INVESTIGATING POVERTY AND LABOUR FORCE PARTICIPATION AMONG OLDER POPULATION IN EGYPT:

A MULTILEVEL SIMULTANEOUS EQUATIONS MODELING APPROACH

by

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ABSTRACT

Egypt is currently going through a significant demographic change in which the population ageing is one of its main characteristics. This phenomenon requires researchers and policy makers to pay attention to the well-being of this most fast growing segment of population. In this study, my main interest is to investigate the relationship between elderly poverty and their labour force participation while accounting for two methodological problem that plague many of the existence researches, endogeneity and hierarchical structure of the data. I have used a nationally represented data set from the Egyptian Household Observatory Survey - Round 7 (IDSC, 2010). I have developed a measure of poverty in old age that captured five broad dimensions of poverty using factor analysis technique. To investigate the relationship between poverty and labour force participation, I have developed four single-level models and four multilevel-models for poverty and labour force participation. I found that poverty is endogenous to labour force participation and to overcome this problem, I have developed a simultaneous equations model that correct for this endogeneity. In addition, I found significant differences among governorates regarding elderly poverty and their labour force participation which detects the assumption of independence. To overcome the problem of the dependences among observation within each governorate and to provide more accurate results for regression parameters and their standard errors, I have developed a multilevel linear model for poverty and a multilevel logistic model for labour force participation. To consider both problems simultaneously, I have proposed a more developed model; a multilevel simultaneous equations model. I have also compared the results among the four implemented models. The most interesting result is the contradiction among models regarding the relationship between poverty and labour force participation. While being in labour force was found to have a positive effect on poverty, this relationship is reversed once I account for the endogeneity. I have also performed a simulation study to formally asses to what extent the endogeneity problem in the hierarchical data structure cannot be ignored. It showed that the biasness and the accuracy of the parameters associated with the endogenous variable differs according to the strength of the endogeneity and based on the level at which the endogeneity occurs.

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CHAPTER 1

INTRODUCTION

Since the last few decades, Egypt is going through a significant demographic change in which the population ageing is one of its main characteristics. Population ageing is a direct consequence of two main demographic factors, fertility and mortality. Throughout the period 1950 to 2005, the total fertility rates decreased significantly from 6.6 children per woman to only three children (Department of Economic and Social Affairs, Population Division, UN, 2007). The decline in the fertility rates contributes to decrease the proportion of children and young people to older people in total population. As fertility rates drop, mortality rates are in decline as well. The crude death rate which stood at the alarmingly high rate of 24 ‰ in 1950 was roughly halved by 1980 and was roughly halved again reaching 6‰ by 2000. In addition, due to the improvements in health sector, life expectancy at birth is expected to increase from 42.4 years during 1950-1955 to over 78 years through 2045 to 2050 (Department of Economic and Social Affairs, Population Division, UN, 2007).

This decrease in fertility levels, assisted by continued declines in mortality levels, presents Egypt with major changes in the age structure of the population. In 1996, there were 5.7% older persons aged 60 and over. By 2006, this ratio increased to 6.1 % of the total population (Central Agency for Public Mobilization and Statistics, 2006). The proportion of persons over the age of sixty in the population is expected to reach 11% by 2025 and it is anticipated to reach 18% by 2050 (Department of Economic and Social Affairs, Population Division, UN, 2007). This expected increase in the older population both in absolute terms and relative to other segments of the Egyptian populations has significant implications with regard to economic vulnerability and potential sources of support of the elderly.

With ageing, often comes restricted ability to work and earn. According to 2006 census data, 23.7% of persons aged 60-64 were engaged in the labour market. This percentage falls to about 15% for persons aged 65-69 and to only 6.6% for the category 75+ (Central Agency for Public Mobilization and Statistics, 2006). Moreover, participation of persons aged 65+ in the labour force is expected to decrease dramatically from 31.9% as of 1980 to merely 7.5% in 2020 (Department of Economic and Social Affairs, Population Division, UN ,2007).

Due to the declining participation in the labour force, the older population is forced to seek other sources of income. Traditionally, the most common source of income for the elderly is the social support system whether formal or informal sources of support. However, many developing countries lack formal social support systems due to resources constraints and limited coverage which put the older persons in a vulnerable position (Khadr, 2004). Depending on the extended families as an informal source of support is unsuitable due to the society's movement away from the tradition of multigenerational families to more nuclear families (Schwarz, 2003. However, even under the traditional structure, older population cannot rely on their family members, in particular with consideration to the decline in fertility rates. The expected increase in the proportion of older persons relative to the number of those of working age has its consequences on their potential supporters as well. The United Nations predicts a substantial decline in the potential support ratio from about 13 supporters per older person in 2007 to only 5 supporters in 2050 (Department of Economic and Social Affairs, Population Division, UN , 2007).

With the increases in life expectancy, this problem becomes more serious. According to the United Nations predictions, life expectancy at birth is expected to increase significantly from 42.4 years through 1950-1955 to reach 78.4 through 2045-2050 (Department of Economic and Social Affairs, Population Division, UN, 2007). An increase in life expectancy entails the need for many older persons to find a way to make their income last over a longer period of time in order to provide for themselves. One solution for this is to continue working after the age of sixty. This situation is particularly dire for the older population who have no opportunity to increase their income, in particular, those who were poor over their life time. In addition, because the incidence of morbidity and health problems increases with age, the longer one lives, the more likely one is to experience health problems. Thus, increasing life expectancy only increases the longevity of people suffering from chronic disease which in turn affects older persons' ability to work and consequently affects their economic status.

The situation of older women is particularly serious. On one hand they tend to have fewer resources than men due to less participation in the labour force and the interrupted work histories among those who were involved. In 2007 only 2.8% of females aged 65 years and over were participating in the labour market compared to 17.5% of males (Department of Economic and Social Affairs, Population Division, UN, 2007). On the other hand, women tend to live longer than men, resulting in higher probability of becoming widows which is further complicated by their lower likelihood to remarry rendering most women to experience economic hardships.

This study explores the main determinants of both elderly poverty and their participation in the labour force. There are two methodological issues that are taken into consideration. The first issue is that the data set in this study is nested (hierarchical) data structure, i.e. it consists of individuals nested within governorates. When the data structure is hierarchical, this affects the independence of the observations. Both poverty and labour force participation showed dependency pattern among observations within each governorate. The statistical model in such case must accommodate for the dependencies by allowing for a more general covariance structure by which the individuals from the same governorate can be correlated. Furthermore, the differences in poverty and labour force participation among governorates require considering not only the individual differences but also the differences among governorates that explains this variation. Moreover, there are several problems associated with ignoring the hierarchical structure of the data as will be discussed later which suggests the need for using the hierarchical analysis. Ignoring the hierarchical structure of the data might result in low estimates of the standard error of the parameter associated with variables measured at higher levels which results in unrealistic significant effect of these variables (Hox, 2002). It also might yield opposite results if the governorates that are highly heterogeneous are considered as one group.

