwe Mandalay and Sagaing Division) and

(4) Hilly region (including Kachin, Kayin, Kayah, Chin and Shan State).

It is evident that each region has its own unique economic activities relevant to its national resources. Economic activities have three dimensions: profession, employment and business. Profession is an occupational career, engineers, etc. They provide specialized services in return for fees. To become a professional, a man

requires specialized knowledge and professional qualification. Employment is a type of occupation under which one person provides his services, physical or mental to someone else in return for whom he gets salary or wage. The person who employs is called employer and the person who is employed called employee or worker. Business is an economic activity concerned with production and distribution of goods and services with the aim to earn profit. It includes all those activities which are directly or indirectly concerned with production, purchase and sales of goods and services. So, production, marketing, warehousing, insurance, banking, etc, are all business activities.

In the case of educational level, there are five categories:

(1) Illiterate level which a person who does not know how to read or write,

(2) Literate and primary level which a person who know how to read and write and does not passed grade 5, passed grade 1, grade 2, grade 3, grade 4,

(3) Middle level (lower secondary) which a person attended grade 6, grade 7, grade 8 and grade 9,

(4) Upper secondary level which a person attended grade 10 and grade 11 and undergraduate level but not graduated

(5) Graduate and above level.

In the IHLCA, occupation categories used are legislators, senior officials and managers; professionals; technicians and associate professionals; clerks; services worker, sales persons at shops and markets; skilled agricultural and fishery workers; craft, construction and related workers; plant and machine operators and assemblers and elementary occupations. However, in the employment status categories this study has considered, only three categories namely,

(1) Self employed (include employer and own account workers);

(2) Salaried worker (include employee, members of producer's cooperative and contributing family members) and

(3) Casual workers (include casual workers and workers not classifiable).

4.2 Probit Model of Poverty

Poverty is measured by using consumption expenditure from IHLCA household survey data. This study has used binary poverty variable directly as dependent variable in a probit regression with household and individual characteristics as explanatory variables.

4.3 Definition of Variables

The poverty variable is a binary one, and monthly per capita household expenditure is used to define whether the household is above or below the poverty line for various years. Household characteristic x_i consists of population characteristics and additional control variables.

Population characteristics are divided into five groups. They are demographic characteristics, individual classification, employment, individual and household characteristics and labour and unemployment.

Demographic Characteristics: The only variable which is much more closely associated with entries into poverty than with chronic poverty is the economic dependency ratio. Households who have escaped poverty have smaller household size, and are more likely to be female-headed, than entrants into poverty and the chronically poor. So, we have used old dependency ratio and female household head as demographic characteristics.

Individual Classification: Entrants into poverty are much less likely than the chronically poor to be associated with agriculture and more likely to be associated with manufacturing, construction, services I and services II. Interestingly, the main economic activity of those who have escaped poverty is similar to that of the chronically poor though the former are less likely to be involved in finishing and much more likely to be involved services I and services II. This latter industry is also more closely associated with those who have escaped poverty.

Employment: Employment can have many dimensions; however, in this study only three dimensions: employment status, industry and educational level are considered.

Individual and household characteristics: The main individual variable is the educational level of workers. Characteristics, which are the same for all household

members, include the religion, the amount of land owned per household member, and the household type. Household type gives the main source of income.

Labour and Unemployment: Households who have entered poverty have lower labour force participation rates and higher unemployment rates than the chronically poor. Households who have escaped poverty have lower unemployment rates, but higher underemployment rates, than entrants into poverty and the chronically poor.

Additional control variables: We also include a dummy variable to control for unobservable heterogeneity between rural and urban areas.

Aggregation of variables: A major challenge of the type of analysis consists in relating individual variables like education and employment to welfare or poverty measures at the household level. So, there are three steps in aggregating these variables. Firstly, each household member is classified into by industry. Second, each household member with specific industry is classified by employment status. Finally, each household member with specific industry and specific employment status are classified by education level. In order to keep all the relevant information, five sectors with the three possible employment statuses, resulting in 15 sector-employment status combinations, are used. In addition, five educational levels are distinguished, leading to 75 possible combinations of educational level, industry and employment status for each household member. In aggregation of household level, each specific household member is combined with like household level.

This approach allows using the information in terms of employment status, industry and education level of all working household members together with household welfare/ poverty measures. The relation of the individual occupation with the household welfare can be of three types: poverty reducing, poverty enhancing or neutral. In which category an occupation falls depends on whether the return of the occupation is high enough to increase expenditures for other household members as well.

Some occupations are of so low productivity that the participation of one household member increases the probability for the entire household being poor. In these cases, the occupation does not even pay the working household members enough to lift their own consumption expenditures above the poverty line. Even though the

individual is working, his presence reduces the probability that per capita household expenditures is above the poverty line. If an occupation just allows the working member to cover basic needs, the occupation will be neutral with respect to household poverty. In this situation, the coefficient in the empirical analysis will not be statistically different from zero. The ideal case is of course that an occupation is poverty reducing. In this case, the occupation earns more than what is needed to cover the basic needs of the working person and therefore increases the consumption of the other household members as well. Employment then reduces the poverty of the household being poor.

4.4 Poverty Incidence of Myanmar at 2005 and 2010

Poverty incidence in Myanmar classified by industry sector and employment status for the two surveys are shown in Table (4.1).

Table (4.1)

Poverty Incidence for Urban, Rural and Union in Myanmar (2005 and 2010) (%)

		Rural				Urban				Union			
		Self-Employed	Salaried	Casual	Sector	Self-Employed	Salaried	Casual	Sector	Self-Employed	Salaried	Casual	Sector
2005	Agriculture	34.72	40.41	50.84	40.1	25.78	37.27	55.49	35.78	34.38	40.26	51	39.93
	Manufacturing	30.45	41.65	54.55	39.76	17.03	25.72	35.33	23.4	25.13	34.01	49.75	33.02
	Construction	20.31	43.58	40.56	39.05	27.07	27.65	37.46	31.83	22.9	37.09	39.44	36.04
	Services I	24.5	32.41	41.8	30.42	18.6	21.64	33.69	21.47	21.61	25.84	39.14	25.95
	Services II	26.35	28.82	50.32	30.54	16.32	18.83	34.41	19.45	21.92	22.84	43.43	24.77
	Employment Status	32.02	38.31	49.31	**37.82**	18.65	22.73	37.58	**22.85**	29.01	33.11	47.52	34.09
2010	Agriculture	24.14	27.44	38.14	28.29	19.9	27.19	27.81	23.62	23.97	27.43	37.84	28.1
	Manufacturing	20.77	35.7	38.31	31.81	7.44	19.79	29.02	16.81	15.97	29.15	36.71	26.42
	Construction	15.9	38.35	36.66	35.57	8.26	17.5	27.6	19.27	13.2	30.62	34.69	30.54
	Services I	20.06	33.88	46.57	33.72	11.01	16.56	32.72	16.02	15.21	24.53	43.4	25.54
	Services II	18.87	22.48	54.06	23.19	9.9	13.49	22.38	12.09	14.53	17.28	44.72	17.47
	Employment Status	22.73	28.94	40.23	**28.78**	10.96	16.38	29.01	**15.21**	19.97	24.87	38.98	25.48

Source: Calculated from IHLCA I and II data

As expected, urban poverty incidence is lower than rural by about 15% in both 2005 and 2010. This study also have found that there was about 9% decrease of rural poverty incidence and about 7.64% decrease of urban poverty incidence from 2005 to 2010. Nationally poverty incidence has decreased by 8.61% over 5 years. The reason for the decrease is not obvious as there was no poverty reduction program between 2005 and 2010. However, one of the possible reasons could be that after 2008, there was an increase of construction works and due to rise in cost of living (consumer price index (CPI) with base year 2006 for 2005 was 79.16% and that of 2010 was 146.85%)(Statistical Year Book, 2006 and 2011); most of the household members have to work, generating more income.

The results for different sectors are quite mixed. The poverty incidence by economic sector across employment status has been found to be changing. In 2005, for rural, self-employed in construction sector has the lowest poverty incidence whereas for urban, self-employed in services II sector has the lowest. In 2010, the situation of rural was the same as 2005. However, the poverty incidence for urban self-employed in construction sector was the lowest. Moreover, in 2005, for rural, casual workers in manufacturing sector has the highest poverty incidence whereas for urban, casual workers in agriculture sector has the highest. In 2010, the situation of urban and rural areas was changing as follow: for rural, casual workers in services II sector has the highest poverty incidence whereas for urban, casual workers in services I sector has the highest.

Furthermore, appendix tables (2) and (3) give the poverty incidence in different regions by employment status combination for two rounds. This is the same poverty incidence in different economic sectors by employment status combination for the two surveys. To give a better picture of the incidence of poverty in different regions by sectors and employment status, the summary tables have been given for 2005 and 2010 in Tables (4.2.a) and (4.2.b) respectively.

Table (4.2 a)

Poverty Incidence in Different Regions by Employment Status (2005)

Region	2005	
	Maximum	Minimum
Coastal Region	casual worker in services II (53.6%)	Self-employed in construction (5.66%)
Delta Region	casual worker in Agriculture (47.16%)	Self-employed in manufacturing (14.56%)
Dry Region	casual worker in Agriculture (53.39%)	Self-employed in services II (26.64%)
Hilly Region	casual worker in manufacturing (58.02%)	Self-employed in services I (24.28%)
National	casual worker in Agriculture (51%)	Self-employed in services I (21.61%)

Source: Table (4.1)

Referring to appendix table (2) the poverty incidence of manufacturing sector in Delta region was the lowest with 20.55**%** and agriculture sector in Dry region was the highest with 51.66**%.** Table (4.2.a) gives poverty incidence by industry sector and region of residence in 2005. In observing by region, the poverty incidence of casual workers working in services II sector is the highest with 53.6% and self-employed working in construction sector was the lowest with 5.66% in the Coastal region. In the Delta region, the poverty incidence of casual workers working in agriculture sector was the highest with 47.16% and self-employed working in manufacturing sector was the lowest with 14.56%. The poverty incidence of salaried worker in agriculture sector was the highest with 53.39% and self-employed working in services II sector was the lowest with 26.64% in Dry region. The poverty incidence of manufacturing casual workers was the highest with 58.02% and self-employed working in services I sector was the lowest with 24.28% in Hilly region. In observing for the whole country, the poverty incidence of agriculture casual workers was the highest with 51% and self-employed working in services I sector was the lowest with 21.61%.

Table (4.2 b)

Poverty Incidence in different Regions by Employment Status (2010)

Region	2010	
	Maximum	Minimum
Coastal Region	casual worker in services II (68.07%)	Self-employed in construction (11.47%)
Delta Region	casual worker in manufacturing (50.77%)	Self-employed in services II (12.32%)
Dry Region	casual worker in manufacturing (43.76%)	Self-employed in manufacturing (12.85%)
Hilly Region	casual worker in construction (37.66%)	Self-employed in construction (8.90%)
National	casual worker in services II (44.72%)	Self-employed in construction (13.20%)

Source: Table (4.1)

As shown in appendix table (3), the poverty incidence of services II sector in the Delta region was the lowest with 14.47% and agriculture sector in the Dry region

was the highest with 39.27%. Table (4.2.b) gives poverty incidence by industry sector and region of residence in 2010. In observing by region, the poverty incidence of casual workers in services II sector in 2010 was not only the highest but increased by 14.47% (68.07%-53.6%) than in 2005, and self-employed worker in construction sector was the lowest with an increase of 5.81% (11.47%-5.66%) compared to 2005 in the coastal region. In the Delta region, the poverty incidence rate of casual worker in manufacturing sector was the highest with 50.77% and self-employed in services II was the lowest with 12.32%. The poverty incidence of manufacturing casual worker was the highest with 43.76% and self-employed in this sector was the lowest with 12.85% in the Dry region**.** In the Hilly region, the poverty incidence rate of construction casual worker was the highest with 37.66% and self-employed in this sector was the lowest with 8.90%. At Union level, casual worker in services II sector was the highest with 44.72% and self-employed working in construction sector was the lowest with 13.20%.

4.5 Results from the Probit Analysis

Employment influences the likelihood of being poor through an interaction of educational level, employment status and industry. The separate influence of each of these three factors in addition to the household variables will be discussed in the following sections. The probit model of poverty for rural and urban areas for the two years 2005 and 2010 are shown below. The model for these two years is estimated, separately so that, changes occurred over time can be compared.

4.5.1 Estimated Probit Model: Rural Areas

Household characteristics: Table (4.3 a) gives probit estimates with the standard errors on the industrial classification of the main economic activity of household members for the reference variables over time for rural areas for the years 2005 and 2010 and marginal effects (i.e, change in poverty level with respect to variables of interest). The household characteristics that have taken into consideration are employment status (Agricultural labour, Casual labour, Self-employed Non-Agriculture, Self-Employed Agriculture), Salaried (Agriculture and Non-Agriculture),

Table (4.3 a)

Probit Estimates for Rural Household Poverty with Household Characteristics in Myanmar (2005 and 2010)

Household variables	2005			2010		
	$\hat{\beta}_k$	**s.e** ($\hat{\beta}_k$)	∂**y/**∂**x**	$\hat{\beta}_k$	**s.e** ($\hat{\beta}_k$)	∂**y/**∂**x**
Reference variable; Household Member Self Employment, Non-Agriculture						
Agriculture Labour	-0.1761**	0.0156	-0.0222	-0.2792**	0.0167	-0.0336
Casual Labour	-0.2970**	0.0158	-0.0374	-0.3633**	0.0164	-0.0438
Self Employment Agriculture	-0.3758**	0.0101	-0.0473	-0.4688**	0.0109	-0.0565
Salaried; Agriculture & Non Agriculture	-0.2125**	0.0073	-0.0267	-0.2195**	0.0073	-0.0265
Remittance	0.0444	0.0308	0.0056	0.0259	0.0293	0.0031
Female Household Head	0.0998**	0.0207	0.0126	0.0551**	0.0208	0.0066
Reference variable; Household Member-Buddhist						
Other Religions	-1.2844**	0.0210	-0.0104	-1.3259**	0.0223	-0.0106
Child Women Ratio	0.2782*	0.1210	0.0022	0.3939*	0.1266	0.0031
Old Dependency Ratio	0.1875*	0.0812	0.0015	0.0412	0.0712	0.0003
Land Per Capita	0.0238	0.0279	0.0002	-0.0140	0.0083	-0.0001
Sample size	18635			18609		

Note: $\hat{\beta}_k$-eatimated coefficient, ∂y/∂x - marginal effect, s.e ($\hat{\beta}_k$)- standard error of estimated coefficient, *and ** indicate significant at 5% and 1% level respectively.

remittances (income sent by family members working away from home), sex of the household head, religion, land per capita, child women ratio and old dependency ratio. The reference variable with household member is self-employed non-agriculture. Compared to this employment status, the probability that whether the household is poor rises, if the main source of income is from labour, whether it is from agriculture or non-agriculture and casual or self-employed. According to the results, the marginal effect for all types for employment status is negative and statistically significant in both 2005 and 2010, indicating that the negative effect of household member with employment status. The negative impact on poverty increases for the employment status with agriculture labour, casual labour and self-employment agriculture by 1.14%, 0.64%, and 0.92% respectively, but the poverty risk decreased for the salaried worker by 0.02% (2.67%- 2.65%) between 2005 and 2010. So, the probability of household being poor clearly depends on the employment status of household member.

It is widely believed that remittances to rural areas play an important role in reducing poverty. Although, the effect of remittance is positive marginal effect but it is not significant in the study for both years 2005 and 2010. However, the marginal effect on poverty of rural households in 2010 is smaller than that of 2005. Female-headed households face a high probability of being poor. Beside wage discrimination, the double burden that female household heads face is probably responsible for differences in earning possibilities, which does not help them to reduce the risk of poverty (Rani and Schmid, 2006). Moreover, many researchers have found that the female-headed households are often relatively small with no other adult helper at home. In those households, the female heads have to fulfill household chores in addition to work, which reduces their flexibility in the labour market.

The fact that women bear a disproportionately greater burden of household survival in poor working class households actually exacerbates their burden. This result clearly supports the fact that the marginal effect of female household head is positive, and also statistically significant, by 1.26% in 2005 and 0.66% in 2010.