The second issue is the simultaneous relationship between poverty and labour force participation. From one point of view, I expect that being poor forces the elderly to engage in labour force as a coping strategy to overcome their poverty which means a positive relationship between these two variables. On the other point of view, poverty might be diminished in response to engagement in labour force which means a negative relationship between these two variables. Accordingly, these two variables are expected to mutually affect each other in addition to the effect of many other factors on them. However, these two topics are separately discussed in the literature. The simultaneous relationship among variables is an important source of the problem of endogeneity. This requires accounting for such endogeneity to get consistent estimate of the parameters.

To account for both issues, it is important to develop a multilevel model that considers this simultaneous relationship. However, as in the single-level regression model, one of the key assumptions of the multilevel model is that all the explanatory variables are uncorrelated with the random disturbance term. In this case, regressors are said to be exogenous and are assumed to be determined outside the model. In many situations, the independence assumption is violated and in this case the regressors are said to be endogenous. In fact, the presence of error terms at each level of the data hierarchy increases the chance of existence of correlation between these error terms at different levels. When this assumption is violated, applying this model would bias the results (Ebbes et al, 2004) and yield inconsistent estimate of the underlying parameters (Spencer and Fielding, 2000). Although the standard hierarchical model assumes that the regressors in the model are independent of the random effects, it cannot produce unbiased and consistent estimates in the presence of endogenous regressor. Thus, with the flexibility provided by applying the multilevel model that considers variables measured at different level of data hierarchy and accounting for the dependence structure within each governorate, additional complexity arises at each stage of statistical modelling. So, I developed a multilevel simultaneous equation model to overcome the problem of endogeneity and the hierarchical structure of the data.

The rest of this chapter is structured as follows. Section one identifies the main objectives of the study. Section two reviews the relevant existent literature. Section three describes the data and defines the variables used for the analysis. Section four presents the statements of the main hypothesis that guide the study.

1. 1 Objective of the study

The main objectives of this study represent both social and statistical concerns. The study aims to:

a) Construct an accurate measure of poverty in old age.
b) Identify the main determinants of poverty among older population both at the individual-level and the governorate-level.
c) Identify the main determinants of labour force participation among older population both at the individual-level and the governorate-level.
d) Investigate the simultaneous relationship between poverty and labour force participation among older population.
e) Develop a model that captures simultaneously the hierarchical structure of the data and the simultaneous relationship between poverty and labour force participation.
f) Examine the effect of the presence of random errors correlation (endogeneity) at different levels on the biasness and the accuracy of the estimates.

There are four distinctive features of this study. It uses a nationally represented data set for the whole Egypt instead of restricting it to a few districts in studies such as Hegazi, (1999) Nwar and Abdelghany (2006). Furthermore, the study focuses on the differences among governorates in both the dependent variables and the effect of the independent variables. Next, I have constructed an index that accurately measures poverty in old age which captures more than one dimension of poverty. Lastly, this study takes into account both the hierarchical structure of the data and the simultaneous relationship between poverty and labour force participation in old age.

1.2 Literature review

The rapid pace of aging process has raised researchers' concerns regarding the challenge of the aging population. There are two major concerns in the existing literature; elderly poverty and their participation in labour force. According to the life-cycle theory, there are two stages of life in which individuals are considered more vulnerable. These stages are childhood and old age (Deaton and Paxon, 1997). At childhood, poverty is less critical than in old age, since the children often depend on their parents for support while in old age, the older persons have relatively imperfect alternatives regarding their sources of support, in particular, as they become older. Lacking a secure source of income might force the elderly to continue in the labour force beyond their 60s. These two topics are rarely discussed in the developing countries in general (Cameron and Cobb-clark, 2002) and in Egypt in particular. Khadr's (2004) review found that the elderly in Egypt are highly under-researched as the transition into aging society is relatively recent. In fact, existent pieces of research mostly focus on related health issues of the elderly in Egypt (e.g, Aly, 1989; Vi, 1997; Khadr and Yount, 2012). However, researches regarding elderly labour force participation are almost non-existent. This can be explained by the limited availability of data on labour force participation of older population, in addition to directing the labour economic researches to the population in working age 15-60 (Khadr, 2004). Poverty in old age has received limited attention as well. Most existent studies are purely descriptive as their aim is to stress on the vulnerability of the elderly without any attempt to model its determinants (e.g, Azer and Afifi, 1990; Hegazi, 1999; Nwar and Mohamed, 2006).

In developed countries, the transition into population aging has been underway for a long time. Consequently, numerous studies that focus on this fast growing segment of the population have been carried out. However, elderly are still the least researched group in the population especially in income inequality studies due to their dependence on support from others (Muramatsu, 2003). Most studies on elderly labour force participation have focused on individual characteristics such as age, gender, marital status, education, and health as the main determinants of elderly labour force participation. A review of these literature showed that health plays a major role in determining elderly labour force participation. Costa (1996) was concerned with the effect of body mass index (BMI) on non-labour force participation among older population aged 50-64 in U.S. Using probit model, the study has examined the effect of BMI along with other variables including age, education, foreign birth, presence of a servant or boarder in the household, monthly pension amount, occupation, property ownership, region and state unemployment rate. The main results suggested that health significantly affects non-labour force participation, however, the impact of BMI on the elasticity of non-labour force participation has diminished in the recent years. Moreover, Costa pointed out that economic status as measured by monthly pension amount is more important than health in determining the elderly labour force participation.

Campolieti (2002) examined the effect of health on a sample of Canadian aged between 45 and 65 using latent variable model. Health status is indicated by self-reporting activity limitations, having long term disabilities, having other specific health problem, and BMI. The results showed that health exerts a significant effect on labour force participation regardless of the health indicator. However, the effect of age, marital status, and unemployment rate is larger when using the self-reported measure while the effect of household size and education level have a larger estimates when body mass index is used to control for health status.

Barnays' (2009) study examined the effect of health using other age groups, including the elderly aged 50-59. The most important finding from this study was the existence of a negative association between health status, especially activity limitation indicator and labour force participation.

Other main individual characteristics affect elderly labour force participation that were beyond the scope of many pieces of research including wife's labour force participation (Shirle, 2008), adult education (Stenberg et al, 2012), and the experience of job loss (Chan and Stevens, 2001). The effect of retirement age and social security pension on elderly labour force participation is of importance as well. Simulation studies have been conducted to find out whether increasing the retirement age or reducing the social security benefits would stimulate the elderly to continue work (French, 2005; Klaauw and Wolpin, 2008).