Another reference variable is household member who is a Buddhist. Number of dependent household members significantly increases the probability of being poor. Dependence in two ways have been measured the child woman ratio and the share of household members who are above the age of 65 years. The child woman ratio measures the drain on the household income caused by children who are non-working members and also the adverse effect children can have on the employment opportunities of woman. As women have to look after the children, they become more restricted in their employment. It has been found that the effect of child women ratio is positive marginal effect and statistically significant in both 2005 and 2010. This is the fact that women often carry children to their places of work and the fact that the younger siblings and joint family system allows flexibility for women to undertake productive work (Gaiha, 1988). Besides children, elders also contribute on other family expenses. In the absence of any social security benefits or pensions, the elderly depend on their families once they stop working. The marginal effect shows that the presence of persons above 65 years significantly raises the risk of poverty for the household in both 2005 and 2010. Moreover, the effect of other religion is negative marginal effect and significant in both years 2005 and 2010.

As shown in Table (4.3 a), remittance in reference variable 'household member self employment, non-agriculture' equation and land per capita in reference variable 'household member-buddhist' equation are not significant. Therefore these variables are deleted and reestimated with significant variables. The results are shown in table (4.3 b). According to this table, the negative impact on poverty increases for the employment status with agriculture labour, casual labour and self-employment agriculture by 1.14%, 0.63%, and 0.88% respectively, but the poverty risk decreased for the salaried worker by 0.03% (2.62%- 2.59%) between 2005 and 2010. In reference variable 'household member self employment, non-agriculture', the changes in value of marginal effect are not so much.

Table (4.3 b)

Probit Estimates for Rural Household Poverty with Household Characteristics in Myanmar (2005 and 2010)

Household variables	2005			2010		
	$\hat{\beta}_k$	s.e ($\hat{\beta}_k$)	$\partial y/\partial x$	$\hat{\beta}_k$	s.e ($\hat{\beta}_k$)	$\partial y/\partial x$
Reference variable; Household Member Self Employment, Non-Agriculture						
Agriculture Labour	-0.1818**	0.0156	-0.0229	-0.2847**	0.0167	-0.0343
Casual Labour	-0.2917**	0.0157	-0.0368	-0.3579**	0.0164	-0.0431
Self Employment Agriculture	-0.3770**	0.0101	-0.0475	-0.4675**	0.0109	-0.0563
Salaried; Agriculture & Non Agriculture	-0.2076**	0.0072	-0.0262	-0.2146**	0.0072	-0.0259
Female Household Head	0.1012**	0.0206	0.0128	0.0559**	0.0207	0.0067
Reference variable; Household Member-Buddhist						
Other Religions	-1.2909**	0.0208	-0.0104	-1.3390**	0.0225	-0.0105
Child Women Ratio	0.2868*	0.1216	0.0023	0.4309**	0.1278	0.0034
Old Dependency Ratio	0.2003*	0.0807	0.0016	0.0220	0.0712	0.0002
Sample size	18635			18609		

Note: $\hat{\beta}_k$-eatimated coefficient, $\partial y/\partial x$ - marginal effect, s.e ($\hat{\beta}_k$)- standard error of estimated coefficient, *and ** indicate significant at 5% and 1% level respectively.

Labour Market Variables: Tables (4.4), (4.5), (4.6), (4.7) and (4.8) give the information of the percentage of rural workers with each employment status at each educational level, marginal effects and standard errors by industries (2005 and 2010) in Myanmar. Furthermore, appendix table (4) represents the number of rural working household members with each employment status at each educational level by industries (2005 and 2010) in Myanmar. The objective of these tables is to help the understanding of changes in poverty level of families with members working in different industries at different employment status and educational levels. Moreover, these results in the tables can be used to compare the effects of employment across employment status and educational level, for different industries. The rows represent the different employment status: self-employed, salaried and casual for each industry group. Different educational levels are presented inside each employment status. This facilitates comparisons between employment status and educational level for a specific industry. The columns provide the result for the two rounds allowing comparisons over time. The results give the change in the probability of a household being poor for each household member with a certain education level, within a certain industry and for a specific employment status.

Agriculture: It is known that, agriculture is the main important sector in the economy of Myanmar. In 2005, 46.82% of the rural workforce and 44.31% of that were from the agriculture sector in 2010. In observing the decrease in percentage participation of rural workers, there is not much change in percentage of self-employed and salaried workers. However, the percentage of casual workers has decreased from 9.78% to 8.89% between 2005 and 2010. Furthermore, when we looked at their educational level the percentage of illiterate has gone down from 8.64% to 0.47% for all employment status combined. Particularly, for self-employed the percentage of illiterates has gone down from 4.84% in 2005 to 0.25% in 2010. It may be either due to the increase in the level of literacy or due to sampling error. In studying the effect on poverty risk of household via employment status and educational level, there were changes between 2005 and 2010. In the change in effect on poverty level of these households with self-employed household members by educational level, it is found that the marginal effect on poverty at the illiterate level it significantly increased from 10.85% to 13.68%, at Primary level from 5.17% to 5.41% and at middle level from 2.6% to 4.47%. However, the poverty level at secondary decreased by 2% in 2005and increased by 1.79% in 2010. This reverse

Table (4.4)

Probit Estimates for Rural Household Poverty in Myanmar's Agriculture Sector (2005 and 2010)

Employment Status	Variables	2005				2010			
		No. of Employees	% of Employees	$\partial y/\partial x$	s.e	No. of Employees	% of Employees	$\partial y/\partial x$	s.e
Self-Employed	Illiterate	1975	4.84	0.1085**	0.0093	107	0.25	0.1368**	0.0459
	Primary	5061	12.39	0.0517**	0.0072	5764	13.67	0.0541**	0.0076
	Middle	1572	3.85	0.0260**	0.0124	1879	4.46	0.0447**	0.0118
	Secondary	986	2.41	-0.0200**	0.0152	1622	3.85	0.0179**	0.0119
	High	141	0.35	-0.1087**	0.044	225	0.53	-0.0250**	0.0351
Salaried	Illiterate	793	1.94	0.1326**	0.0156	46	0.11	0.1044**	0.0759
	Primary	2757	6.75	0.0375**	0.0089	2965	7.03	0.0442**	0.0093
	Middle	981	2.40	0.0295**	0.0142	1142	2.71	0.0158**	0.0149
	Secondary	712	1.74	-0.0102	0.0158	995	2.36	-0.0150**	0.0150
	High	145	0.36	-0.0516**	0.0359	190	0.45	-0.1299**	0.0428
Casual	Illiterate	761	1.86	0.0900**	0.0175	47	0.11	0.2094**	0.0777
	Primary	2446	5.99	0.0446**	0.0114	2662	6.31	0.0391**	0.0115
	Middle	522	1.28	-0.0191**	0.0206	643	1.52	0.0208**	0.0201
	Secondary	243	0.60	-0.0479**	0.0312	383	0.91	0.0323**	0.0238
	High	23	0.06	-0.1429**	0.1036	15	0.04	-0.1434**	0.1436

Note: $\partial y/\partial x$ - marginal effect; s.e - standard error, %- of employee = % of workers in that category out of total sample, ** indicates significant at 1% level, N.A- Non Applicable.

marginal effect number of self employment employees increased from 986 in 2005 to 1622 and the results are also statistically significant. Moreover, the marginal effect on poverty at high education level decreased. The rates decreased from 10.87% to 2.5% between 2005 and 2010. For salaried household members, the marginal effect on poverty level of the household increased at primary level from 3.75% to 4.42% and at illiterate and middle educational level, it decreased from 13.26% to 10.44% and from 2.95% to 1.58% respectively. At the secondary and high education level, the probability of poverty decreased in both years 2005 and 2010. But, these rates increased by from 1.02% to 1.5% and from 5.16% to 12.99% respectively. For casual household members, the impact on poverty level decreased from 4.46% to 3.91% at primary education level and increased 9% to 20.94% at illiterate educational level. However, at middle and secondary education level, the poverty level decreased from 4.81% in 2005 to 1.02% in 2010, increased by 2.08% and 3.23% respectively. The marginal effect on poverty at high education level has decreased in both years. These decreased rates did not change in between 2005 and 2010. These marginal effects are also statistically significant. Here, educational level has significant effect on reducing poverty level in rural agriculture sector is observed.

Manufacturing: In comparing the percentage of rural workforce in 2005 and 2010, manufacturing sector is the second smallest sector in Myanmar. Out of nearly 9% of rural workforce in this sector, the percentage of self-employed decreased from 23.34% in 2005 to 18.32% in 2010. However, the percentage of rural salaried workers increased from 23.45% to 29.88% between 2005 and 2010, showing the change in economic situation in the country.

In observing the marginal effect on poverty level of household for this sector by employment status and educational level, although we find that marginal effect on poverty level of these household with salaried and casual household members at high educational level decreased in 2005. In 2010, the poverty level increased. These marginal effects are also statistically significant. The poverty level of household with illiterate education household members in this sector increased in 2005. However, in 2010, such household did not include in the sample and hence it cannot be compared with the situation in 2005. The marginal effect on poverty level of household with

Table (4.5)

Probit Estimates for Rural Household Poverty in Myanmar's Manufacturing Sector (2005 and 2010)

Employment Status	Variables	2005				2010			
		No. of Employees	% of Employees	∂y/∂x	s.e	No. of Employees	% of Employees	∂y/∂x	s.e
Self-Employed	Illiterate	114	0.28	0.2922**	0.0639	0	0.00	N.A	N.A
	Primary	406	0.99	0.1208**	0.0366	343	0.81	0.0660**	0.0371
	Middle	181	0.44	0.0966**	0.0478	162	0.38	0.0233	0.0517
	Secondary	138	0.34	0.0155	0.0514	161	0.38	0.0012	0.0457
	High	35	0.09	0.0349	0.0938	43	0.10	-0.1407**	0.1204
Salaried	Illiterate	52	0.13	0.0695**	0.0626	0	0.00	N.A	N.A
	Primary	382	0.94	0.0999**	0.0291	491	1.16	0.0797**	0.0276
	Middle	178	0.44	0.0070	0.0388	261	0.62	0.0831**	0.0360
	Secondary	182	0.45	0.0148	0.0381	305	0.72	-0.0201	0.0374
	High	85	0.21	-0.0540*	0.0630	100	0.24	-0.1901**	0.0664
Casual	Illiterate	41	0.10	0.1155**	0.0859	0	0.00	N.A	N.A
	Primary	216	0.53	0.0436**	0.0378	256	0.61	0.0157	0.0459
	Middle	90	0.22	0.0715**	0.0561	106	0.25	0.0106	0.0615
	Secondary	56	0.14	0.0083	0.0818	104	0.25	0.0246	0.0593
	High	6	0.01	-0.0100	0.2004	8	0.02	0.0020	0.1865

Note: ∂y/∂x - marginal effect; s.e - standard error, %- of employee = % of workers in that category out of total sample, *, ** indicate significant at 5% and 1% level respectively, N.A- Non Applicable.

remaining educational level household members in this sector increased. The rate of increase in marginal effect on poverty level of these households went down from 2005 to 2010. It is found that in rural manufacturing sector, employment status and educational level has little effect on reducing the marginal effect on poverty level of the households.

Construction: The percentage of rural workforce in construction sector is the smallest among different sectors in both 2005 and 2010. Comparing the change in percentage of rural workforce, this study found that it increased from 2.95% to 4.87% during and 2010. In observing the increase in percentage participation of rural workforce, the percentage of self-employed decreased from 8.14% to 6.16% during 2005 and 2010. But, the percentage of salaried and casual workers increased from 25.42% to 30.39%, from 22.03% to 29.77% respectively. According to these results, it is found that the number of poor household increased to a certain extent from 2005 to 2010.

In studying the marginal effect on poverty level of household for this sector by employment status and educational level, there was a negative impact on poverty of household with self employment household members, but these rates were not significant at 2005, except household member with illiterate level which were not included in the sample. Although there was positive impact on poverty for illiterate and middle level, it has a negative impact on poverty at primary, secondary and high level in 2010. These marginal effects are not statistically significant in both 2005 and 2010. For salaried household members, it has a positive impact on poverty at secondary and below educational level in 2005 and 2010. These positive rates decreased at primary and secondary educational level from 15.31% to 7.43% and 15.54% to 0.88% respectively in both 2005 and 2010. Furthermore, casual household members have a positive impact on poverty level of household at 2005, but these rates are not significant in illiterate and middle educational level. In 2010, although the marginal effect on poverty of household decreased at illiterate, secondary and high educational level by 3.69%, 1.77% and 28.62% respectively, it increased at primary and middle by 9.62% and 1.1%. But, these marginal rates are not significant except

Table (4.6)

Probit Estimates for Rural Household Poverty in Myanmar's Construction Sector (2005 and 2010)

Employment Status	Variables	2005				2010			
		No. of Employees	% of Employees	$\partial y/\partial x$	s.e	No. of Employees	% of Employees	$\partial y/\partial x$	s.e
Self-Employed	Illiterate	0	0.00	N.A	N.A	3	0.01	0.5042**	0.3591
	Primary	9	0.02	-0.3553	1.2337	78	0.18	-0.0447	0.1607
	Middle	47	0.12	-0.6084	1.2235	26	0.06	0.0907*	0.1483
	Secondary	30	0.07	-0.4830	1.2154	19	0.05	-0.0040	0.2085
	High	11	0.03	-0.6550	1.2074	4	0.01	-0.8699	6.3790
Salaried	Illiterate	28	0.07	0.0672	0.1021	3	0.01	0.1532	0.2456
	Primary	150	0.37	0.1531**	0.0558	292	0.69	0.0743**	0.0364
	Middle	71	0.17	0.0478	0.0741	164	0.39	0.1030**	0.0418
	Secondary	45	0.11	0.1554**	0.0824	136	0.32	0.0088	0.0514
	High	14	0.03	-0.1250	0.1854	27	0.06	-0.0455	0.0955
Casual	Illiterate	27	0.07	0.0734	0.102	7	0.02	-0.0369	0.2472
	Primary	129	0.32	0.0883**	0.0583	324	0.77	0.0962**	0.0335
	Middle	65	0.16	0.0119	0.0626	167	0.40	0.0110	0.0467
	Secondary	45	0.11	0.0715*	0.0790	105	0.25	-0.0177	0.0511
	High	0	0.00	N.A	N.A	10	0.02	-0.2862**	0.2223

Note: $\partial y/\partial x$ **- marginal effect; s.e - standard error, %- of employee = % of workers in that category out of total sample,**

***, ** indicate significant at 5% and 1% level respectively, N.A- Non Applicable.**

primary and high level. From this result, it is found that educational level has a positive marginal effect on the reduction of poverty level in the construction sector.

Services I: The percentage of rural workforce in services I was 22.93% in 2005 and 16.51% in 2010, showing a decrease of about 6.42%. In observing the decrease in percentage participation of rural workforce, the percentage of salaried and casual household members increased from 10.95% in 2005 to 15.38% in 2010 and from 10.34% in 2005 to 15.14% in 2010 respectively. However, the percentage of self-employed workers decreased 25.47% and 17.44%.

In studying the marginal effect of poverty level of household for this sector by employment status and educational level, it is found that marginal effect on poverty level of these household with self-employed household members at illiterate and primary educational levels were positive in 2005. It is statistically significant. But, the impact on poverty level of these household with self-employed household members at high level significantly decreased in both 2005 and 2010. These marginal rates of this household on the risk level of reduction poverty level increased by from 12.83% to 5.42% between 2005 and 2010. For salaried household members, the poverty level of these household at secondary and high educational levels significantly decreased in 2005. But, in 2010, the marginal effect on poverty level of these household at secondary level did not significantly decrease. The decreased negative marginal effects of household poverty level decrease by 10.46% to 1.77% and 14.59% to
8.65% respectively. In 2005, the marginal effect of poverty of household in this sector was negatively affected by at illiterate level, but not statistically significant. No comparison could be made with 2010 as such household did not include in the sample. For casual household members, the impact on poverty level of these household at primary educational level significantly increased in both 2005 and 2010. These negative marginal effects increased from 8.38% to 9.04% at the increasing level. Although the poverty level of these household at middle and high educational level decreased by 2.7% and 30.49% in 2005, although not statistically significantly in middle level. In 2010, the negative marginal effects increased by 7.44% and 13.1%,

Table (4.7)

Probit Estimates for Rural Household Poverty in Myanmar's Services I (2005 and 2010)

Employment Status	Variables	2005				**2010**			
		No. of Employees	% of Employees	$\partial y/\partial x$	s.e	No. of Employees	% of Employees	$\partial y/\partial x$	s.e
Self- Employed	Illiterate	311	0.76	0.1162**	0.0313	7	0.02	0.1785**	0.2060
	Primary	1045	2.56	0.0676**	0.0217	519	1.23	0.0964**	0.040
	Middle	503	1.23	0.0274**	0.0266	270	0.64	0.0439**	0.046
	Secondary	424	1.04	-0.0553**	0.0299	338	0.80	0.0094	0.043
	High	101	0.25	-0.1283**	0.0640	80	0.19	-0.0542**	0.077
Salaried	Illiterate	79	0.19	-0.0040	0.0576	0	0.00	N.A	N.A
	Primary	363	0.89	0.0529**	0.0274	359	0.85	0.0195	0.0300
	Middle	235	0.58	-0.0401**	0.0338	243	0.58	0.0040	0.0374
	Secondary	257	0.63	-0.1046**	0.0360	365	0.87	-0.0177	0.0310
	High	89	0.22	-0.1459**	0.0588	103	0.24	-0.0865**	0.0580
Casual	Illiterate	170	0.42	0.0740**	0.0391	10	0.02	0.2155**	0.1450
	Primary	489	1.20	0.0838**	0.0293	610	1.45	0.0904**	0.0260
	Middle	167	0.41	-0.0270	0.0497	235	0.56	0.0744**	0.0350
	Secondary	128	0.31	0.1011**	0.0462	181	0.43	0.0528**	0.0430
	High	12	0.03	-0.3049**	0.1790	18	0.04	-0.1172*	0.1310

Note: **$\partial y/\partial x$ - marginal effect; s.e - standard error, %- of employee = % of workers in that category out of total sample, *, ** indicate significant at 5% and 1% level respectively, N.A- Non Applicable.**

but it is also significant. According to these results, the impact on poverty level of employment status depends on the educational level in this rural services I sector.

Services II: In services II sector, the percentage of rural workforce has increased by 7.79% from 14.04% in 2005 to 21.83% in 2010. Although the percentage of rural workforce in services I was the second largest in 2005, the percentage of rural workforce in services II was the second largest in 2010. In observing the increase in percentage participation of rural workforce, the percentages of salaried and casual workers have decreased from 18.95% to 17.87% and from 5.63% to 3.16% between 2005 and 2010, respectively. However, the percentage of self-employed has increased from 20.23% in 2005 to 23.27% in 2010.

Looking at the poverty level of household for this sector by employment status and educational level, it has been found that negative marginal effect on poverty level of these households with self-employed household members at middle and secondary educational level were statistically significant in both 2005 and 2010. These rates decreased by (5.49%- 0.45%=5.04%) and (45.3%-2.65%=42.65%) respectively. The impact on poverty level of household with high educational level household members was positive in 2005, but it was also statistically significant. However, in 2010, for the same type of household the marginal effect on poverty level was negative and statistically significant. The positive impact on poverty level of these households with salaried household member at illiterate educational level was statistically significant by 16.68% in 2005, but the rates increased only by (42.70%-16.68%=26.02%) which was not significant. Furthermore, the negative marginal effect on poverty level of these household with household members at high educational level was 3.63% in 2005 and significant. However, the negative marginal effect on poverty of household was 1.70% in 2010 but not significant. For the casual household members, the positive marginal effect on poverty level of household at illiterate educational level was 11.38% in 2005, and significant. However, in 2010, such household did not include in the sample and hence it cannot be compared with the situation in 2005. Moreover, the impact on poverty level of household at secondary level was negative in 2005 , not significant but significant in 2010 . These marginal rates have decreased from 7.78% in 2005 to 3.54% in 2010. Based on the results, educational level has positive marginal effect on poverty level of household in this sector.

Table (4.8)

Probit Estimates for Rural Household Poverty in Myanmar's Services II (2005 and 2010)

Employment Status	Variables	2005				2010			
		No. of Employees	% of Employees	∂y/∂x	s.e	No. of Employees	% of Employees	∂y/∂x	s.e
Self-Employed	Illiterate	149	0.36	0.0735**	0.0478	25	0.06	0.1230**	0.1066
	Primary	524	1.28	0.0343**	0.0278	1053	2.50	0.0385**	0.0303
	Middle	204	0.50	-0.0549**	0.0442	392	0.93	-0.0045**	0.0359
	Secondary	216	0.53	-0.453**	0.0445	494	1.17	-0.0265**	0.0346
	High	67	0.16	0.0817**	0.0644	180	0.43	-0.1178**	0.0561
Salaried	Illiterate	47	0.12	0.1668**	0.0773	4	0.01	0.4270**	0.2695
	Primary	229	0.56	0.0543**	0.0334	351	0.83	0.1506**	0.0298
	Middle	138	0.34	-0.0027	0.0416	211	0.50	0.0564**	0.0376
	Secondary	272	0.67	0.0542**	0.0355	449	1.06	0.0489**	0.0279
	High	399	0.98	-0.0363**	0.0323	629	1.49	-0.0170	0.0300
Casual	Illiterate	74	0.18	0.1138**	0.0733	0	0.00	N.A	N.A
	Primary	163	0.40	0.0445*	0.0563	166	0.39	0.2146**	0.0680
	Middle	45	0.11	0.0801*	0.0840	55	0.13	0.1500**	0.0807
	Secondary	34	0.08	-0.0778	0.1089	56	0.13	0.2839**	0.0940
	High	7	0.02	0.0201	0.1552	16	0.04	-0.0382	0.1335

Note: **∂y/∂x - marginal effect; s.e - standard error, %- of employee = % of workers in that category out of total sample,**

***, ** indicate significant at 5% and 1% level respectively, N.A- Non Applicable.**

4.5.2 Estimated Probit Model: Urban Areas

Household Characteristics: Table (4.9.a) shows probit estimates with the standard errors for each household variable under different control variables over time, 2005 and 2010 for poverty level of urban household in Myanmar by household characteristics and marginal effect. As cost of living for each household in urban areas is different from and higher than that of in rural areas, the employment status for household members in each household in urban areas differs from that in rural areas. Here employment status for urban areas was defined differently from that in rural areas. There are five categories in the employment status for rural areas, namely;

(1) Self-employed, non-agriculture

(2) Agriculture labour

(3) Casual labour

(4) Self-employed, agriculture and

(5) Salaried (agriculture & non-agriculture).

However, there are only three in employment status for urban areas namely;

(1) Self-employed

(2) Salaried and

(3) Casual labour.

The reference employment status is based on the main source of income accrued from employment status of household members. Households with self-employed, salaried and casual household members in urban areas have effect in reducing poverty risk which is similar to that in rural areas, in both 2005 and 2010. The marginal effect for salaried and casual household members in urban areas was negative and significant in 2005. Also, in 2010, the marginal effect was negatively significant. Poor households in urban areas (towns) are likely to send out one or more of their adult members to other locations (cities), to improve their earnings in some ways. It is also found that the effect of remittance would be able to reduce the risk of poverty in urban households. The marginal effect for remittance was negative and significant in both years although the effect in 2010 was higher than in 2005.

Table (4.9 a)

Probit Estimates for Urban Household Poverty with Household Characteristics in Myanmar (2005 and 2010)

Household variables	2005			2010		
	$\hat{\beta}_k$	s.e ($\hat{\beta}_k$)	$\partial y/\partial x$	$\hat{\beta}_k$	s.e ($\hat{\beta}_k$)	$\partial y/\partial x$
Reference variable; Household Member-Self Employment						
Household member; Salaried	-0.1806**	0.0164	-0.0184	-0.1922**	0.0167	-0.0684
Household member; Causal	-0.4199**	0.0291	-0.0427	-0.4673**	0.0313	-0.1662
Remittances	-0.2374**	0.0633	-0.0241	-0.2773**	0.0621	-0.0987
Female household head	-0.1760**	0.0458	-0.0179	-0.1434**	0.0443	-0.0510
Reference variable; Household Member-Buddhist						
Other Religions	-1.1575**	0.0234	-0.2936	-1.0552**	0.0190	-0.2675
Child Women Ratio	0.0436	0.1651	0.0110	0.4395*	0.1704	0.1114
Old Dependency Ratio	0.2818**	0.0948	0.0715	0.1615**	0.0692	0.0409
Land per capita	-0.0089	0.0249	-0.0025	-0.0024	0.0187	-0.0006
sample size	5208			5316		

Note: $\hat{\beta}_k$-eatimated coefficient, $\partial y/\partial x$ - marginal effect, s.e ($\hat{\beta}_k$)- standard error of estimated coefficient, *and ** indicate significant at 5% and 1% level respectively.

In other countries like Uganda, female-headed households face a higher probability of being poor. It is still true even though this study control for labour market characteristics in addition to household size, household composition, education and land holding. These channels are usually used to explain differences in the poverty risk for men and women (Appleton, 1996). The results indicate that women face an additional disadvantage, which can be attributed to any of the independent variables. Besides wage discrimination, the double burden that female heads of household face can be taken account of probably differences in earning possibilities, which does not help them to reduce the risk of poverty. However, in the case of Myanmar, for self-employed females in urban areas the results are not the same as those in other countries in both 2005 and 2010. The effect of female household head on poverty is statistically significant.

When the reference variable was household member Buddhist, the marginal effect on poverty level in household with other religion was negative and statistically significant for both years 2005 and 2010. Furthermore, the marginal effect of other household characteristics; child women ratio, old dependency ratio and land per capita are also studied. The marginal effect of child women ratio is positive on poverty level of households and statistically significant in both 2010 and 2005. Moreover, the marginal effect on poverty level in household with old dependency ratio was positive significant in both 2005 and 2010. Observing the same marginal effect on poverty level deeper,it has been found that the increasing poverty level in 2010 was slower than that of 2005, by 0.06%. The marginal effect of land per capita on poverty level of households in urban areas was negative but not significant in both 2005 and 2010.

As shown in table (4.9 a) land per capita in reference variable' household member-buddhist' is not significant. Therefore, this variable is deleted and reestimated with significant variables. The results are shown in table (4.9 b). In this table, there shows the marginal effects, standard errors and the regression coefficients for each household variable under different control variables over time, 2005 and 2010 for poverty level of urban household in Myanmar by household characteristics. According to this table, the changes in value of marginal effect of other religions and that of old dependency ratio from 2005 to 2010 are very little, but the marginal effect

Table (4.9 b)

Probit Estimates for Urban Household Poverty with Household Characteristics in Myanmar (2005 and 2010)

Household variables	2005			2010		
	$\hat{\beta}_k$	**s.e** ($\hat{\beta}_k$)	∂**y**/∂**x**	$\hat{\beta}_k$	s.e ($\hat{\beta}_k$)	∂**y**/∂**x**
Reference variable; Household Member-Self Employment						
Household member; Salaried	-0.1806**	0.0164	-0.0184	-0.1922**	0.0167	-0.0684
Household member; Causal	-0.4199**	0.0291	-0.0427	-0.4673**	0.0313	-0.1662
Remittances	-0.2374**	0.0633	-0.0241	-0.2773**	0.0621	-0.0987
Female household head	-0.1760**	0.0458	-0.0179	-0.1434**	0.0443	-0.0510
Reference variable; Household Member-Buddhist						
Other Religions	-1.1675**	0.0236	-0.0126	-1.0585**	0.0190	-0.2681
Child Women Ratio	0.0654	0.1663	0.0007	0.4752**	0.1693	0.1204
Old Dependency Ratio	0.2903**	0.0949	0.0031	0.1643*	0.0687	0.0416
sample size	5208			5316		

Note: $\hat{\beta}_k$-eatimated coefficient, **∂y/∂x - marginal effect, s.e ($\hat{\beta}_k$)- standard error of estimated coefficient, *and ** indicate significant at 5% and 1% level respectively.**

of child women ratio is 10.04% in table (4.9 a) and it is 11.97% in the estimation by omitting nonsignificant variable as shown in table (4.9 b).

Labour Market Variables: Tables (4.10), (4.11), (4.12), (4.13) and (4.14) present the marginal effects, standard errors and the percentage of urban workers with different employment status and educational level by industries for 2005 and 2010, in Myanmar. Furthermore, appendix table (4) represents the numbers of urban working household members with each employment status at each educational level by industries (2005 and 2010) in Myanmar. These tables facilitate the comparison of the effects of structural changes, including the share of workers with the respective employment status-industry- education level combination on the total workforces over time. The rows represent the different employment status for each industry group. Inside each employment status, different educational levels are presented.

Agriculture: Urban agriculture workforce in Myanmar was 4.08% in 2005 and 3.66% in 2010 and it was only one fifth of the percentage of rural agriculture workforce in both years. In the percentage of urban agriculture workforce by educational level, the percentage of illiterate workforce for all three employment status, decreased from 0.62% in 2005 to 0.04% in 2010, although the percentages at other educational levels did not change noticeably between 2005 and 2010. Observing the percentage of urban agriculture workforce by employment status, any noticeable changes could not be found.

In studying the marginal effect on poverty level of household in this sector by employment status and educational level, it is found that negative marginal effect on poverty level of these households with self-employment at high educational level was 38.09% and statistically significant in 2005. In 2010, it was 16.62% and also significant. For the salaried household members, the impact on poverty level of these households at illiterate level was positive and statistically significant and it decreased from 6.58% in 2005 to 5.44% in 2010 but not significant. Moreover, the marginal effect of poverty level on household at high level was negative at 23.44% and significant in 2005 and it was still negative at 15.44% in 2010, also significant. At the secondary educational level, the negative marginal effect of poverty level on household in 2005 was statistically significant, but it was not signifiant in 2010. The positive marginal effect on poverty level of household with casual household members at illiterate educational level was 11.03% significant in 2005.

Table (4.10)

Probit Estimates for Urban Household Poverty in Myanmar's Agriculture Sector (2005 and 2010)

Employment Status	Variables	2005				2010			
		No. of Employees	% of Employees	$\partial y/\partial x$	s.e	No. of Employees	% of Employees	$\partial y/\partial x$	s.e
Self-Employed	Illiterate	126	0.31	0.0647**	0.0409	9	0.02	0.2591**	0.1657
	Primary	284	0.70	0.0707**	0.0385	347	0.82	0.0139	0.0343
	Middle	165	0.40	0.0061	0.0396	159	0.38	0.0619**	0.0427
	Secondary	184	0.45	0.0759**	0.0386	247	0.59	-0.0074	0.0371
	High	43	0.11	-0.3809**	0.1478	63	0.15	-0.1662**	0.0985
Salaried	Illiterate	68	0.17	0.0658**	0.0479	7	0.02	-0.0544	0.1971
	Primary	172	0.42	0.0265**	0.0290	168	0.40	0.0538**	0.0447
	Middle	95	0.23	0.0379*	0.0481	94	0.22	0.0462**	0.0506
	Secondary	118	0.29	-0.0537**	0.0479	141	0.33	-0.0050	0.0409
	High	74	0.18	-0.2344*	0.0827	67	0.16	-0.1544**	0.0950
Casual	Illiterate	57	0.14	0.1103**	0.0681	0	0.00	N.A	N.A
	Primary	144	0.35	0.1424**	0.0524	120	0.28	0.0390**	0.0450
	Middle	77	0.19	0.0361	0.0550	50	0.12	0.0504*	0.0754
	Secondary	54	0.13	0.0655*	0.0728	66	0.16	-0.0606**	0.0698
	High	3	0.01	0.2854**	0.2998	6	0.01	-1.005	6.2226

Note: **$\partial y/\partial x$ - marginal effect; s.e - standard error, %- of employee = % of workers in that category out of total sample,**

****, * indicates significance at 1% and 5% level respectively, N.A- Non Applicable.**

No comparison could be made with 2010 as such household were not included in the sample**.** Furthermore, the positive marginal effect on poverty level of household at secondary and high educational level were 6.55% and 28.54% respectively and it was significant in 2005, but, in 2010, this impact on poverty level of household has become negative by 6.06% and 100.5% respectively and it is not statistically significant in high level. Based on the small sample included, it was found that the effect of secondary and high educational level has changed between 2005 and 2010, showing the importance of higher education in poverty reduction.

Manufacturing: The percentage of urban manufacturing workforce in Myanmar is the second smallest in both years 2005 and 2010. The total urban workforce of 3.27% in 2010 is smaller than that of 3.88% in 2005 by 0.61%. In observing the decrease in percentage participation of rural workforce, the percentage of self-employed and casual workers has decreased by 42.27% to 32.72% and 10.05% to 8.56% between 2005 and 2010, respectively. However, the percentage of salaried worker increased from 47.68% in 2005 to 58.72% in 2010.