A limited number of studies captured variables measured at the state-level. However, some of the attempts to address the effect of these variables have been met with some methodological difficulties. Yamada (1990) used Japanese aggregate census data to identify the elderly labour supply determinants. The explanatory variables included wealth, education, presence of spouse , social security benefits, full time and part time male wage, family structure, health measured by life expectancy and percentage of local noise pollution complaints, and unemployment rate. The major findings from this study identified two main determinants of elderly labour force participation namely; social security retirement benefits and unemployment rate. Other important variables include family structure and the environmental surroundings. Although the study depends on aggregated data to perform the analysis which result in the problem of ecological fallacy (Robinson, 1950), making implications on aggregate labour force participation may justify the use of aggregate data and lessen the aggregation bias.

Other studies have combined both individual-level and state level variables. Munnell et al (2008) were interested in the importance of the unemployment rate, the age structure of the population and the nature of employment along with individual characteristics in examining the elderly labour force participation. They used a probit regression model to examine the effect of individual-level and state-level variables on elderly labour supply. It is worth noting that this study is one amongst very few studies that takes the economic environment and state-level variables into consideration when examining elderly labour force participation. However, combining individual-level variables and state level variables into a single fixed effect model violates the assumption of the independence of error and yields a high significant effect of the predictors due to an estimated standard error that is too low (Hox, 2002; Steenbergen and Jones, 2002).

Parsons (1989) was interested in the effect of economic environment and health on the elderly labour force participation in the United States. The economic indicators included potential social security benefits, index of welfare generosity, the wage rate and the fraction of year unemployed. All these variables showed a significant negative effect on the probability of working. Other demographic variables that were included in the analysis were age, education, marital status, wife's education if married, health, race and occupation. Among these variables, only race and occupation showed insignificant effect on the labour force decision. Furthermore, the effect of mortality as an objective indicator of health was particularly significant. The study has paid a particular attention to potential simultaneous relationship of subjective measure of health as represented by self-reported health and the decision to work. Thus, the model was estimated twice. Firstly, self-reported health was examined in place of the objective measure. Secondly, the health variables were omitted from the model. Both of these two models showed biased estimation either due to the endogeneity of self-reported health or due to the omission of a significant variable. However, the bias due to variable omission was less severe.

Regardless of the methodological problem occurred due to disaggregating economic environment variables to the individual level, this study provides a valuable analysis of the effect of health and economic environment in determining the elderly labour force participation. It stresses on the importance of addressing the endogeneity in self-reported health by making a comparison between the determinants of labour force participation using different indicators of health. This in fact sheds the light on another methodological issue that should be taken into consideration. As noted by Chang and Yen (2011), the simultaneous relationship among variables is an important issue that should be taken into consideration whenever it exists; otherwise it causes inconsistent results for the effect of key variables.

A considerable number of the existent studies on the determinants of elderly labour force participation have stressed the importance of taking the endogeneity problem into consideration.

Bound et al (2010) have estimated a dynamic programming model to examine the relationship among financial resources, health, and labour supply for single men aged between 50 and 62. The study underlines the endogeneity of self-reported health. They found out that unhealthy people are more likely to retire compared to healthy people. Taking the availability of financial resources into account showed that those in good health are less likely to retire unless they have grand economic resources.

However, a research done by Dwyer and Mitchell (1999) found no support to the evidence of the endogeneity of self-reported health. They have examined the relative importance of poverty and health in the expected retirement age. The findings from this study showed that self-reported work limitation is not endogenous with elderly labour supply. Moreover, both subjective and objective indicators perform similarly as proxy indicators of health status. The results showed also that poverty exerts a significant effect on retirement decision and its effect remains significant after controlling for health status. However, unlike the findings of the previously mentioned study by Costa (1996) the effect of health in this study is found to be stronger than the poverty.

Researchers were interested in examining the endogeneity of other variables as well. Cameron and Cob-Clark (2002) were interested in examining the endogeneity of receiving transfers from children to old age labour supply. The findings from this study provided a little support to the hypothesis of the negative effect of receiving transfers on the elderly labour supply. It showed that receiving transfers exerts a significant effect on decreasing only the co resident mother labour supply. More recently, Cameron and Cob-Clark (2008) also estimated a simultaneous equation model, using the same dataset, with control for co residence with children as another endogenous variable that should simultaneously, along with children's transfers, determines labour supply in old age. The findings from this study showed unexpectedly that both co residency and transfers from children do not exert a significant effect on elderly labour supply.

Life satisfaction is found to be another endogenous variable when modelling the elderly labour force participation. In Chang and Yen (2011) study of the relationship between employment status and life satisfaction of the elderly in Taiwan, an ordinal treatment effect model was estimated to account for the simultaneity between the two variables of their interest. The endogenous variables were elderly employment and an index of life satisfaction that has been constructed by assigning equal weights to 12 indicators of life satisfaction. The results of the endogeneity test showed strong correlation among the two variables of interest. To investigate the importance of taking the simultaneous nature between the two key variables into consideration, an ordinary least square model has been estimated to examine the relationship between life satisfaction and employment. The results showed that being full time workers does not exert any significant effect on life satisfaction which contradicts the effect of this variable when the endogeneity between the key variables is taken into account. According with findings from most studies, this study investigated also other variables that affect the elderly decision to work. For example, age, education, having chronic disease, and receiving assistance from children are negatively related to the likelihood of being working while being male, life style and engagement in social services are positively related to being working.

Poverty was found to be another endogenous variable when modelling work. Amuedo-Dorantes (2004) was interested in the relationship between poverty and working in informal sector for household heads regardless of their age. He used the simultaneous equation probit model due to the endogeneity of poverty to household head's participation in informal sector. The analysis is done separately for men and women headed household. The findings showed that, in all models, there are a positive relationship between poverty and working in informal sector. Other important significant factors in determining household poverty and working in informal sector were age, family size, years of schooling, and number of household members work in informal sector.

1.3 Data

The study uses the data from The Egyptian Household Observatory Survey - Round 7, Egypt 2010 database (IDSC, 2010). This survey was administrated under the supervision of the information and decision support centre in Egypt. It is a nationally represented household survey that was conducted to provide statistical information on a range of topics related to individuals' social, health, economic, and perception about a wide range of services. The definitions of variables and summary statistics used in the study are presented in Table 1-1.

Meanwhile, three variables that are measured at the governorate-level are merged to the data-set. These variables describe the unemployment rate, percentage of population in labour force, and inequality for each governorate at the same year. The merged data are obtained from Egypt Human Development Report (UNDP, 2010) and is presented in Table 1-2.

In this thesis, I have considered the head of the household as the unit of analysis rather than considering all the older individuals within the household. The first reason behind this is that there are some variables in the data set that are measured only for the head of the household which results in missing values problem for other individual within the same household. The second and the most important reason is that the variables used as indicators of poverty are measured for the household as a whole not for each individual.