In observing the marginal effect on poverty level of household in this sector by employment status and educational level, It was found that positive marginal effect on poverty level of these households with self-employed household member at illiterate educational level was 2.82% in 2005, but not significant. No comparison could be made with 2010 as such household did not include in the sample**.** In the secondary and high educational level, the marginal effect on poverty level of households was negative in both years 2005 and 2010, statistically significant. The rates of marginal effect on poverty of household had decreased by (4.58% - 4%=0.58%) and (13.89% - 7.33%=6.56%) between 2005 and 2010 respectively. For

salaried household members, the marginal effect on poverty level of household at high educational level was negative in 2005 and significant, but not significant in 2010. At illiterate educational level, the impact on poverty level of household was negative in both years, but not significant. The positive impact on poverty level of household at primary educational level has in both years 2005 and 2010, it was statistically significant. The rate of marginal effect on poverty level of household has decreased from 15.39% in 2005 to 11.8% in 2010. The marginal effect on poverty level of households at the secondary educational level

Table (4.11)

Probit Estimates for Urban Household Poverty in Myanmar's Manufacturing Sector (2005 and 2010)

Employment Status	Variables	2005				2010			
		No. of Employees	% of Employees	∂y/∂x	s.e	No. of Employees	% of Employees	∂y/∂x	s.e
Self-Employed.	Illiterate	61	0.15	0.0282	0.0588	0	0.00	N.A	N.A
	Primary	165	0.40	0.0600**	0.0470	109	0.26	0.0149	0.0851
	Middle	132	0.32	-0.0166	0.0566	86	0.20	0.0024	0.0942
	Secondary	232	0.57	-0.0458**	0.0520	189	0.45	-0.0400**	0.0737
	High	78	0.19	-0.1389**	0.0865	67	0.16	-0.0733**	0.1214
Salaried	Illiterate	31	0.05	-0.0047	0.0570	2	0.00	-0.0670	0.3829
	Primary	183	0.45	0.1539**	0.0386	189	0.45	0.1180**	0.0368
	Middle	134	0.33	0.0902**	0.0434	140	0.33	0.0607**	0.0471
	Secondary	239	0.59	0.0835**	0.0360	292	0.69	-0.0366**	0.0385
	High	169	0.41	-0.0316*	0.0435	185	0.44	-0.0229	0.0445
Casual	Illiterate	11	0.03	0.1848**	0.1507	0	0.00	N.A	`N.A
	Primary	51	0.12	0.0789**	0.0663	41	0.10	-0.0687*	0.0824
	Middle	44	0.11	0.2001**	0.0840	28	0.07	0.1843**	0.1390
	Secondary	40	0.10	0.0267	0.0762	40	0.09	-0.0208	0.1170
	High	14	0.03	0.1220**	0.0126	10	0.02	-0.2201**	0.2210

Note: **∂y/∂x - marginal effect; s.e - standard error, %- of employee = % of workers in that category out of total sample, **, * indicates significance at 1% and 5% level respectively, N.A- Non Applicable.**

was positive at 8.35% in 2005 which was significant,but, that of 2010 was negative at 3.66% and significant. The positive impact on poverty level of household with casual household members at illiterate educational level was 18.48% in 2005 and significant. In this case again no comparison could be made with 2010 as such household members were not included in the sample. At secondary level, the impact of marginal effect on poverty level of households was not statistically significant in both 2005 and 2010. At high school level, the impact of marginal effect on poverty level of households was 12.28% with positive in 2005 and 22.05% with negative in 2010. Both were statistically significant.

Construction: Compared to other sectors the percentage of urban construction workforce in Myanmar was the smallest sector in both 2005 and 2010. The percentage of urban workforce in 2010 (1.63%) was higher than that of in 2005(1.31%). Studying the percentage of urban workforce by educational level, the percentage of urban workforce at illiterate educational level decreased by 0.09% and at secondary educational level increased by 0.25% in between 2005 and 2010. Observing the percentage of urban workforce by employment status, the percentage of urban workforce at salaried workers increased by 0.22%, but the remaining employment status did not nearly change anything between 2005 and 2010.

In studying the marginal effect on poverty level of households in construction sector by employment status and educational level, it was found that the marginal effect on poverty level of self-employed households with middle and secondary educational level were negative at 28.02% and 15.94% in 2005 respectively, but impact on poverty level of such household change to be positive at 5.3% and 1.94% respectively in 2010, though not significant. It was noticed that household members at illiterate and high educational level were not included in the sample in 2005 and household members at illiterate level were not included in the sample in 2010. The positive impact on poverty level of household at high level was 4.06% though not significant. For salaried household members, the marginal effects on poverty level of households at middle and above educational level were negative in both 2005 and 2010. These marginal effects on poverty level decreased by 11.7% at high level within five years. The positive marginal

Table (4.12)

Probit Estimates for Urban Household Poverty in Myanmar's Construction Sector (2005 and 2010)

Employment Status	Variables	2005				2010			
		No. of Employees	% of Employees	∂y/∂x	s.e	No. of Employees	% of Employees	∂y/∂x	s.e
Self-Employed	Illiterate	0	0.00	N.A	N.A	0	0.00	N.A	N.A
	Primary	28	0.07	0.0277	0.1606	16	0.04	-0.0356	0.2616
	Middle	26	0.06	-0.2808**	0.1955	31	0.07	0.0530	0.1680
	Secondary	19	0.05	-0.1594*	0.2014	25	0.06	0.0194	0.1753
	High	0	0.00	N.A	N.A	7	0.02	0.0406	0.2627
Salaried	Illiterate	10	0.02	-0.2351**	0.2048	2	0.00	0.2210	0.4262
	Primary	100	0.24	0.0406	0.0652	92	0.22	0.0636**	0.0600
	Middle	52	0.13	-0.0540*	0.0803	90	0.21	-0.0058	0.0724
	Secondary	76	0.19	-0.1285**	0.0808	131	0.31	-0.0413	0.0700
	High	30	0.07	-0.2532**	0.1339	57	0.14	-0.1362**	0.1010
Casual	Illiterate	27	0.07	0.0613*	0.0722	0	0.00	N.A	N.A
	Primary	70	0.17	0.3399**	0.1176	63	0.15	0.0620**	0.0651
	Middle	54	0.13	0.3275**	0.1211	66	0.16	0.0528*	0.0816
	Secondary	43	0.11	0.2813**	0.1124	99	0.23	-0.0095	0.0655
	High	0	0.00	N.A	N.A	9	0.02	-0.0571	0.1871

Note: **∂y/∂x - marginal effect; s.e - standard error, %- of employee = % of workers in that category out of total sample, **, * indicates significance at 1% and 5% level respectively, N.A- Non Applicable.**

effect on poverty level of these households with casual household members at primary, middle and secondary educational level were 33.99%, 32.75% and 28.13% in 2005 and significant, but in 2010, the marginal effect on poverty level of household were still positive at middle education level. Those at secondary and high levels were not statistically significant. The household members at high educational level were not included in the sample in 2005.

Services I: The percentage of urban workforce in services I sector was the highest in 2005 and the second highest in 2010. Comparing the changes in percentage of urban workforce between 2005 and 2010, the percentage of urban workforce in self-employed workers was the highest decrease with 2.49%, wherein, the percentage of urban workforce in self-employed status at primary educational level was the highest decrease with 0.89%, and illiterate educational level was the second highest decrease with 0.44%. Studying the percentage of urban workforce by educational level primary educational level has the highest decrease with 1.26%, between 2005 and 2010.

In studying the marginal effect on poverty level of household in this sector by employment status and educational level, it was found that the marginal effects on poverty level for the households with self-employed household member at high educational level were negative at 7.87% in 2005 and 11.42% in 2010. At illiterate educational level, the marginal effect on poverty level of household was positive at 11.45% and significant in 2005, but, it was negative at 1.65% and not significant in 2010. Moreover, the marginal effects on poverty level of household at primary and middle educational level were positive and significant in 2005, but the marginal effect on poverty level of household were positive and significant in 2010. The marginal effect on poverty of household at high educational level was negative at 7.87% in 2005 and 11.42% in 2010 and was significant in both years. For salaried household members, the positive marginal effect on poverty of the household was significant at primary educational level both 2005 and 2010. There was a decrease of 1.06% between two years**.** Although the marginal effect on poverty level of household at high educational level was negative at 6.06% and significant in 2005, it was negative at 6.32% in 2010, but also significantly. At secondary educational level, the negative marginal effect on poverty level of household was not statistically significant in both

Table (4.13)

Probit Estimates for Urban Household Poverty in Myanmar's Services I (2005 and 2010)

Employment Status	Variables	2005				2010			
		No. of Employees	% of Employees	∂y/∂x	s.e	No. of Employees	% of Employees	∂y/∂x	s.e
Self-Employed	Illiterate	188	0.46	0.1145**	0.0358	8	0.02	-0.0165	0.1867
	Primary	774	1.90	0.0957**	0.0197	428	1.01	0.0520**	0.0301
	Middle	547	1.34	0.0628**	0.0243	345	0.82	0.0217**	0.0348
	Secondary	873	2.13	0.0220**	0.0209	656	1.56	-0.0165*	0.0278
	High	328	0.80	-0.0787**	0.0356	312	0.74	-0.1142**	0.0517
Salaried	Illiterate	65	0.16	-0.0120	0.0481	0	0.00	N.A	N.A
	Primary	324	0.79	0.0679**	0.0262	238	0.56	0.0573**	0.0347
	Middle	320	0.78	0.0367**	0.0259	213	0.51	0.0854**	0.0374
	Secondary	559	1.37	-0.0039	0.0241	585	1.39	-0.0208*	0.0329
	High	370	0.91	-0.0606**	0.0269	306	0.73	-0.0632**	0.0435
Casual	Illiterate	71	0.17	0.1410**	0.0578	5	0.01	0.5049**	0.3019
	Primary	254	0.62	0.1190**	0.0357	202	0.48	0.1166**	0.0433
	Middle	138	0.34	-0.0135	0.0405	112	0.27	0.1007**	0.0636
	Secondary	152	0.37	-0.0160	0.0467	181	0.43	0.0310	0.0499
	High	28	0.07	-0.2113**	0.121	35	0.08	0.1068**	0.0729

Note: ∂y/∂x - marginal effect; s.e - standard error, %- of employee = % of workers in that category out of total sample, **, * indicates significance at 1% and 5% level respectively, N.A- Non Applicable.

years 2005 and 2010. Between 2005 and 2010, there was an increase of 1.69%. For casual household members, the positive marginal effect on poverty level of household at the primary level was significant in both 2005 and 2010, with not much difference. At middle and above educational level, the marginal effect on poverty level of household was negative and not significant in 2005 except high level, but it was positive in 2010 through not significant only secondary level. According to the findings, the marginal effect on poverty level of households with any employment status in this sector has been affected by a kind of interaction between employment status and educational level.

Services II: Services II sectors changed from the second highest percentage of urban workforce in 2005 to the highest percentage of urban workforce in 2010 in Myanmar. Studying the increasing percentage of urban workforce from 2005 to 2010 by employment status, self-employed worker was the highest with 2.68% and the second highest was salaried workers with 1.91%. Observing the increasing percentage of urban workforce by educational level for all employment status, in secondary educational level was the second highest with 1.74% and high educational level was the highest with 1.6%.

In studying the marginal effect on poverty level of household in this sector by employment status and educational level, It was found that marginal effect on poverty level of these household with self employed at high educational level was negative in both years 2005 and 2010, the marginal effects being 9.03% in 2005 and 6.39% in 2010. At the secondary educational level, although the marginal effect on poverty level of households with self-employed household member at middle educational level in 2005 was smaller than 2010, at secondary and high educational level in 2005 was higher than that of 2010. It has been founded that the impact on poverty level of household with salaried household members, the marginal effect on poverty level was negative at primary and above educational level in both 2005 and 2010. The rate of change in 2005 was smaller than that of 2010.

Table (4.14)

Probit Estimates for Urban Household Poverty in Myanmar's Services II (2005 and 2010)

Employment Status	Variables	2005				2010			
		No. of Employees	% of Employees	∂y/∂x	s.e	No. of Employees	% of Employees	∂y/∂x	s.e
Self-Employed	Illiterate	84	0.21	0.1040**	0.0547	10	0.02	0.0173	0.2161
	Primary	306	0.75	0.0985**	0.0380	611	1.45	0.0323**	0.0331
	Middle	199	0.49	0.0534**	0.0450	417	0.99	0.0525**	0.0348
	Secondary	355	0.87	0.0066	0.0384	805	1.91	-0.0003	0.0265
	High	209	0.51	-0.0903**	0.0526	475	1.13	-0.0639**	0.0375
Salaried	Illiterate	42	0.10	0.0052	0.0785	0	0.00	N.A	N.A
	Primary	203	0.50	0.0423**	0.0304	251	0.60	0.4521**	0.0289
	Middle	183	0.45	0.0307**	0.0322	278	0.56	0.0582**	0.0292
	Secondary	458	1.12	-0.0260**	0.0288	778	1.85	0.0092**	0.0195
	High	860	2.11	-0.0581**	0.0240	1302	3.09	-0.0162**	0.0194
Casual	Illiterate	33	0.08	0.0399	0.1068	4	0.01	0.2609**	0.2370
	Primary	102	0.25	0.0850**	0.0604	73	0.17	0.0214	0.0961
	Middle	49	0.12	0.0917**	0.0615	44	0.10	0.0932**	0.0937
	Secondary	65	0.16	0.1299**	0.0643	56	0.13	0.0314	0.0918
	High	18	0.04	-0.3627**	0.1896	16	0.04	-0.0212	0.1527

Note: ∂y/∂x - marginal effect; s.e - standard error, %- of employee = % of workers in that category out of total sample, **, * indicates significance at 1% and 5% level respectively, N.A- Non Applicable.

CHAPTER V
CONCLUSION

This chapter presents findings, recommendations and further research which are obtained from the study of the relationship between household characteristics, employment and poverty by using probit model, which could be useful in planning for reduction in poverty of household in Myanmar. The study is based on the data from Integrated Household Living Conditions Assessment Survey conducted in 2005 and 2010.

5.1 Findings

At the micro level, the relationship between household characteristics and poverty are important for poverty reduction in both rural and urban areas. According to this study, in rural areas, the poverty risk of households with employment status, self-employed in agriculture can be reduced than other employment status: agriculture labour, casual labour and salaried (agriculture and non-agriculture) between 2005 and 2010. In urban areas, the poverty risk of household with salaried workers can be reduced more than casual household member. It can be concluded that the probabilities of household being poor are clearly linked to the employment status in both rural and urban areas. Furthermore, in studying the other household characteristics such as remittance, female household head, other religions, child women ratio, old dependency ratio and land per capita, the poverty risk of urban household can be reduced more than that of rural household. On the other hand, it has been found that the probability of household being poor clearly depends on the regions in Myanmar.

Moreover, the relationship between employment and poverty also reveals the importance of employment status and education for poverty reduction in both rural and urban areas. The methodology adopted in this analysis has tried to isolate the effects of labour market characteristics, employment status, industry and education of the worker to reduce poverty risks for the households. In rural agriculture and manufacturing sectors, the poverty risk of household with salaried household members can be reduced more than other employment status: self-employed and casual household members. Especially, in studying the educational level, the poverty risk for household of salaried

workers with high educational level household members can be reduced more than other educational level: illiterate, primary, middle and secondary educational level in rural areas. In construction sector, the poverty risk of household for each household member with any employment status at any educational level has been found to be the same in both urban and rural areas between 2005 and 2010. In services I and services II sectors, the poverty risk of household for each rural household member with any employment status at any educational level cannot be reduced, but, for urban household members with employment status across by educational level can contribute reduction of poverty level. Base on the results, it can be concluded that the probability of household being poor clearly depends on the educational level and employment status as well as by sector of the economy in both rural and urban areas.

In rural agriculture and manufacturing, it has been found that the poverty risks of household with self-employed and casual household members depend on educational level and skill. Because of this, self-employed and casual household members working in rural agriculture and manufacturing sectors at low educational level and low skill have produced low productivity. Furthermore, the important roles of labour market/employment status for poverty reduction have been exposed. Working household members with rather high education level are needed to substantially reduce the risk of poverty for households. The need for education is especially high in urban areas. It has been found that to reduce poverty in Myanmar for urban households with wholesale and retail trade including repairs,hotels and restaurants transports, storage and communication and other community, social and personal services,financial intermediation, real estate, renting and business acivities, public administration, education, health and social work, activities of private household head as employers and extra-territorial organization and bodies are very important. Moreover, it has been found that the probability of households being poor in Myanmar does not clearly depend on education in construction sector.

Across the employment status category household members with salaried workers were better off than self-employed in most industries, except construction sector, in both rural and urban areas. The households with casual labour were worse off irrespective of the industry they were employed in. The findings show that in both rural and urban areas, the probability of household being poor clearly depends on the sector across by employment status and educational level. This means that education alone is

not enough to reduce poverty risks but the sector or structure of employment is also important.

As some of the jobs need experience the opportunities for workers to enter the workforce in some sectors, despite having the capabilities or the educational levels, are small. Service I industry, which observed high growth in employment, has not been able to reduce poverty except at higher levels of education for the salaried and self-employed categories. An interesting difference between rural and urban areas is that the effect of education is smaller in urban areas than in rural areas. In other workers, with the same level of education, the probability of being poor is higher in urban areas. The lower values of marginal effect are a reflection of the higher importance that education has in urban settings. The importance of education clearly comes out in the analysis as a major determinant of poverty in both the rural and urban areas. There are clear pay-offs from education in terms of job quality and improvements in the consumption levels.

5.2 Recommendations

Myanmar has a total of 12.25 million hectares of arable land and permanent crops, the 25th-largest endowment in the world despite the fact that Myanmar is only the 38th-largest country by total area. Although the country's endowment of water and fertile land is abundant, productivity in Myanmar's agriculture sector is low. The sector's low productivity and the low level of inputs such as seeds, fertilizers, water, and machinery suggest that there is significant room to grow. There is also large scope to increase the share of fruits, vegetables, coffee, palm oil, rubber, and other high-value crops as well as the production of fisheries.

Myanmar has large assets of national resources in timber, fisheries, oil, gas-it's most important export and precious minerals such as rubies, sapphires, and jade. Many of these natural resource reserves are largely unexplored today-with new technologies, the potential could be much higher than current estimates.

Myanmar's labour costs today are comparatively low, giving the country an opportunity to boost output in labour-intensive manufacturing sectors. However, labour productivity in the manufacturing sector is also weak. To compete in the region, Myanmar will need to improve labour productivity. To achieve the objective of that higher productivity, there is scope over time to make the transition to more value-added

sectors. Myanmar's infrastructure is not sufficient today to support the higher growth and future demand driven by developing industrial sectors and an urbanizing population.

Moreover, Education, training and lifelong learning foster a virtuous circle of higher productivity, more employment of better quality, income growth and development.

In developing countries, the education and literacy rates are lowest for girls and women in rural areas. Broader availability of better quality education is needed to enable young people to acquire core skills and then be able to learn occupational and work skills. Ways of improving training and employment services for disadvantaged young persons, especially those who have been removed from child labour, live in rural areas or whose families work in the informal economy, with a view to helping them enter the formal labour market and improving their long-term employability.

Productivity improvements can also be made at different levels. The productivity of individuals may be reflected in employment rates, wage rates, stability of employment, job satisfaction or employability across jobs or industries. Productivity of enterprises, in addition to output per worker, may be measured in terms of market share and export performance. The benefits to societies from higher individual and enterprise productivity may be evident in increased competitiveness and employment or in a shift of employment from low to higher productivity sectors.

Productivity growth can raise incomes and reduce poverty in a vicious circle. Productivity growth reduces production costs and increases returns on investments, some of which turn into income for business owners and investors and some of which are turned into higher wages. Prices may go down, consumption and employment grow and people move out of poverty. The vicious circle is also fed through the investment side of the economy when some productivity gains are reinvested by a firm into product and process innovations, plant and equipment improvements and measures to expand into new markets, which spurs further output growth and productivity.

In the long term, productivity is the main determinant of income growth. Productivity gains increase real income in the economy, which can be distributed through higher wages. A low-wage, low-skill development strategy is unsustainable in the long term and incompatible with poverty reduction. Investment in education and skills helps to "pivot" an economy towards higher value added activities and dynamic growth sectors.

Myanmar can be able to reduce the poverty of households their skills base so as to increase both the quantity and the productivity of labour employed in the economy. Inadequate education and skills development keep economies trapped in a vicious circle of low education, low productivity and low income.

Myanmar may use strategies to upgrade and enhance the relevance of skill training and to improve access to skills for more women and men can instead help poverty of Myanmar move to a vicious circle of higher productivity, employment and incomes growth, and development. Skill development is central to improving productivity. In turn, productivity is an important source of improved living standards and growth.

Effective skills development systems which connect education to technical training, technical training to labour market entry and labour market entry to workplace and lifelong learning can help poverty reduction, sustain productivity growth and translate that growth into more and better jobs.

Furthermore, Myanmar may push the technological frontier. Myanmar must move to reduce the poverty of households towards that frontier. Experience of other developing countries could be use for investment in non-traditional sectors and for the application of new technologies to a broader variety of economic activities. This means that skills and technology have to be enhanced simultaneously in order to ensure the sustainability of productivity growth and development. At the early stage of technological development, it is essential to achieve a minimum level of educational attainment in the population. Technological and industrial advancement requires the broad availability of high-quality secondary education and vocational training. Finally, the ability to innovate as well as to adopt more complex and sophisticated technologies requires technical and vocational education and training at the tertiary level, and particularly skills in research and development.

5.3 Further Research

(1) As concerned with model adequacy the probit estimates for urban poverty with the reference variable 'Household Members Self-Employmant' showed a good fit to the model only in 2010. The chi-square value was 4219.912 with the 24.7 percent of significance level. Other estimates in each model represented poor fit with large chi-square values with very small significance level. Therefore, it will be one of future

researches to be extended for this thesis. In order to obtain the estimates with good model adequacy.

(2) As an another further research, by changing the poverty lines and measure the marginal effects of different exogenous variables on the poverty are intended to extended, which is a kind of sensitivity analysis. Furthermore, this study can be extended to investigate growth and relation between employment and GDP can be best studied on a macro level. For the present data, Oaxaca decomposition can be also used.

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APPENDICES

AppendiceTable (1)

List of IHLCA's Stratum and Sample Townships

No	Stratum Name	State/Region	Township Name	No. of Township	n
1	Yangon City	Yangon	Pabedan, Lanmadaw, Thingangyun, North Okkalapa, Thakayta, Mingaladon, Dagon Myothit	7	1224
2	Yangon Other	Yangon	Thanlyin, Taikkyi	2	552
3	Mandalay City	Mandalay	Chan MyaTharzi, MaharAung	2	372
4	Kyauk Se	Mandalay	Sint Kai, Ta Da U	2	312
5	Nyaung U	Mandalay	Nyaung U	1	192
6	PyinOoLwin	Mandalay	Mogok, Madaya	2	336
7	Myingyan	Mandalay	Myingyan, Kyauk Pa Ta	2	432
8	MDY other 1	Mandalay	Patheingyi,AmaraPura	2	240
9	Meiktila	Mandalay	Wun dwin, Meiktila	2	360
10	Ya Me Thin	Mandalay	Le Way, Pyawbwe	2	444
11	Putao	Kachin	Putao	1	156
12	Bhamo	Kachin	Man si, Bhamo	2	204
13	Myintkyina	Kachin	Myintkyina, Mogaung	2	156
14	Mohnyin	Kachin	Mogaung, Mohnyin	2	156
15	Loi kaw	Kayah	Liokaw	1	156
16	Pha An	Kayin	Thantaung, Pha An	2	384
17	Kaw KaYei	Kayin	Kaw KaYei	1	180
18	Myawaddy	Kayin	Myawaddy	1	156
19	Falam	Chin	Haka, Tedim	2	168
20	Min Dat	Chin	Ma Tu Pi, Min Dat	2	156
21	Ka Lay	Sagaing	Ka Lay, Mingin	2	152
22	KaThar	Sagaing	Kaw Lin, WunTho	2	312
23	Kham Tee	Sagaing	Home Ma Lin, Khan Tee	2	156
24	Sagaing	Sagaing	Sagaing, Mayung	2	288
25	Tamu	Sagaing	Tamu	1	156
26	MonYwa	Sagaing	Yin Mar Pin, Mon Ywa	2	432
27	Maw Laik	Sagaing	Maw Laik, Phaungpyin	2	156
28	Shwe Bo	Sagaing	Wet Let, Kant Ba Lu	2	468
29	Kawthoung	Tanintharyi	Kawthoung, Bokepyin	2	156
30	Dawei	Tanintharyi	Yebyu, Lounglon	2	276
31	Myeik	Tanintharyi	Myeik, Palaw	2	288
32	Bago	Bago (E)	Nyaung lebin, Daik U	2	528
33	Toungoo	Bago (E)	Yaedashe, Pyu	2	408
34	Pyay	Bago (W)	Thegon, Shwedaung	2	384
35	Thayawady	Bago (W)	Monyo, Gyobingauk	2	456

List of IHLCA's Stratum and Sample Townships (Continuous)

table continuous					
36	GanGaw	Magway	Gangaw,Htilin	2	192
37	Pakokku	Magway	Pauk, Pakokku	2	408

38	Magway	Magway	Natmauk, Magway	2	480
39	Minbu	Magway	Pwintphyu, Salin	2	324
40	Thayet	Magway	Sin paungwe, Kamma	2	348
41	Mawlamyine	Mon	Ye,Thanbyuzayat	2	432
42	Thaton	Mon	Bilin, Paung	2	336
43	KyaukPhyu	Rakhine	Yan Bye, KyaukPhyu	2	288
44	Sittway	Rakhine	Sittway, Yathedaung	2	432
45	Maungtaw	Rakhine	Maungtaw, Buthidaung	2	300
46	Thandwe	Rakhine	Toungup, Gwa	2	228
47	Loilin	Shan (S)	Loilin	1	156
48	Taunggyi	Shan (S)	Phekon, Taunggyi	2	468
49	Lashio	Shan (N)	Tantyan, Lashio	2	250
50	Kyaukme	Shan (N)	Shipaw, Naungkhio	2	300
51	Muse	Shan (N)	Kukia, Namkham	2	228
52	Laukine	Shan (N)	Laukine	1	-
53	Kunlon	Shan (N)	Kunlon	1	156
54	Minesat	Shan (E)	Maing Ton(*), Minesat	2	84
55	Kengtung	Shan (E)	Kengtung, Minekat	2	204
56	Mingphyat	Shan (E)	Minephyat	1	156
57	Tachileik	Shan (E)	Tachileik	1	156
58	Pathein	Ayeyarwaddy	Pathein, Kangyidaunt	2	504
59	Phyarpon	Ayeyarwaddy	Bogale, Kyaiklatt	2	372
60	Myaungmya	Ayeyarwaddy	Myaungmya, Labutta	2	468
61	Maupin	Ayeyarwaddy	Maupin,Nyaung Don	2	408
62	Hinthada	Ayeyarwaddy	Hinthada, Zalun	2	480
Total					18660

Sources: Integrated Household Living Conditions Assessment Survey (2005 and 2010)

Appendix Table (2)

Poverty Incidence by Region in Myanmar (2005)

2005	Coastal region				Delta region				Dry region				Hilly region				Union			
	SE	Sal	Casu	Total	SE	Sal	Casu	Total	SE	Sal	Casu	Total	SE	Sal	Casu	Total	SE	Sal	Casu	Total
Agri	28.46	40.16	50.02	37.26	22.55	32.29	47.16	32.86	50.92	53.39	50.84	**51.66**	34.66	40.14	55.56	40.74	34.38	40.26	51	39.93
Manu	26.9	23.47	51.18	31.79	14.56	22.84	30.41	**20.55**	32.21	38.78	41.12	36.02	31.23	45.97	58.02	43.12	25.13	34.01	49.75	33.02
Const	5.66	43.82	34.76	33.78	22.09	28.27	35.26	29.88	29.84	42.3	50.01	42.47	30.11	44.91	43.15	42.48	22.9	37.09	39.44	36.04
Ser-I	18.62	20.12	42.3	23.78	18.47	21.2	33.12	21.99	30.22	36.11	36.45	32.75	24.28	31.38	47.66	30.51	21.61	25.84	39.14	25.95
Ser-II	20.73	15.85	53.6	25.25	19.09	18.91	39.28	20.**97**	26.64	30.81	46.38	30.35	26.07	29.42	40.83	29.44	21.92	22.84	43.43	24.77
Total	24.04	29	47.79	31.3	20.08	24.87	42.36	26.66	44.29	46.33	47.45	45.35	31.62	37.94	53.29	38.06	29.01	33.11	47.52	34.09

Note: S.E-Self-Employed; Sal-Salaried: Casu- Casual; Agri-Agriculture; Manu-Manufacturing; Const-Construction; Ser-I-Services I; Ser-II-Services II.

Appendix Table (3)

Poverty Incidence by Region in Myanmar (2010)

2010	Coastal region				Delta region				Dry region				Hilly region				Union			
	S.E	Sal	Casu	Total	S.E	Sal	Casu	Total	S.E	Sal	Casu	Total	S.E	Sal	Casu	Total	S.E	Sal	Casu	Total
Agri	23.72	32.27	52.40	33.39	16.65	29.47	37.15	26.04	39.67	41.93	32.86	**39.27**	20.12	20.75	36.00	23.44	23.97	27.43	37.84	28.10
Manu	21.45	42.80	40.52	36.26	18.71	25.28	50.77	26.21	12.85	17.91	43.76	20.61	14.09	33.20	26.04	26.39	15.97	29.15	36.71	26.42
Const	11.47	31.26	38.06	33.09	14.75	28.77	33.71	28.90	19.15	31.93	26.19	27.08	8.90	32.15	37.66	31.98	13.20	30.62	34.69	30.54
Ser-I	11.48	25.47	53.23	28.25	16.79	20.91	45.16	25.79	14.19	23.41	42.40	22.99	15.25	30.38	33.98	25.15	15.21	24.53	43.40	25.54
Ser-II	21.33	16.74	68.07	25.22	12.32	14.88	42.10	**14.47**	18.34	21.85	27.26	20.56	13.10	19.43	29.49	16.90	14.53	17.28	44.72	17.47
Total	20.53	27.71	51.41	30.52	15.42	22.55	39.64	23.21	31.95	32.11	34.19	32.35	17.78	23.85	34.54	23.17	19.97	24.87	38.98	25.48

Note: S.E-Self-Employed; Sal-Salaried: Casu- Casual; Agri-Agriculture; Manu-Manufacturing; Const-Construction; Ser-I-Services-I; Ser-II-Services-II.

Appendix Table (4)

The Numbers of Rural/Urban Working Household Members with each Employment Status at each Educational Level by Industries (2005 and 2010) in Myanmar

Sector	2005						2010					
	Rural		Urban		Total	Total %	Rural		Urban		Total	Total %
	Number of employing	%	Number of employing	%	Number of employing		Number of employing	%	Number of employing	%	Number of employing	
Agriculture	19118	46.82	1664	4.08	20782	50.90	18685	44.31	1544	3.66	20229	47.97
Manufacturing	2162	5.29	1584	3.88	3746	9.17	2340	5.55	1378	3.27	3718	8.82
Construction	671	1.64	535	1.31	1206	2.95	1365	3.24	688	1.63	2053	4.87
Services I	4373	10.71	4991	12.22	9364	22.93	3338	7.92	3626	8.6	6964	16.51
Services II	2568	6.29	3166	7.75	5734	14.05	4081	9.68	5123	12.14	9204	21.83

Sources: Calculated from IHLCA I and II data

Urban household member characteristics in reference variables, household member buddhistic (2005)

Data Information

		N of Cases
Valid		5530
Rejected	Out of Range[a]	0
	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		17161
Poverty_Status	0	4294
	1	1236

a. Cases rejected because of out of range group values.