Consequently, the individual within the same household will have the same values on these indicators which results in dependency among the observations within the same household. To avoid the problems associated with this dependency, I have considered the head of the household as a representative of each household. All the households headed by elderly aged 60 and over are used in this study; overall there are 2102 older persons who are the heads the household are represented in the sample.

The sample is drawn according to a multistage sampling procedure that includes 24 governorates in Egypt. The frontier governorates were excluded due to its low population density. In 2010, Egypt was divided for administrative purpose into 29 governorates representing four main regions (see figure 1-1). The first region is Metropolitan governorates which comprise the five major cities of Cairo, Helwan, Alexandria, Port-Said and Suez. Lower Egypt governorates which comprise nine governorates of Damitta, Daqahlya, Sharqya, Qalyobia, Kafr Elshekh, Gharbya, Menofia, Bhera and Ismaillia that are located in the region of the Nile delta. Upper Egypt governorates which comprise ten governorates of Giza, 6th October, Fayoum, Banisuif, Menia, Asuit, Sohag, Qina, Luxor and Aswan that are located in south Egypt. The frontier governorates which comprise five governorates of Matruh, New Valley (El Wadi ElGadid), Red sea, South Sinai, and North Sinai that are less populated desert areas. Some of these governorates consists of urban areas only and includes mainly Cairo, Helwan Alexandria, Port Said and Suez. All other governorates consist of both urban and rural areas. The included governorates present the first three major regions. The frontier governorates are excluded from the analysis due to their lower population. These governorates differ among each other in many attributes especially with respect to education and poverty. In this study I take into consideration the hierarchical structure of this data since the individuals are (nested) within governorates.

Figure 1-1: Map of Egypt's Administrative Divisions/Governorates
(Source:http://www.fao.org/ag/agp/agpc/doc/counprof/egypt/egypt.html)

Table 1-1: Variable definitions

Variable	Variable definition	Mean	S.D
AG0	A dummy variable which takes the value 1 if the elderly is between 60-64 years old and 0otherwise.	.412	.492
AG1	A dummy variable which takes the value 1 if the elderly is between 65-69 years old and 0 otherwise.	.258	.438
AG2	A dummy variable which takes the value 1 if the elderly is 70 years old or above and 0 otherwise.	.33	.47
M	A dummy variable which takes the value 1 if the elderly is male and 0 if female.	.726	.446
MRR	A dummy variable which takes the value 1 if the elderly is currently married and 0 otherwise.	.641	.479
ILLTER	A dummy variable which takes the value 1 if the elderly is illiterate and 0 otherwise.	.53	.499
EDU	A dummy variable which takes the value 1 if the elderly has education degree less than university and 0 otherwise.	.364	.481
UNI+	A dummy variable which takes the value 1 if the elderly has university degree or above and 0 otherwise.	.105	.307
DISB	A dummy variable which takes the value 1 if the elderly has disability and 0 otherwise.	.014	.117
CHR	A dummy variable which takes the value 1 if the elderly has chronic disease and 0 otherwise.	.585	.493
DISBCHR	A dummy variable which takes the value 1 if the elderly has both chronic disease and disability and 0 otherwise.	.025	.157
HHSUP	A continuous variable represents the ratio of working family members aged 15-59 to the elderly aged 60+.	.622	.868

Variable	Variable definition	Mean	S.D
PI	A continuous variable ranges from 0 to 100 which represents the constructed poverty index where 0 are the richest and 100 are the poorest.	54.71	21.38
INLAB	A dummy variable which takes the value 1 if the elderly is currently working and 0 otherwise.	.266	.442
OUTLAB	A dummy variable which takes the value 1 if the elderly is currently not working and 0 otherwise.	.734	.442
PEXP	A continuous variable represents the per capita expenditure within the household.	430.6	416.1
INCS	A dummy variable which takes the value 1 if the elderly receives other sources of income than from work.	.8297	.376
INCS	A dummy variable which takes the value 1 if the elderly receives other sources of income than from work.	.8297	.376
UNEMP	A continuous variable represents the unemployment rate for each governorate.	10.51	5.518
PRIN	A continuous variable represents the percentage of population in labour force for each governorate.	30.3	5.07
INEQUAL	A continuous variable represents inequality in each overnorate it ranges from 0 to 100 where 0 indicate perfect equality and 100 indicates perfect inequality.	.264	.061
RU	A dummy variable which takes the value 1 if the elderly reside in rural area and 0 otherwise.	.489	.5
UR	A dummy variable which takes the value 1 if the elderly reside in urban area and 0 otherwise.	.5114	.5

Table 1- 2: Frequency distribution of variables measured at governorate-level

Governorate	N	Gini Coefficient (INEQUAL)	% of population in labour force (PRIN)	Unemployment rate (UNEMP)
Cairo	163	38%	29.21%	12.04%
Helwan	71	38%	24.30%	10.69%
Alex	128	30%	25.93%	14.11%
Portsaid	73	34%	37.46%	27.25%
Suez	61	29%	28.97%	15.29%
Damitta	64	21%	30.61%	7.01%
Daqahlya	112	22%	34.29%	13.81%
Sharqya	97	19%	29.67%	8.88%
Qalyobia	102	23%	29.01%	7.87%
Kafr Alshekh	64	21%	31.47%	9.05%
Gharbya	114	24%	33.58%	10.54%
Menofia	63	23%	36.20%	6.75%
Bhera	107	19%	39.64%	9.53%
Ismailia	40	27%	32.05%	9.53%
6th October	53	38%	25.29%	4.67%
Giza	94	34%	26.79%	11.34%
Banisuif	73	21%	37.77%	3.34%
Fayoum	73	21%	28.93%	3.56%
Menia	130	24%	33.20%	4.36%
Asuit	92	27%	27.45%	9.60%
Sohag	103	23%	24.86%	7.47%
Qina	92	23%	32.91%	9.51%
Aswan	75	27%	29.45%	25.77%
Luxor	58	24%	12.79%	15.32%

1.4 Hypotheses Tests

Based on the objectives of the study and a review of the relevant literature, I am interested in two major sets of variables that are expected to impact both poverty and labour force participation among the elderly. The first set of variables are the individual demographic and socio-economic characteristics such as age, gender, marital status, educational attainment, health status, household potential support ratio, receiving other sources of income and place of residence. The second set of variables represents the characteristic of the governorate to which the individual belongs. These variables include income inequality, unemployment rate and percentage of population in labour force. The impact of these variables will be tested for each of poverty models and labour force participation models.

1.4.1 Hypotheses tests for poverty models

1.4.1.1 Individual demographic and socio-economic characteristics

The individual characteristics considered in this study include age, gender, marital status, educational attainment, health status, household potential support ratio, labour force participation , receiving other sources of income, and place of residence. Regarding age, it is expected to have association with poverty since the older people become more vulnerable as they are getting old. So, I test these two hypotheses against the null hypothesis of no effect $H_1 : \beta_{AG1} > 0$ and $H_2 : \beta_{AG2} > 0$. I expect to accept the alternative hypotheses and to find that the older groups are more likely to be poor than the age group 60-64. Females are considered more vulnerable to suffer economic hardship. So, I expect that males are less likely to be poor than females. That is, against the null hypothesis of no effect, I test $H_3 : \beta_M < 0$. For Marital status, being married is expected to maintain higher level of economic status so married persons are less likely to be poor than unmarried ones. That is, I test $H_4 : \beta_{MRR} < 0$. Educational attainment is one of the most important candidates to determine poverty. I expect to find illiterates to be more likely to be poor and those with university degree and above are less likely to be poor than other educated groups. Thus, I test these two hypotheses against the null hypothesis of no effect $H_5 : \beta_{\mathrm{ILLTER}} > 0$ and $H_6 : \beta_{UNI} < 0$. I expect to accept the alternative hypothesis, and to stress on the importance of education in determining poverty. Poverty in this study is measured based, not only on individual resources, but also on household's resources, so, household potential support ratio is expected to have a negative association with poverty. Thus I test $H_7 : \beta_{\mathrm{HHSUP}} < 0$. With respect to health, it is expected to find those who have health problems are positively associated with poverty. That is I test the alternative $H_8 : \beta_{\mathrm{CHR}} > 0$, $H_9 : \beta_{\mathrm{DISB}} > 0$ and $H_{10} : \beta_{\mathrm{CHRDISB}} > 0$. Regarding labour force participation, it is expected to have a significant relationship with poverty but the direction of this relationship will be investigated. Being working might decrease poverty and in this case I expect to find a negative association. On another point of view, being poor might force the individual to work, accordingly, the relationship between poverty and labour force participation might be positive. Thus, against the null hypothesis of no association, the test is $H_{11}: \beta_{\text{INLAB}} \neq 0$. In addition, as I discussed earlier, I expect to find that labour force participation is endogenous to poverty. So, I also test $H_{12}:$ INLAB is endogenous to poverty against the null hypothesis of exogeneity of labour force participation. Beside income from work, older persons might have other sources of income like income assistance from their children and/or relatives, returns on saving, retirement pension and governmental assistance. Receiving other sources of income is expected to decrease poverty. That is I test $H_{13}: \beta_{\text{INCS}} < 0$. Regarding place of residence, rural residents are expected to be poorer than urban residents. Thus I test $H_{14}: \beta_{\text{RU}} > 0$.

1.4.1.2 Governorate characteristics

Governorate characteristics considered in this study are unemployment rate, percentage of population in labour force, and income inequality. An increase in unemployment rate is expected to increase poverty, so I test $H_{15}: \beta_{\text{UNEMP}} > 0$. Regarding percentage of population in labour force, it is expected to find that increasing in percentage of population in labour force decreases poverty. Thus I test, $H_{16}: \beta_{\text{PRIN}} < 0$. Income inequality within governorates is expected to have association with poverty but I do not hold a prior expectation as the inequality might exist in favour of a certain group of population, so I test $H_{17}: \beta_{\text{INEQUAL}} \neq 0$.

It is worth mentioning that, due to the hierarchical structure of the data and the effects of variables measured at both individual and governorate level, it is appropriate to implement a multilevel model. This requires further tests to investigate whether the variance of level-2 residuals differs significantly among governorates or not. Thus for the intercept and each variable I test H_0 : var(τ_{ii}) $= 0$ against H_{18} : var(τ_{ii}) > 0. I expect to find, specifically, var(τ_{00}) > 0 which stresses on the importance of the multilevel model.

1.4.2 Hypotheses tests for labour force participation models

1.4.2.1 Individual demographic and socio-economic characteristics

Similarly, the individual characteristics considered in this study include age, gender, marital status, educational attainment, health status, household potential support ratio, poverty index, receiving other sources of income, and place of residence.

Since people often lack the ability to work as they are getting older, I test these two hypotheses against the null hypothesis of no effect $H_{19} : \beta^{*}_{\mathrm{AG1}} < 0$ and $H_{20}: \beta^{*}_{AG2} < 0$. I expect to accept the alternative hypothesis, and to find that the older groups are less likely to be in labour force than the age group 60-64. Females in general have lower labour force participation than males, so I expect that males are more likely to be in labour force than females. That is, against the null hypothesis of no effect, I test $H_{21} : \beta^{*}_{MALE} > 0$. For marital status, I expect that it exerts a significant effect on labour force participation. However, I do not have a prior expectation about the direction. Married individuals might need to work to support their families while unmarried individuals might need to work because they have no one to support them. So I test $H_{22} : \beta^{*}_{MRR} \neq 0$. Regarding educational attainment, it is expected to find that both illiterates and those with university degree and above are more likely to be in labour force than other educated groups. Thus, I test these two hypotheses against the null hypothesis of no effect $H_{23} : \beta^{*}_{ILLTER} > 0$ and $H_{24} : \beta^{*}_{UNI+} > 0$. Increasing of household potential support ratio is expected to decreases labour force participation since the elderly may not need to work as they have potential supporters. Thus I test $H_{25} : \beta^{*}_{\mathrm{HHSUP}} < 0$. Health is one among the most important correlates to labour force participation, it is expected to find those who have any health problems are less likely to be in labour force. So, I test the alternatives $H_{26} : \beta^{*}_{\mathrm{CHR}} < 0$, $H_{27} : \beta^{*}_{\mathrm{DISB}} < 0$ and $H_{28} : \beta^{*}_{CHRDISB} < 0$. It is expected to accept the alternatives hypothesis according with the evidence of previous literature about the importance effect of health on elderly labour force participation. Regarding poverty, it is expected to have a significant relationship with labour force participation, but the direction of this relationship will be investigated. Increasing poverty might force the individual to engage the labour force to cope with the economic hardships; accordingly, the relationship between poverty and labour force participation might be positive. On another point of view, poverty might result from being out of labour force and in this case I expect to find a negative association between poverty and being in labour force. Thus, the test is $H_{29} : \beta^{*}_{\mathrm{PI}} \neq 0$. In addition, as discussed earlier, poverty might be endogenous to labour force participation. So, I also test

H_{30} : poverty is endogenous to labour force participation against the null hypothesis of exogeneity of poverty. Receiving other sources of income could indicate that an individual does not need to work as they have alternative sources of income and accordingly, it is expected to decrease labour force participation. That is I test $H_{31} : \beta^{*}_{\mathrm{INCS}} < 0$. Regarding place of residence, rural residents are expected to be more likely to work than urban residents due to their engagement in agricultural activates and no age bound for retirement. The hypothesis I test is $H_{32} : \beta^{*}_{\mathrm{RU}} > 0$.