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Parameter Estimates

Parameter			Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
PROBIT[a]	HHM_Reg_Other_Exp_Bud		-1.157	.023	-49.430	0.000	-1.203	-1.112
	Child_Women_Ratio		.044	.165	.264	.792	-.280	.367
	Old_Age_Depend_Ratio		.282	.095	2.972	.003	.096	.468
	Land_Per_Capita		-.009	.025	-.358	.721	-.058	.040
	Intercept[b]	0	2.931	.066	44.112	0.000	2.865	2.997
		1	3.347	.132	25.394	.000	3.215	3.479

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	$337235.3731 \times 10^{10}$	5524	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member characteristic in reference variable, household member buddhist (2005)

Data Information

		N of Cases
Valid		13105
Rejected	Out of Range[a]	0
	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		34718
Poverty_Status	0	8474
	1	4631

a. Cases rejected because of out of range group values.

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Reg_Other_Exp_Bud	-1.284	.021	-61.265	0.000	-1.326	-1.243
	Child_Women_Ratio	.278	.121	2.299	.022	.041	.515
	Old_Age_Depend_Ratio	.188	.081	2.309	.021	.028	.347
	Land_Per_Capita	.024	.028	.852	.394	-.031	.079
	Intercept[b] 0	3.254	.068	48.185	0.000	3.186	3.321
	1	3.347	.080	41.663	0.000	3.266	3.427

a. PROBIT model: PROBIT(p) = Intercept + BX

b. Corresponds to the grouping variable Poverty_Status.

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	$136889.577 \times 10^{20}$	13099	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member characteristics in reference variables, household member buddhistic (2010)

Data Information

		N of Cases
Valid		5523
Rejected	Out of Range[a]	0
	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		17340
Poverty_Status	0	4722
	1	801

a. Cases rejected because of out of range group values.

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Parameter Estimates

Parameter			Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
PROBIT[a]	HHM_Reg_Other_Exp_Bud		-1.055	.019	-55.611	0.000	-1.092	-1.018
	Child_Women_Ratio		.440	.170	2.580	.010	.106	.773
	Old_Age_Depend_Ratio		.162	.069	2.335	.020	.026	.297
	Land_Per_Capita		-.002	.019	-.130	.897	-.039	.034
	Intercept[b]	0	2.753	.054	51.069	0.000	2.699	2.807
		1	2.911	.103	28.241	.000	2.808	3.014

a. PROBIT model: PROBIT(p) = Intercept + BX

b. Corresponds to the grouping variable Poverty_Status.

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	$153233.7810^{*}10^{13}$	5517	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member characteristics in reference variables, household member buddhistic (2010)

Data Information

		N of Cases
Valid		13086
Rejected	Out of Range[a]	0
	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		35242
Poverty_Status	0	9667
	1	3419

a. Cases rejected because of out of range group values.

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Reg_Other_Exp_Bud	-1.326	.022	-59.445	0.000	-1.370	-1.282
	Child_Women_Ratio	.394	.127	3.111	.002	.146	.642
	Old_Age_Depend_Ratio	.041	.071	.579	.563	-.098	.181
	Land_Per_Capita	-.014	.008	-1.696	.090	-.030	.002
	Intercept[b] 0	3.288	.064	51.447	0.000	3.224	3.352
	1	3.592	.102	35.205	.000	3.490	3.694

a. PROBIT model: PROBIT(p) = Intercept + BX

b. Corresponds to the grouping variable Poverty_Status.

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	$505678.1151 \times 10^{11}$	13080	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member characteristics in reference variables, household member self employment non agriculture (2005)

Data Information

		N of Cases
Valid		4177
Rejected	Out of Range[a]	0
	Missing	13105
	Number of Responses > Number of Subjects	1353
Control Group		11946
Poverty_Status	0	3227
	1	950

a. Cases rejected because of out of range group values.

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	12	Yes

- **Parameter Estimates**

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Empyee	-.181	.016	-11.012	.000	-.213	-.148
	HHM_EmpCas	-.420	.029	-14.435	.000	-.477	-.363
	HH_GET_Remit	-.237	.063	-3.750	.000	-.361	-.113
	Head_female	-.176	.046	-3.840	.000	-.266	-.086
	Intercept[b]	.406	.033	12.270	.000	.373	.439
		.360	.053	6.767	.000	.307	.413

a. PROBIT model: PROBIT(p) = Intercept + BX

b. Corresponds to the grouping variable Poverty_Status.

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	4368.058	4171	.017

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member characteristics in reference variables, household member self employment non agriculture (2005)

Data Information

		N of Cases
Valid		13105
Rejected	Out of Range[a]	0
	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		60358
Poverty_Status	0	8474
	1	4631

a. Cases rejected because of out of range group values.

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Indust_AL	-.176	.016	-11.263	.000	-.207	-.145
	HHM_Indust_CL	-.297	.016	-18.744	.000	-.328	-.266
	HHM_Indust_SE_Agr	-.376	.010	-37.206	.000	-.396	-.356
	HHM_Indust_Agr_Other	-.212	.007	-29.195	.000	-.227	-.198
	HH_GET_Remit	.044	.031	1.444	.149	-.016	.105
	Head_female	.100	.021	4.826	.000	.059	.140
	Intercept[b] 0	-.930	.012	-74.893	0.000	-.942	-.917
	1	-1.087	.017	-65.328	0.000	-1.103	-1.070

a. PROBIT model: PROBIT(p) = Intercept + BX

b. Corresponds to the grouping variable Poverty_Status.

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	112614.008	13097	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member characteristics in reference variables, self employment non agriculture (2010)

Data Information

		N of Cases
Valid		4164
Rejected	Out of Range[a]	0
	Missing	13086
	Number of Responses > Number of Subjects	1359
Control Group		11569
Poverty_Status	0	3557
	1	607

a. Cases rejected because of out of range group values.

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	13	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Empyee	-.192	.017	-11.486	.000	-.225	-.159
	HHM_EmpCas	-.467	.031	-14.914	.000	-.529	-.406
	HH_GET_Remit	-.277	.062	-4.467	.000	-.399	-.156
	Head_female	-.143	.044	-3.240	.001	-.230	-.057
	Intercept[b] 0	.595	.035	16.987	.000	.560	.630
	1	.587	.065	8.985	.000	.522	.652

a. PROBIT model: PROBIT(p) = Intercept + BX

b. Corresponds to the grouping variable Poverty_Status.

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	4219.912	4158	.247

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member characteristics in reference variables, self employment non agriculture (2010)

Data Information

		N of Cases
Valid		13086
Rejected	Out of Range[a]	0
	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		57006
Poverty_Status	0	9667
	1	3419

a. Cases rejected because of out of range group values.

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	42216.644	13078	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Indust_AL	-.279	.017	-16.694	.000	-.312	-.246
	HHM_Indust_CL	-.363	.016	-22.096	.000	-.395	-.331
	HHM_Indust_SE_Agr	-.469	.011	-43.006	0.000	-.490	-.447
	HHM_Indust_Agr_Other	-.220	.007	-30.237	.000	-.234	-.205
	HH_GET_Remit	.026	.029	.886	.376	-.031	.083
	Head_female	.055	.021	2.654	.008	.014	.096
	Intercept[b] 0	-.782	.015	-53.559	0.000	-.797	-.768
	1	-.909	.022	-42.019	0.000	-.931	-.888

a. PROBIT model: PROBIT(p) = Intercept + BX

b. Corresponds to the grouping variable Poverty_Status.

CamScanner

Probit estimates dropping land per capita variable in Table (4.3 a) 2005

Data Information

		N of Cases
Valid		13105
Rejected	Out of Range[a]	0
	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		29218
Poverty_Status	0	8474
	1	4631

a. Cases rejected because of out of range group values.

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Reg_Other_Exp	-1.291	.021	-62.116	0.000	-1.332	-1.250
	Child_Women_Ratio	.287	.122	2.359	.018	.049	.525
	Old_Age_Depend_Ratio	.200	.081	2.483	.013	.042	.358
	Intercept[b] 0	3.244	.062	52.121	0.000	3.182	3.306
	1	3.327	.079	42.280	0.000	3.249	3.406

a. PROBIT model: PROBIT(p) = Intercept + BX

b. Corresponds to the grouping variable Poverty_Status.

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	$377950.4789 \times 10^{20}$	13100	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Probit estimates dropping land per capita variable in Table (4.3 a) (2010)

Data Information

		N of Cases
Valid		13086
Rejected	Out of Range[a]	0
	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		29807
Poverty_Status	0	9667
	1	3419

a. Cases rejected because of out of range group values.

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Parameter Estimates

Parameter			Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
PROBIT[a]	HHM_Reg_Other_Exp		-1.339	.022	-59.606	0.000	-1.383	-1.295
	Child_Women_Ratio		.431	.128	3.370	.001	.180	.681
	Old_Age_Depend_Ratio		.022	.071	.309	.757	-.118	.162
	Intercept[b]	0	3.257	.062	52.421	0.000	3.195	3.319
		1	3.590	.103	34.959	.000	3.487	3.693

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	$171085.3305 \times 10^{11}$	13081	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Probit estimates dropping land per capita variable in Table (4.9 a) (2005)

data Information

		N of Cases
Valid		5530
Rejected	Out of Range[a]	0
	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		12398
Poverty_Status	0	4294
	1	1236

a. Cases rejected because of out of range group values.

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Reg_Other_Exp	-1.167	.024	-49.528	0.000	-1.214	-1.121
	Child_Women_Ratio	.065	.166	.393	.694	-.261	.391
	Old_Age_Depend_Ratio	.290	.095	3.060	.002	.104	.476
	Intercept[b] 0	2.908	.065	44.699	0.000	2.843	2.973
	1	3.341	.132	25.275	.000	3.209	3.474

a. PROBIT model: PROBIT(p) = Intercept + BX

b. Corresponds to the grouping variable Poverty_Status.

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	$803402.5790 \times 10^{10}$	5525	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Probit estimates dropping land per capita variable in Table (4.9 a) (2010)

Data Information

		N of Cases
Valid		5523
Rejected	Out of Range[a]	0
	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		12567
Poverty_Status	0	4722
	1	801

a. Cases rejected because of out of range group values.

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Reg_Other_Exp	-1.059	.019	-55.624	0.000	-1.096	-1.021
	Child_Women_Ratio	.475	.169	2.807	.005	.143	.807
	Old_Age_Depend_Ratio	.164	.069	2.393	.017	.030	.299
	Intercept[b] 0	2.733	.053	51.766	0.000	2.680	2.786
	1	2.894	.102	28 290	.000	2.792	2.996

a. PROBIT model: PROBIT(p) = Intercept + BX

b. Corresponds to the grouping variable Poverty_Status.

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	$253540.1549 \times 10^{13}$	5518	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Probit estimates dropping remittance variable in Table (4.3 a) (2010)

Data Information

		N of Cases
Valid		13086
Rejected	Out of Range[a]	0
	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		45008
Poverty_Status	0	9667
	1	3419

a. Cases rejected because of out of range group values.

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Indust_AL	-.285	.017	-16.999	.000	-.318	-.252
	HHM_Indust_CL	-.358	.016	-21.879	.000	-.390	-.326
	HHM_Indust_SE_Agr	-.467	.011	-42.870	0.000	-.489	-.446
	HHM_Indust_Agr_Other	-.215	.007	-29.779	.000	-.229	-.200
	Head_female	.056	.021	2.694	.007	.015	.097
	Intercept[b] 0	-.788	.015	-54.264	0.000	-.803	-.774
	1	-.913	.022	-42.449	0.000	-.935	-.892

a. PROBIT model: PROBIT(p) = Intercept + BX

b. Corresponds to the grouping variable Poverty_Status.

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	42264.220	13079	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Probit estimates dropping remittance variable in Table (4.3 a) (2005)

Data Information

		N of Cases
Valid		13105
Rejected	Out of Range[a]	0
	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		48058
Poverty_Status	0	8474
	1	4631

a. Cases rejected because of out of range group values.

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Indust_AL	-.182	.016	-11.627	.000	-.212	-.151
	HHM_Indust_CL	-.292	.016	-18.526	.000	-.323	-.261
	HHM_Indust_SE_Agr	-.377	.010	-37.266	.000	-.397	-.357
	HHM_Indust_Agr_Other	-.208	.007	-28.793	.000	-.222	-.194
	Head_female	.101	.021	4.907	.000	.061	.142
	Intercept[b]						
	0	-.931	.012	-75.553	0.000	-.943	-.919
	1	-1.085	.017	-65.579	0.000	-1.102	-1.069

a. PROBIT model: PROBIT(p) = Intercept + BX

b. Corresponds to the grouping variable Poverty_Status.

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	116259.510	13098	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member self employment agriculture (2005)

Data Information

		N of Cases
Valid		5800
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		21729

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	12	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu111	.304	.009	32.577	.000	.286	.323
	HHM_Ind_Occ_Edu112	.145	.007	20.020	.000	.131	.159
	HHM_Ind_Occ_Edu113	.073	.012	5.862	.000	.049	.097
	HHM_Ind_Occ_Edu114	-.055	.015	-3.626	.000	-.085	-.025
	HHM_Ind_Occ_Edu115	-.305	.044	-6.924	.000	-.391	-.218
	Intercept	-.541	.012	-43.588	0.000	-.553	-.529

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	33172.659	5794	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member self employment agriculture (2010)

Data Information

		N of Cases
Valid		6080
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		22997

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	14	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu111	.438	.046	9.541	.000	.348	.528
	HHM_Ind_Occ_Edu112	.173	.008	22.876	.000	.158	.188
	HHM_Ind_Occ_Edu113	.143	.012	12.087	.000	.120	.166
	HHM_Ind_Occ_Edu114	.057	.012	4.805	.000	.034	.081
	HHM_Ind_Occ_Edu115	-.080	.035	-2.285	.022	-.149	-.011
	Intercept	-.878	.013	-67.810	0.000	-.891	-.865

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	33095.433	6074	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member salaried agriculture (2005)

Data Information

		N of Cases
Valid		2658
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		9587

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	11	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu121	.364	.016	23.324	.000	.333	.394
	HHM_Ind_Occ_Edu122	.103	.009	11.560	.000	.086	.120
	HHM_Ind_Occ_Edu123	.081	.014	5.688	.000	.053	.109
	HHM_Ind_Occ_Edu124	-.028	.016	-1.770	.077	-.059	.003
	HHM_Ind_Occ_Edu125	-.142	.036	-3.942	.000	-.212	-.071
	Intercept	-.446	.019	-23.248	.000	-.465	-.427

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	16188.632	2652	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member salaried agriculture (2010)

Data Information

		N of Cases
Valid		2847
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		10444

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	14	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu121	.319	.076	4.204	.000	.170	.468
	HHM_Ind_Occ_Edu122	.135	.009	14.550	.000	.117	.153
	HHM_Ind_Occ_Edu123	.048	.015	3.243	.001	.019	.078
	HHM_Ind_Occ_Edu124	-.046	.015	-3.079	.002	-.076	-.017
	HHM_Ind_Occ_Edu125	-.397	.043	-9.268	.000	-.481	-.313
	Intercept	-.686	.020	-34.963	.000	-.705	-.666

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	16798.908	2841	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member causal agriculture (2005)

Data Information

		N of Cases
Valid		2217
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		8285

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	11	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu131	.240	.018	13.667	.000	.205	.274
	HHM_Ind_Occ_Edu132	.119	.011	10.447	.000	.096	.141
	HHM_Ind_Occ_Edu133	-.051	.021	-2.466	.014	-.091	-.010
	HHM_Ind_Occ_Edu134	-.127	.031	-4.080	.000	-.189	-.066
	HHM_Ind_Occ_Edu135	-.380	.104	-3.669	.000	-.583	-.177
	Intercept	-.167	.023	-7.401	.000	-.190	-.145

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	11835.396	2211	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member causal agriculture (2010)

Data Information

		N of Cases
Valid		1997
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		7497

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	12	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu131	.568	.078	7.308	.000	.415	.720
	HHM_Ind_Occ_Edu132	.106	.012	9.207	.000	.083	.128
	HHM_Ind_Occ_Edu133	.056	.020	2.807	.005	.017	.096
	HHM_Ind_Occ_Edu134	.087	.024	3.673	.000	.041	.134
	HHM_Ind_Occ_Edu135	-.389	.144	-2.709	.007	-.670	-.107
	Intercept	-.437	.025	-17.499	.000	-.462	-.412

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	10312.969	1991	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member self employment manufacturing (2005)

Data Information

		N of Cases
Valid		695
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		2711