1.4.2.2 Governorate characteristics

Similarly, governorate characteristics considered in this study are unemployment rate, percentage of population in labour force, and income inequality. An increase in unemployment rate is expected to decrease labour force participation, so I test $H_{33} : \beta^{*}_{\mathrm{U}NEMP} < 0$. Regarding percentage of population in labour force; it is expected to find that increasing this percentage decreases labour force participation since Increasing in percentage of population in labour force might be seen as increasing the potential supporters who are working which might result in decreasing the older persons need to engage to labour force. Thus I test, $H_{34} : \beta^{*}_{\mathrm{PRIN}} < 0$. Income inequality within governorates is expected to have association with labour force participation. However, no prior expectation is hold about this relationship. Thus, against the null hypothesis of no effect I test $H_{35} : \beta^{*}_{\mathrm{INEQUAL}} \neq 0$. Similarly, due to the hierarchical structure of the data I should investigate whether the variance of level-2 residual differs significantly among governorates or not. Thus for the intercept and each variable I test $H_0 : \mathrm{var}(\tau^*_{ii}) = 0$ against $H_{36} : \mathrm{var}(\tau^*_{ii}) > 0$. I expect to find, specifically, $\mathrm{var}(\tau_{00}) > 0$ which stresses on the importance of the multilevel model.

CHAPTER 2

MEASURING POVERTY

2.1 Overview of poverty measures

Over the last two decades there has been a wide acceptance to define poverty as a multidimensional phenomenon that reflects a state of deprivation from a decent life rather than only lack of income (Egypt Human Development Report, 2010). For example, the United Nation Development Program (UNDP) has defined five important dimensions of poverty; namely, per capita income, per capita expenditure, economic security, housing condition and affordability of basic needs (UNDP, 2003).

The most widely handled dimension of poverty is a money metric dimension. According to this dimension, a standard poverty line is drawn and the individual whose income/expenditure falls below this line is considered as poor. A review of the literature on poverty measures showed that different studies favoured the use of expenditure. It is worth, in this context, to mention the empirical considerations that favour the use of expenditure rather than income as a money metric indicator of poverty. Firstly, the amount of expenditure reflects the household real welfare as people may consume more than what they earn and might compensate through assistance or liquidation of assets. On the counter, they may consume less than what they earn and save the rest of their income (UNDP, 2003). Secondly, income tends to fluctuate within a year in some developing countries where household's income is largely dependent on crop harvesting while expenditure is a long run welfare indicator as it tends to smooth the fluctuations in income (Falkingham and Namazie, 2002; UNDP, 2003). Thirdly, income data are often subject to the problem of under-reporting, and survey respondents are more willing to reveal their expenditure patterns rather than to report their income (UNDP, 2003). Finally, expenditure is preferable than income in studying poverty among older people since a considerable number of them receive assistance from others and are more willing to exclude these assistance if they are asked explicitly to report their income (Falkingham and Namazie, 2002).

Another important dimension that should be considered is wealth. Wealth can be measured through various indicators of household welfare such as durable goods ownership and housing conditions (Osman et al, 2006; Zimmer, 2008). A number of study have recommended wealth as a measure of poverty. In fact, well-being is a combination of having not only the basic requirements but also having a range of goods that are considered to be necessary for quality of life (Noumbissis, 2004; Baker et al, 2005; Burholt and Windle, 2006). Furthermore, measuring poverty among the elderly requires taking wealth into consideration since it is accumulated over their life. Moreover, wealth is one of the safety nets that play an important role in protecting the elderly against economic uncertainty (Radner, 1992; Rendall 1996). However, some problems arise when using wealth as a measure of poverty. Wealth is a measure of a stock so it is unable to measure the current economic status (Osman et al, 2006). Furthermore, the construction of a measure of wealth does not often reflects the quantity nor the quality of the goods owned by the household (Falkingham and Namazie, 2002).

Insecurity due to the lack of health insurance and inability to afford the necessary medical treatment is another major aspect of poverty. The heads of households feel more secured if they have access to health insurance scheme, employment insurance or pensions (UNDP, 2003). This problem is more severe among older people since they face an increasing incidence of morbidity and they are more likely to experience health problems which have an impact on their economic status. UNDP (2003) report has emphasized that "uncertainty about the future seems an integral aspect of the experience of poverty in Egypt". Thus, security is an important factor to be considered when measuring poverty.

Recent studies have stressed on the subjective dimension of poverty. This dimension relies upon person's own perception about his/her economic status. For example, the heads of the households are often asked to determine the minimum level of income that is acceptable for living during the survey. Then, these levels are compared with the reported income to set the subjective poverty line (UNDP, 2003). The subjective approach can also be addressed by using some indicators of subjective well-being such as, asking the respondent to assess his/her economic condition, asking about their feeling of economic security or asking about the efficiency of monthly income and etc. (Saunders, 2004). This approach reveals people's perception about their economic status from their own perspectives. Thus, it provides information about poverty from those who are directly experienced it. Moreover, it coincides to a great extent with the difficulties the individuals face especially if individuals expenditure exceeds their income (UNDP, 2003). It also presents a direct way to measure the economic status and simplifies data collection empirically (Baker et al., 2005; Burholt and Windle, 2006).

2.2 Literature review

Economic status commonly follows a life-cycle pattern; childhood and old age are characterized with increased incidence of poverty whereas adulthood is the stage in which the individuals accumulate their earnings and income. Children and their economic status have been the focus of many studies while only limited research on the well-being of older persons are available. Furthermore, less attention and investigation have been directed to this issue in developing countries while this issue has been extensively studied in developed countries. The following is a summary of some of previous studies, which is organised into three subsections that deal with measures of economic status in both developing and developed countries in general and in Egypt in particular.

2.2.1 Measures of poverty in developed countries

The transition into ageing society has been underway in developed countries for a long time. Consequently, concerns regarding the well-being of older people have been at the centre of researchers and policy makers' interest. Assessment of older persons' poverty has been well studied, with particular attention to non-cash income and wealth. This combination of multiple measures of economic status added more validity to their results.

Moon (1979) examined poverty among the older people aged 65 and above between 1966 and 1971 in United State by using an expanded measure which included income, as well as non-income component as in-kind public and private transfers, tax liabilities, net worth and intra family transfers .

Several points about assessing poverty of the older people were presented by Radner (1992) who discussed the complexities in making accurate assessment of poverty of older people. The findings of this study showed that by the inclusion of non-cash income and wealth in addition to cash income, the economic status of the older people tended to improve relative to non-older people. Similar result was repeated by Rendall (1996) who found that inclusion of assets' value in the measure of poverty has contributed to the reclassification of many poor older people to the non-poor category.

Burholt and Windle (2006) were concerned with objective and subjective indicators to measure poverty. In their study, the objective indicator was based on material resources index that included sources of income, employment status, home ownership, ability to pay for one's food and having private health insurance. The subjective indicator was based on current financial satisfaction, which was constructed using person's perception about his/her financial situation in comparison to others in the same age.

2.2.2 Measures of poverty in developing countries

Interest in the economic status of older persons is relatively recent in developing countries. Deaton and Paxon (1997) were concerned with relative poverty among people in different age groups in South Africa and a set of other developing countries including Ghana, Pakistan, Taiwan, Thailand and Ukraine. They highlighted the disadvantages of using per capita household expenditure as a welfare measure .They took into consideration family size and its composition, as well as different costs of each household member when measuring poverty.

Saunders's (2004) has used objective and subjective indicators to measure poverty. He used the mean of the income as an objective indicator to measure poverty while his subjective indicators were measured in terms of person's perception about his/her economic status and his/her feeling of economic security. The results showed that while there were substantial improvements in the mean income through this period, the economic security perceived by older adults declined.

Using objective and subjective indicators to measure poverty for the older people was presented also by Baker et al (2005). However, they combined both indicators into a single measure. The objective indicator was based on the possession of assets and the respondent's and his/her spouse's (if married) monthly income, while the subjective indicator was based on the adequacy of income and person's satisfaction with his/her income.

Noumbissis (2004) has constructed an index of standard of living, which included household characteristics, the possessed goods by the household and services available to the household.

2.2.3 Measures of poverty in Egypt

Poverty among older persons has received limited attention among researchers and scholars in Egypt. Furthermore, researches concerned with this issue were mainly descriptive with the objective of stressing the vulnerable living conditions of older persons.

Azer and Afifi (1990) have studied a sample of 296 older persons in Giza governorate. Their study found that 60.1% of all cases were living in households with monthly income lower than 149 LE[1]. The respondents were asked about their sources of income and found that 68.6% received pensions. Out of those who received pensions, more than 77% reported that pensions are their main source of income. Furthermore, 44.6% of older people reported receiving support from their children, 45.45% of them stated that this support is their main source of income. The study also revealed that except public

[1] The findings on income distribution derived from this study were shared with consultants in the central agency for general mobilization resulting in the adoption of the following monthly income categories, less than 50 L.E = very low, 50-149= low, 150-249 = middle, 250- 349= high, 350+ = highest.

pensions; the main source of income varied by gender specially, receiving support from others (12.1% of males and 38.1% of females) which stresses the fact that women are more vulnerable than men.

The authors also referred to a study that was carried out by Marzouk and Kodsi (1971) on 369 older persons in Alexandria governorate. This study examined several problems faced older persons. Among these problems were that 44% of all cases had no source of income apart from their pensions which provide them with very low amount in most cases.

In the same study, the authors referred to a survey that was undertaken by Egyptian Society for social studies in Cairo (1974) on 500 older adults in Cairo. The study showed that 56% of the sample reported that their monthly income fell short of covering the cost of living.

Hegazi (1999) undertook another study on 657 older persons in Ikhtab village in Dakahlya governorate. He found that 63.9% of the sample received income from wages and salaries, 37.4% received returns from agricultural lands and only 15.4% received retirement pensions. The older adults, particularly those who were living alone, reported that transfers from relatives, state, and non-kins are an important part of their income.

Nwar and Mohamed (2006) have studied a sample of 2000 older persons in six governorates; two in Metropolitan, two in Lower Egypt, and two in Upper Egypt. The study investigated several aspects regarding the demographic and socio-economic characteristics of the older persons. The study constructed a socio-economic index using

26 indicator variables representing the living conditions and ownership of durable goods. The values of the index ranged from zero to 26 with mean of 9.7 for older males and 9.3 for older females. The study also addressed the sources of income for the older persons. Their findings showed that the most common source of income is pension followed by income from work. The respondents were asked to identify whether they receive adequate income or not, the results showed that only 18% of males received sufficient income compared to 35% of females. Furthermore, 70% of older males and 59% of older females stated that they need to receive assistance, from the government and from their sons.

Gabr (2009) has examined poverty among older people aged 50+ in fifteen governorates in Egypt representing two metropolitan governorates, six governorates in Upper Egypt, and six governorates in Lower Egypt. She constructed two separate measures of poverty that represents both objective and subjective dimensions. The objective measure was an index that captures three indicators representing ownership of durable goods, ownership of assets, and housing conditions. The subjective measure was an index that captures three indicators representing subjective feeling of security about house, wealth and health.

2.3 Poverty index construction using Factor Analysis

Due to the multidimensional nature of poverty, it is important to assign a certain weight to be given to each dimension when measuring poverty rather than depending on subjective assignments of these weights. A multivariate statistical technique like factor analysis can be used to assign these weights. In this section, factor analysis method is used to construct an index of poverty.

2.3.1 Factor analysis method

Factor analysis is a statistical technique used to describe the covariance relationship among correlated set of variables in terms of a few underlying but unobservable random quantities called factors that best capture the common information (Johnson and Wichern, 2002) . It assumes that the relationships between the variables are due to the effect of underlying factors. The factor analysis model can be expressed as:

$$X - \mu_{(p\times 1)} = L_{p\times m} F_{m\times 1} + \varepsilon_{p\times 1} \tag{2-1}$$

where l_{ij} is the loading of the ith variable on the jth factor, i.e the matrix L is a matrix of factor loadings, F1, F2,…..Fm are the common factors which are assumed to have a mean of 0 and an identity variance covariance matrix, $\varepsilon_{1,}\varepsilon_{2},\dots,\varepsilon_{p}$ are the specific factors that are assumed to follow normal distribution with mean 0 and a diagonal variance covariance matrix.

Factor analysis requires a few assumptions about the data. It requires the data to be measured on a continuous scale. However, in practice this requirement is relaxed and ordered categorical data can be included in the analysis (Hutcheson and Sofroniou, 1999). Furthermore, as the identification of the factors depends on the correlation between variables, it follows that the variables should be correlated to each other. Moreover, for the factor model to be appropriate, a large enough sample is required to yield reliable estimates of the correlation among the variables. It is recommended that the data set should contain at least 300 cases (Comrey and Lee 1992).