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	15	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu211	.917	.064	14.356	.000	.792	1.043
	HHM_Ind_Occ_Edu212	.379	.037	10.362	.000	.308	.451
	HHM_Ind_Occ_Edu213	.303	.048	6.351	.000	.210	.397
	HHM_Ind_Occ_Edu214	.049	.051	.944	.345	-.052	.149
	HHM_Ind_Occ_Edu215	.110	.094	1.168	.243	-.074	.293
	Intercept	-1.006	.049	0.0000	.000	0.0000	-.957

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	3919.993	689	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member self employment manufacturing (2010)

Data Information

		N of Cases
Valid		540
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		1544

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	16	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu212	.227	.037	6.129	.000	.155	.300
	HHM_Ind_Occ_Edu213	.080	.052	1.553	.120	-.021	.181
	HHM_Ind_Occ_Edu214	.004	.046	.094	.925	-.085	.094
	HHM_Ind_Occ_Edu215	-.484	.120	-4.024	.000	-.720	-.249
	Intercept	-.897	.050	-17.811	.000	-.947	-.847

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	3020.605	535	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member salaried manufacturing (2005)

Data Information

		N of Cases
Valid		608
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		2313

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	11	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu221	.197	.063	3.143	.002	.074	.319
	HHM_Ind_Occ_Edu222	.283	.029	9.709	.000	.226	.340
	HHM_Ind_Occ_Edu223	.020	.039	.509	.611	-.056	.096
	HHM_Ind_Occ_Edu224	.042	.038	1.102	.271	-.033	.117
	HHM_Ind_Occ_Edu225	-.153	.063	-2.424	.015	-.276	-.029
	Intercept	-.409	.043	-9.606	.000	-.452	-.366

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	3678.972	602	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member salaried manufacturing (2010)

Data Information

		N of Cases
Valid		814
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		2307

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	13	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu222	.238	.028	8.609	.000	.183	.292
	HHM_Ind_Occ_Edu223	.248	.036	6.888	.000	.177	.318
	HHM_Ind_Occ_Edu224	-.060	.037	-1.600	.110	-.133	.013
	HHM_Ind_Occ_Edu225	-.567	.066	-8.539	.000	-.697	-.437
	Intercept	-.519	.042	-12.231	.000	-.562	-.477

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	4816.911	809	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member causal manufacturing (2005)

Data Information

		N of Cases
Valid		266
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		1008

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	10	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu231	.308	.086	3.589	.000	.140	.477
	HHM_Ind_Occ_Edu232	.116	.038	3.077	.002	.042	.190
	HHM_Ind_Occ_Edu233	.191	.056	3.401	.001	.081	.301
	HHM_Ind_Occ_Edu234	-.022	.082	-.270	.787	-.183	.138
	HHM_Ind_Occ_Edu235	-.027	.200	-.133	.894	-.419	.366
	Intercept	-.066	.066	-1.000	.317	-.132	.000

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	1528.493	260	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member causal manufacturing (2010)

Data Information

		N of Cases
Valid		357
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		1028

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	10	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu232	.043	.046	.942	.346	-.047	.133
	HHM_Ind_Occ_Edu233	.029	.062	.472	.637	-.092	.150
	HHM_Ind_Occ_Edu234	.068	.059	1.138	.255	-.049	.184
	HHM_Ind_Occ_Edu235	.006	.186	.030	.976	-.360	.371
	Intercept	-.393	.066	-5.989	.000	-.458	-.327

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	2024.836	352	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member self employment construction (2005)

Data Information

		N of Cases
Valid		86
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		252

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu311	-1.168	1.234	-.947	.344	-3.586	1.250
	HHM_Ind_Occ_Edu312	-2.000	1.223	-1.635	.102	-4.398	.398
	HHM_Ind_Occ_Edu313	-1.588	1.215	-1.306	.191	-3.970	.795
	HHM_Ind_Occ_Edu314	-2.153	1.207	-1.783	.075	-4.519	.214
	Intercept	1.283	1.220	1.052	.293	.063	2.503

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	417.033	81	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member self employment construction (2010)

Data Information

		N of Cases
Valid		115
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		452

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu311	1.726	.359	4.801	.000	1.021	2.430
	HHM_Ind_Occ_Edu312	-.153	.161	-.952	.341	-.468	.162
	HHM_Ind_Occ_Edu313	.310	.148	2.092	.036	.020	.601
	HHM_Ind_Occ_Edu314	-.014	.209	-.066	.947	-.422	.395
	HHM_Ind_Occ_Edu315	-2.977	6.379	-.467	.641	-15.480	9.526
	Intercept	-.669	.175	-3.823	.000	-.843	-.494

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	617.919	109	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member salaried construction (2005)

Data Information

		N of Cases
Valid		235
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		913

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	14	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu321	.186	.102	1.818	.069	-.015	.386
	HHM_Ind_Occ_Edu322	.423	.056	7.575	.000	.313	.532
	HHM_Ind_Occ_Edu323	.132	.074	1.780	.075	-.013	.277
	HHM_Ind_Occ_Edu324	.429	.082	5.212	.000	.268	.591
	HHM_Ind_Occ_Edu325	-.345	.185	-1.862	.063	-.708	.018
	Intercept	-.545	.079	-6.889	.000	-.624	-.466

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	1394.038	229	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member salaried construction (2010)

Data Information

		N of Cases
Valid		456
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		1755

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	12	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu321	.431	.246	1.756	.079	-.050	.913
	HHM_Ind_Occ_Edu322	.209	.036	5.750	.000	.138	.280
	HHM_Ind_Occ_Edu323	.290	.042	6.938	.000	.208	.372
	HHM_Ind_Occ_Edu324	.025	.051	.480	.631	-.076	.125
	HHM_Ind_Occ_Edu325	-.128	.095	-1.341	.180	-.315	.059
	Intercept	-.591	.050	-11.720	.000	-.642	-.541

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	2662.205	450	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member causal construction (2005)

Data Information

		N of Cases
Valid		193
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		548

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	9	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu331	.195	.102	1.909	.056	-.005	.395
	HHM_Ind_Occ_Edu332	.234	.058	4.017	.000	.120	.348
	HHM_Ind_Occ_Edu333	.032	.063	.504	.614	-.091	.154
	HHM_Ind_Occ_Edu334	.190	.079	2.399	.016	.035	.345
	Intercept	-.343	.079	-4.346	.000	-.422	-.264

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	1121.222	188	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member causal construction (2010)

Data Information

		N of Cases
Valid		443
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		1706

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	14	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu331	-.102	.247	-.411	.681	-.586	.383
	HHM_Ind_Occ_Edu332	.265	.034	7.919	.000	.200	.331
	HHM_Ind_Occ_Edu333	.030	.047	.646	.518	-.061	.122
	HHM_Ind_Occ_Edu334	-.049	.051	-.954	.340	-.149	.051
	HHM_Ind_Occ_Edu335	-.789	.222	-3.549	.000	-1.225	-.353
	Intercept	-.413	.051	-8.126	.000	-.464	-.362

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	2560.395	437	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member self employment services I (2005)

Data Information

		N of Cases
Valid		1815
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		6976

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	15	Yes

Covariances (below) and Correlations (above).

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu411	.355	.031	11.342	.000	.294	.416
	HHM_Ind_Occ_Edu412	.207	.022	9.504	.000	.164	.249
	HHM_Ind_Occ_Edu413	.084	.027	3.146	.002	.032	.136
	HHM_Ind_Occ_Edu414	-.169	.030	-5.651	.000	-.227	-.110
	HHM_Ind_Occ_Edu415	-.392	.064	-6.119	.000	-.517	-.266
	Intercept	-.690	.028	-24.675	.000	-.718	-.662

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	10029.131	1809	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member self employment services I (2010)

Data Information

		N of Cases
Valid		999
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		3881

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	18	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu411	.661	.206	3.216	.001	.258	1.064
	HHM_Ind_Occ_Edu412	.357	.040	8.911	.000	.279	.436
	HHM_Ind_Occ_Edu413	.163	.046	3.572	.000	.073	.252
	HHM_Ind_Occ_Edu414	.035	.043	.805	.421	-.050	.120
	HHM_Ind_Occ_Edu415	-.201	.077	-2.606	.009	-.352	-.050
	Intercept	-1.092	.047	-23.085	.000	-1.139	-1.045

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	5420.730	993	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member salaried services I (2005)

Data Information

		N of Cases
Valid		737
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		2816

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	12	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu421	-.011	.058	-.194	.846	-.124	.102
	HHM_Ind_Occ_Edu422	.148	.027	5.378	.000	.094	.201
	HHM_Ind_Occ_Edu423	-.112	.034	-3.312	.001	-.178	-.046
	HHM_Ind_Occ_Edu424	-.292	.036	-8.100	.000	-.363	-.221
	HHM_Ind_Occ_Edu425	-.407	.059	-6.919	.000	-.522	-.292
	Intercept	-.169	.037	-4.515	.000	-.206	-.131

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	4533.222	731	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member salaried services I (2010)

Data Information

		N of Cases
Valid		829
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		2368

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	11	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu422	.055	.030	1.802	.072	-.005	.114
	HHM_Ind_Occ_Edu423	.011	.037	.301	.763	-.061	.083
	HHM_Ind_Occ_Edu424	-.050	.031	-1.593	.111	-.111	.011
	HHM_Ind_Occ_Edu425	-.243	.058	-4.162	.000	-.357	-.128
	Intercept	-.360	.039	-9.230	.000	-.399	-.321

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	4979.400	824	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member causal services I (2005)

Data Information

		N of Cases
Valid		674
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		2576

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	13	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu431	.200	.039	5.102	.000	.123	.276
	HHM_Ind_Occ_Edu432	.226	.029	7.706	.000	.169	.284
	HHM_Ind_Occ_Edu433	-.073	.050	-1.467	.142	-.170	.024
	HHM_Ind_Occ_Edu434	.273	.046	5.914	.000	.183	.364
	HHM_Ind_Occ_Edu435	-.823	.179	-4.599	.000	-1.174	-.472
	Intercept	-.381	.045	-8.432	.000	-.426	-.336

a. PROBIT model: PROBIT(p) = Intercept + BX

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	3735.470	668	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member causal services I (2010)

Data Information

		N of Cases
Valid		829
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		2368

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	11	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu431	.578	.146	3.950	.000	.291	.865
	HHM_Ind_Occ_Edu432	.243	.026	9.210	.000	.191	.294
	HHM_Ind_Occ_Edu433	.200	.035	5.749	.000	.132	.268
	HHM_Ind_Occ_Edu434	.142	.043	3.263	.001	.057	.227
	HHM_Ind_Occ_Edu435	-.314	.131	-2.405	.016	-.571	-.058
	Intercept	-.433	.042	-10.369	.000	-.474	-.391

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	4979.400	824	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member self employment services II (2005)

Data Information

		N of Cases
Valid		925
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		3598

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	12	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu511	.218	.048	4.570	.000	.125	.312
	HHM_Ind_Occ_Edu512	.102	.028	3.660	.000	.047	.156
	HHM_Ind_Occ_Edu513	-.163	.044	-3.688	.000	-.250	-.076
	HHM_Ind_Occ_Edu514	-.135	.044	-3.027	.002	-.222	-.047
	HHM_Ind_Occ_Edu515	.243	.064	3.766	.000	.116	.369
	Intercept	-.550	.039	-14.241	.000	-.588	-.511

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	5068.508	919	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member self employment services II (2010)

Data Information

		N of Cases
Valid		1746
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		6778

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	16	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu511	.427	.107	4.010	.000	.218	.636
	HHM_Ind_Occ_Edu512	.134	.030	4.417	.000	.074	.193
	HHM_Ind_Occ_Edu513	-.016	.036	-.440	.660	-.086	.055
	HHM_Ind_Occ_Edu514	-.092	.035	-2.661	.008	-.160	-.024
	HHM_Ind_Occ_Edu515	-.409	.056	-7.294	.000	-.519	-.299
	Intercept	-.796	.036	-22.157	.000	-.831	-.760

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	9198.275	1740	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member salaried services II (2005)

Data Information

		N of Cases
Valid		831
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		3236

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	12	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu521	.476	.077	6.158	.000	.324	.627
	HHM_Ind_Occ_Edu522	.155	.033	4.640	.000	.089	.220
	HHM_Ind_Occ_Edu523	-.008	.042	-.183	.854	-.089	.074
	HHM_Ind_Occ_Edu524	.154	.035	4.355	.000	.085	.224
	HHM_Ind_Occ_Edu525	-.104	.032	-3.206	.001	-.167	-.040
	Intercept	-.468	.039	-12.002	.000	-.507	-.429

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	4931.250	825	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member salaried services II (2010)

Data Information

		N of Cases
Valid		1215
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		4700

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	14	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu521	1.464	.270	5.432	.000	.936	1.992
	HHM_Ind_Occ_Edu522	.516	.030	17.345	.000	.458	.575
	HHM_Ind_Occ_Edu523	.193	.038	5.144	.000	.120	.267
	HHM_Ind_Occ_Edu524	.168	.028	6.013	.000	.113	.222
	HHM_Ind_Occ_Edu525	-.058	.030	-1.951	.051	-.117	.000
	Intercept	-.925	.035	-26.064	.000	-.960	-.889

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	6944.865	1209	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member causal services II (2005)

Data Information

		N of Cases
Valid		239
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		924

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	11	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu531	.307	.073	4.187	.000	.163	.451
	HHM_Ind_Occ_Edu532	.120	.056	2.131	.033	.010	.230
	HHM_Ind_Occ_Edu533	.216	.084	2.571	.010	.051	.381
	HHM_Ind_Occ_Edu534	-.210	.109	-1.925	.054	-.423	.004
	HHM_Ind_Occ_Edu535	.054	.155	.350	.726	-.250	.359
	Intercept	-.030	.080	-.372	.710	-.110	.050

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	1293.894	233	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member causal services II (2010)

Data Information

		N of Cases
Valid		221
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		633

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	15	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu532	.608	.068	8.879	.000	.474	.742
	HHM_Ind_Occ_Edu533	.425	.081	5.269	.000	.267	.583
	HHM_Ind_Occ_Edu534	.804	.094	8.554	.000	.620	.989
	HHM_Ind_Occ_Edu535	-.108	.134	-.811	.417	-.370	.153
	Intercept	-.872	.090	-9.667	.000	-.962	-.781

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	1260.345	216	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member self employment agriculture (2005)

Data Information

		N of Cases
Valid		560
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		2120

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	17	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu111	.196	.041	4.777	.000	.115	.276
	HHM_Ind_Occ_Edu112	.214	.038	5.553	.000	.138	.289
	HHM_Ind_Occ_Edu113	.018	.040	.466	.641	-.059	.096
	HHM_Ind_Occ_Edu114	.229	.039	5.938	.000	.154	.305
	HHM_Ind_Occ_Edu115	-1.151	.148	-7.787	.000	-1.440	-.861
	Intercept	-.659	.044	-14.866	.000	-.703	-.614

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	3380.130	554	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member self employment agriculture (2010)

Data Information

		N of Cases
Valid		590
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		2252

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	16	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu111	.882	.166	5.324	.000	.557	1.207
	HHM_Ind_Occ_Edu112	.047	.034	1.377	.169	-.020	.114
	HHM_Ind_Occ_Edu113	.211	.043	4.936	.000	.127	.294
	HHM_Ind_Occ_Edu114	-.025	.037	-.680	.496	-.098	.047
	HHM_Ind_Occ_Edu115	-.566	.098	-5.744	.000	-.759	-.373
	Intercept	-.768	.047	-16.508	.000	-.814	-.721

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	3324.350	584	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member salaried agriculture (2005)

Data Information

		N of Cases
Valid		321
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		1197

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	13	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu121	.186	.048	3.887	.000	.092	.280
	HHM_Ind_Occ_Edu122	.075	.029	2.585	.010	.018	.132
	HHM_Ind_Occ_Edu123	.107	.048	2.231	.026	.013	.202
	HHM_Ind_Occ_Edu124	-.152	.048	-3.180	.001	-.246	-.058
	HHM_Ind_Occ_Edu125	-.664	.083	-8.030	.000	-.826	-.502
	Intercept	-.132	.055	-2.421	.015	-.187	-.078

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	2014.334	315	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member salaried agriculture (2010)

Data Information

		N of Cases
Valid		295
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		1101

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	15	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu121	-.175	.197	-.889	.374	-.562	.211
	HHM_Ind_Occ_Edu122	.173	.045	3.877	.000	.086	.261
	HHM_Ind_Occ_Edu123	.149	.051	2.939	.003	.050	.248
	HHM_Ind_Occ_Edu124	-.016	.041	-.393	.695	-.096	.064
	HHM_Ind_Occ_Edu125	-.497	.095	-5.235	.000	-.683	-.311
	Intercept	-.658	.066	-9.963	.000	-.724	-.592

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	1775.317	289	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member causal agriculture (2005)

Data Information

		N of Cases
Valid		206
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		769

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	13	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu131	.307	.068	4.503	.000	.173	.440
	HHM_Ind_Occ_Edu132	.396	.053	7.512	.000	.293	.500
	HHM_Ind_Occ_Edu133	.100	.055	1.827	.068	-.007	.208
	HHM_Ind_Occ_Edu134	.182	.073	2.501	.012	.039	.325
	HHM_Ind_Occ_Edu135	.794	.300	2.648	.008	.206	1.382
	Intercept	-.220	.075	-2.940	.003	-.295	-.145

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	1203.330	200	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban l household member causal agriculture (2010)

Data Information

		N of Cases
Valid		151
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		426

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	No[a]

a. Parameter estimates did not converge.

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu132	.125	.045	2.781	.005	.037	.213
	HHM_Ind_Occ_Edu133	.162	.075	2.144	.032	.014	.310
	HHM_Ind_Occ_Edu134	-.194	.070	-2.785	.005	-.331	-.058
	HHM_Ind_Occ_Edu135	-3.224	6.223	-.518	.604	-15.420	8.972
	Intercept	-.553	.088	-6.315	.000	-.640	-.465

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	844.972	146	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member self employment manufacturing (2005)

Data Information

		N of Cases
Valid		512
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		1975

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	16	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu211	.095	.059	1.623	.105	-.020	.211
	HHM_Ind_Occ_Edu212	.203	.047	4.321	.000	.111	.295
	HHM_Ind_Occ_Edu213	-.056	.057	-.994	.320	-.167	.055
	HHM_Ind_Occ_Edu214	-.155	.052	-2.981	.003	-.257	-.053
	HHM_Ind_Occ_Edu215	-.470	.086	-5.437	.000	-.640	-.301
	Intercept	-.684	.057	-11.934	.000	-.741	-.626

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	2889.134	506	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member self employment manufacturing (2010)

Data Information

		N of Cases
Valid		340
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		972

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	20	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu212	.082	.085	.960	.337	-.085	.248
	HHM_Ind_Occ_Edu213	.013	.094	.141	.888	-.171	.198
	HHM_Ind_Occ_Edu214	-.219	.074	-2.971	.003	-.364	-.075
	HHM_Ind_Occ_Edu215	-.402	.121	-3.310	.001	-.640	-.164
	Intercept	-1.112	.094	-11.842	.000	-1.206	-1.018

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	1883.590	335	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member salaried manufacturing (2005)

Data Information

		N of Cases
Valid		521
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		1987

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	14	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu221	-.014	.057	-.244	.807	-.126	.098
	HHM_Ind_Occ_Edu222	.460	.039	11.909	.000	.384	.535
	HHM_Ind_Occ_Edu223	.269	.043	6.207	.000	.184	.354
	HHM_Ind_Occ_Edu224	.249	.036	6.925	.000	.179	.320
	HHM_Ind_Occ_Edu225	-.094	.044	-2.169	.030	-.180	-.009
	Intercept	-.752	.047	-15.921	.000	-.799	-.705

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	3061.386	515	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member salaried manufacturing (2010)

Data Information

		N of Cases
Valid		564
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		2168

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	15	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu221	-.224	.383	-.585	.559	-.974	.527
	HHM_Ind_Occ_Edu222	.395	.037	10.708	.000	.322	.467
	HHM_Ind_Occ_Edu223	.203	.047	4.308	.000	.111	.295
	HHM_Ind_Occ_Edu224	-.122	.038	-3.176	.001	-.198	-.047
	HHM_Ind_Occ_Edu225	-.076	.045	-1.717	.086	-.164	.011
	Intercept	-.768	.050	-15.236	.000	-.819	-.718

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	3272.970	558	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member causal manufacturing (2005)

Data Information

		N of Cases
Valid		109
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		420

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	12	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu231	.510	.151	3.385	.001	.215	.805
	HHM_Ind_Occ_Edu232	.218	.066	3.291	.001	.088	.348
	HHM_Ind_Occ_Edu233	.552	.084	6.573	.000	.387	.717
	HHM_Ind_Occ_Edu234	.074	.076	.968	.333	-.076	.223
	HHM_Ind_Occ_Edu235	.337	.126	2.676	.007	.090	.583
	Intercept	-.509	.097	-5.261	.000	-.605	-.412

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	667.913	103	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member causal manufacturing (2010)

Data Information

		N of Cases
Valid		88
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		247

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	14	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu232	-.209	.082	-2.538	.011	-.370	-.048
	HHM_Ind_Occ_Edu233	.561	.139	4.034	.000	.288	.833
	HHM_Ind_Occ_Edu234	-.063	.118	-.538	.591	-.294	.167
	HHM_Ind_Occ_Edu235	-.670	.221	-3.030	.002	-1.103	-.236
	Intercept	-.433	.136	-3.178	.001	-.569	-.297

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	506.662	83	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member self employment construction (2005)

Data Information

		N of Cases
Valid		66
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		130

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	12	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu312	.079	.161	.490	.624	-.236	.393
	HHM_Ind_Occ_Edu313	-.797	.195	-4.077	.000	-1.180	-.414
	HHM_Ind_Occ_Edu314	-.452	.201	-2.245	.025	-.847	-.057
	Intercept	.239	.187	1.279	.201	.052	.426

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	390.788	62	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member self employment construction (2010)

Data Information

		N of Cases
Valid		68
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		197

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	14	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu312	-.145	.262	-.556	.578	-.658	.367
	HHM_Ind_Occ_Edu313	.216	.168	1.287	.198	-.113	.545
	HHM_Ind_Occ_Edu314	.079	.175	.450	.652	-.265	.423
	HHM_Ind_Occ_Edu315	.166	.263	.630	.529	-.349	.680
	Intercept	-1.094	.191	-5.725	.000	-1.285	-.903

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	363.861	63	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member salaried construction (2005)

Data Information

		N of Cases
Valid		201
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		776

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	15	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu321	-.695	.205	-3.392	.001	-1.096	-.293
	HHM_Ind_Occ_Edu322	.120	.065	1.841	.066	-.008	.248
	HHM_Ind_Occ_Edu323	-.160	.080	-1.986	.047	-.317	-.002
	HHM_Ind_Occ_Edu324	-.380	.081	-4.702	.000	-.538	-.221
	HHM_Ind_Occ_Edu325	-.748	.134	-5.585	.000	-1.011	-.486
	Intercept	-.116	.088	-1.315	.189	-.204	-.028

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	1236.891	195	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Rural household member salaried construction (2010)

Data Information

		N of Cases
Valid		299
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		1158

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	14	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu321	.717	.426	1.682	.093	-.118	1.552
	HHM_Ind_Occ_Edu322	.206	.060	3.440	.001	.089	.324
	HHM_Ind_Occ_Edu323	-.019	.072	-.259	.796	-.161	.123
	HHM_Ind_Occ_Edu324	-.134	.070	-1.913	.056	-.271	.003
	HHM_Ind_Occ_Edu325	-.442	.101	-4.373	.000	-.640	-.244
	Intercept	-.577	.076	-7.550	.000	-.654	-.501

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	1763.000	293	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member causal construction (2005)

Data Information

		N of Cases
Valid		148
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		428

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	18	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu331	.180	.072	2.491	.013	.038	.321
	HHM_Ind_Occ_Edu332	.998	.118	8.486	.000	.767	1.228
	HHM_Ind_Occ_Edu333	.961	.121	7.937	.000	.724	1.199
	HHM_Ind_Occ_Edu334	.826	.112	7.346	.000	.606	1.046
	Intercept	-1.226	.126	-9.717	.000	-1.352	-1.100

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	867.137	143	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member causal construction (2010)

Data Information

		N of Cases
Valid		171
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		486

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	13	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu332	.187	.065	2.876	.004	.060	.315
	HHM_Ind_Occ_Edu333	.160	.082	1.956	.050	.000	.319
	HHM_Ind_Occ_Edu334	-.029	.066	-.436	.663	-.157	.100
	HHM_Ind_Occ_Edu335	-.172	.187	-.921	.357	-.539	.194
	Intercept	-.650	.088	-7.367	.000	-.739	-.562

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	952.328	166	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member self employment services I (2005)

Data Information

		N of Cases
Valid		1917
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		7273

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	16	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu411	.408	.036	11.408	.000	.338	.479
	HHM_Ind_Occ_Edu412	.341	.020	17.307	.000	.303	.380
	HHM_Ind_Occ_Edu413	.224	.024	9.240	.000	.177	.272
	HHM_Ind_Occ_Edu414	.078	.021	3.752	.000	.037	.119
	HHM_Ind_Occ_Edu415	-.281	.036	-7.895	.000	-.350	-.211
	Intercept	-1.028	.026	-39.554	0.000	-1.054	-1.002

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	10913.311	1911	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member self employment services I (2010)

Data Information

		N of Cases
Valid		1308
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		5017

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	17	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu411	-.071	.187	-.378	.705	-.437	.295
	HHM_Ind_Occ_Edu412	.222	.030	7.374	.000	.163	.281
	HHM_Ind_Occ_Edu413	.093	.035	2.670	.008	.025	.161
	HHM_Ind_Occ_Edu414	-.070	.028	-2.534	.011	-.125	-.016
	HHM_Ind_Occ_Edu415	-.488	.052	-9.436	.000	-.590	-.387
	Intercept	-.987	.034	-28.678	.000	-1.022	-.953

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	6981.541	1302	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member salaried services I (2005)

Data Information

		N of Cases
Valid		1091
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		4123

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	14	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu421	-.038	.048	-.782	.434	-.132	.057
	HHM_Ind_Occ_Edu422	.213	.026	8.124	.000	.162	.264
	HHM_Ind_Occ_Edu423	.115	.026	4.454	.000	.065	.166
	HHM_Ind_Occ_Edu424	-.012	.024	-.509	.611	-.060	.035
	HHM_Ind_Occ_Edu425	-.190	.027	-7.081	.000	-.243	-.138
	Intercept	-.633	.031	-20.747	.000	-.664	-.603

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	6503.428	1085	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member salaried services I (2010)

Data Information

		N of Cases
Valid		976
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		2765

Convergence Information

	Number of Iterations	Optimal Soiution Found
PROBIT	15	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu422	.217	.035	6.246	.000	.149	.285
	HHM_Ind_Occ_Edu423	.323	.037	8.641	.000	.250	.397
	HHM_Ind_Occ_Edu424	-.079	.033	-2.401	.016	-.143	-.015
	HHM_Ind_Occ_Edu425	-.240	.043	-5.511	.000	-.325	-.154
	Intercept	-.885	.043	-20.780	.000	-.927	-.842

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	5428.554	971	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member causal services I (2005)

Data Information

		N of Cases
Valid		458
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		1748

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	14	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu431	.401	.058	6.944	.000	.288	.514
	HHM_Ind_Occ_Edu432	.338	.036	9.473	.000	.268	.408
	HHM_Ind_Occ_Edu433	-.038	.040	-.949	.343	-.118	.041
	HHM_Ind_Occ_Edu434	-.045	.047	-.975	.330	-.137	.046
	HHM_Ind_Occ_Edu435	-.601	.121	-4.964	.000	-.838	-.364
	Intercept	-.470	.047	-9.979	.000	-.517	-.423

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	2655.205	452	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member causal services I (2010)

Data Information

		N of Cases
Valid		390
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		1496

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	14	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu431	1.495	.302	4.950	.000	.903	2.086
	HHM_Ind_Occ_Edu432	.345	.043	7.962	.000	.260	.430
	HHM_Ind_Occ_Edu433	.298	.064	4.686	.000	.173	.423
	HHM_Ind_Occ_Edu434	.092	.050	1.840	.066	-.006	.190
	HHM_Ind_Occ_Edu435	.316	.073	4.335	.000	.173	.459
	Intercept	-.794	.062	-12.872	.000	-.855	-.732

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	2170.288	384	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member self employment services II (2005)

Data Information

		N of Cases
Valid		871
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		3345

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	16	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu511	.375	.055	6.859	.000	.268	.482
	HHM_Ind_Occ_Edu512	.355	.038	9.330	.000	.280	.430
	HHM_Ind_Occ_Edu513	.192	.045	4.281	.000	.104	.281
	HHM_Ind_Occ_Edu514	.024	.038	.619	.536	-.052	.099
	HHM_Ind_Occ_Edu515	-.325	.053	-6.191	.000	-.429	-.222
	Intercept	-.950	.044	-21.397	.000	-.994	-.905

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	4712.690	865	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member self employment services II (2010)

Data Information

		N of Cases
Valid		1776
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		6845

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	17	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu511	.074	.216	.343	.731	-.349	.498
	HHM_Ind_Occ_Edu512	.139	.033	4.196	.000	.074	.204
	HHM_Ind_Occ_Edu513	.225	.035	6.466	.000	.157	.293
	HHM_Ind_Occ_Edu514	-.001	.027	-.036	.971	-.053	.051
	HHM_Ind_Occ_Edu515	-.274	.037	-7.310	.000	-.348	-.201
	Intercept	-1.069	.036	-29.929	.000	-1.104	-1.033

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	9472.382	1770	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member salaried services II (2005)

Data Information

		N of Cases
Valid		1196
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		4597

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	14	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu521	,017	,078	,223	,824	-,136	,171
	HHM_Ind_Occ_Edu522	,143	,030	4,688	,000	,083	,202
	HHM_Ind_Occ_Edu523	,103	,032	3,218	,001	,040	,166
	HHM_Ind_Occ_Edu524	-,088	,029	-3,040	,002	-,144	-,031
	HHM_Ind_Occ_Edu525	-,196	,024	-8,149	,000	-,243	-,149
	Intercept	-,598	,033	-18,169	,000	-,631	-,565

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	6741,451	1190	,000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member salaried services II (2010)

Data Information

		N of Cases
Valid		1683
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		4724

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	14	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu522	.176	.029	6.100	.000	.119	.233
	HHM_Ind_Occ_Edu523	.227	.029	7.780	.000	.170	.284
	HHM_Ind_Occ_Edu524	.036	.020	1.839	.066	-.002	.074
	HHM_Ind_Occ_Edu525	-.063	.019	-3.240	.001	-.101	-.025
	Intercept	-.961	.029	-33.623	.000	-.990	-.932

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	9191.991	1678	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member causal services II (2005)

Data Information

		N of Cases
Valid		199
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		772

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	16	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu531	.113	.107	1.062	.288	-.096	.323
	HHM_Ind_Occ_Edu532	.241	.060	3.996	.000	.123	.360
	HHM_Ind_Occ_Edu533	.260	.062	4.233	.000	.140	.381
	HHM_Ind_Occ_Edu534	.369	.064	5.741	.000	.243	.495
	HHM_Ind_Occ_Edu535	-1.030	.190	-5.435	.000	-1.402	-.659
	Intercept	-.475	.076	-6.255	.000	-.551	-.399

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	1125.861	193	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

CamScanner

Urban household member causal services II (2010)

Data Information

		N of Cases
Valid		150
Rejected	Missing	0
	Number of Responses > Number of Subjects	0
Control Group		580

Convergence Information

	Number of Iterations	Optimal Solution Found
PROBIT	17	Yes

Parameter Estimates

Parameter		Estimate	Std. Error	Z	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
PROBIT[a]	HHM_Ind_Occ_Edu531	.953	.237	4.020	.000	.488	1.417
	HHM_Ind_Occ_Edu532	.078	.096	.815	.415	-.110	.267
	HHM_Ind_Occ_Edu533	.341	.094	3.636	.000	.157	.524
	HHM_Ind_Occ_Edu534	.115	.092	1.251	.211	-.065	.295
	HHM_Ind_Occ_Edu535	-.078	.153	-.508	.611	-.377	.222
	Intercept	-1.026	.114	-9.009	.000	-1.140	-.912

a. PROBIT model: PROBIT(p) = Intercept + BX

Chi-Square Tests

		Chi-Square	df[a]	Sig.
PROBIT	Pearson Goodness-of-Fit Test	899.154	144	.000

a. Statistics based on individual cases differ from statistics based on aggregated cases.

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