Two main tests are applied to test the appropriateness of the model. They are Bartlett's test of sphericity and Kaiser- Meyer- Olkin measure of sampling adequacy. Bartlett's test of sphericity evaluates the null hypothesis that the correlation matrix is an identity matrix which indicates that there is no correlation among the variables and thus it is unacceptable to proceed with the factor analysis. The test statistic is applied according to the following formula

$$\chi^2 = [(n-1) - 1/6\ (2p + 1 + 2/p)][\ln|S| + p \ln \frac{1}{p} \sum Ij\ ] \tag{2-2}$$

with $df = (P-1)(P-2)/2$ where, p is the number of variables, $|S|$ is the determinant of the correlation matrix (S) of all variables, n is the sample size, and I_j is the j^{th} eigen value of (S). If we cannot reject the null hypothesis, we should not proceed with the factor analysis.

Ka iser- Meyer- Olkin measure of sampling adequacy is an indicator of how well suited the sample data are for factor analysis. It is applied according to the following formula:

$$KMO = \frac{\sum_{i \neq j} S_{ij}^2}{\sum_{i \neq j} S_{ij}^2 + \sum_{i \neq j} a_{ij}^2} \tag{2-3}$$

Where S_{ij} is the correlation matrix of all variables, a_{ij} is the partial correlation matrix. Small value of KMO indicates that factor analysis may not be appropriate for the data. Values of KMO ranges between zero to one and values below 0.5 are unacceptable.

The most commonly used method for factor extraction is the principal component analysis (PCA). In this method, the first principal component is a weighted linear combination of variables that accounts for the largest amount of variability in the sample. This method of extraction is used to constructs the poverty index from a combination of the available variables in the dataset that captures the previously mentioned poverty dimensions.

When factor analysis is applied, three concepts are introduced:

- The communalities that show the amount of variance in each variable that is accounted for the factor. Large communalities indicate that a large amount of variance has been extracted by the factor solution.

- Factor loading which represents the correlation between a specific observed variable and the factor.
- The factor score coefficients that show the weights given to each variable to construct the index. This score is estimated as a linear combination of the original variables. Thus, for the case K, the factor score is calculated according to the following formula,

$$F_k = \sum_{i=1}^{p} w_i x_{ik} \tag{2-4}$$

where, F_k is the score of the case K, w_i is the factor score coefficient of the ith variable, x_{ik} is the standardized value of the ith variable for the case k, and p is the number of variables.

2.3.2 The Empirical results of the factor analysis

To capture more than one dimension of poverty in a single measure I have constructed a composite index using factor analysis. The poverty dimensions include indicators on ownership of durable goods (e.g air conditions, private car…etc), on housing conditions (e.g sewerage system, type of floor,…etc) , on poverty status according to Egyptian objective poverty line, on subjective poverty and on security that measured by indicators of access to health insurance and access to pension scheme. Factor analysis is used in three stages as follow:

First I have applied factor analysis to construct an index of the durable goods owned by the household. The result obtained from this step is a durable goods index that is used as a variable in constructing the poverty index.

Second I have applied factor analysis to construct an index of the housing conditions of the household. The result obtained from this step is a housing condition index that is used as a variable in constructing the poverty index.

Third, the two previously constructed indices along with other four variables that represent different dimensions of poverty are used to construct the poverty index. These variables include poverty status according to Egyptian objective poverty line, subjective poverty, access to health insurance and access to pension scheme

2.3.2.1 Durable goods index

Factor analysis is used to construct the durable goods index (DGI). These variables include nine items; the ownership of: deep freezer, DVD/video, air condition ,electric heater, water heater, automatic washing machine, vacuum cleaner, computer/laptop and private car. The variables are dichotomous where one means having the item and zero not having it. The definitions of variables used to construct this index are presented in Table (2-1).

Table (2-2) indicates the results of constructing the durable goods index including; the communalities, the proportion of the variance explained by the model, the loading of the variable on the factor, the factor score coefficients for each variable and the test of model appropriateness.

As shown in Table 2-2, the communalities of the variables used to construct DGI range from 0.31 to 0.635. The amount of variance that is accounted for by the principal component is about 47.197%.The test of model fitness shows that the K-M-O value is 0.885 which is higher than the unacceptable value. Moreover, the Bartlett's test of sphericity is significant at 0.01 level. The factor loadings of the variables used to construct DGI range from 0.557 to 0.797. Equation 2-4 is applied to construct DGI based on the results reported in Table 2-2 as follow:

$$\begin{aligned} DGI = {} & 0.149DF + 0.145DV + 0.175AC + 0.131EH + 0.147WH + \\ & 0.177AWM + 0.188VC + 0.163COM + 0.173CR \end{aligned} \tag{2-5}$$

The factor was rescaled to range between zero and one and then multiplied by 100. Therefore, each individual is assigned a score of durable goods index that lies between zero and 100.

Table 2-1: Definition of variables used to construct durable goods index

Variable	Variable definition	Mean	S.D
DF	A dummy variable which takes the value 1 if the individual owns deep freezer and 0 otherwise	0.07	0.257
DV	A dummy variable which takes the value 1 if the individual owns a DVD/Video and 0 otherwise	0.04	0.207
AC	A dummy variable which takes the value 1 if the individual owns air condition and 0 otherwise	0.08	0.266
EH	A dummy variable which takes the value 1 if the individual owns electric heater and 0 otherwise	0.04	0.197
WH	A dummy variable which takes the value 1 if the individual owns water heater and 0 otherwise	0.42	0.494
AWM	A dummy variable which takes the value 1 if the individual owns automatic washing machine and 0 otherwise	0.27	0.444
VC	A dummy variable which takes the value 1 if the individual owns vacuum cleaner and 0 otherwise	0.15	0.354
COM	A dummy variable which takes the value 1 if the individual owns computer/ labtop and 0 otherwise	0.14	0.351
CR	A dummy variable which takes the value 1 if the individual owns private car and 0 otherwise	0.07	0.258

Table 2-2: Results of factor analysis of durable goods index

Variables	Factor loading	Factor score	Communalities
DF	0.632	0.149	0.400
DV	0.618	0.145	0.381
AC	0.744	0.175	0.554
EH	0.557	0.131	0.31
WH	0.624	0.147	0.389
AWM	0.750	0.177	0.563
VC	0.797	0.188	0.635
COM	0.691	0.163	0.478
CR	0.733	0.173	0.538
% of variance:			47.197
K-M-O test of sampling adequacy :			0.885
Bartlett's test of sphericity:			$\chi^2 = 6853.389, p = 0)$
Number of observations:			2102

2.3.2.2 Housing conditions index

Factor analysis is used to construct the housing condition index (HCI). These variables include six items; Type of dwelling, type of floor, type of kitchen, type of toilet, type of sewerage system, and access to land line. The variables are dichotomous where one means acceptable condition of the item and zero unacceptable condition. The definitions of variables used to construct this index are presented in Table (2-3).

Table (2-4) indicates the results of constructing the housing condition index including; the communalities, the proportion of the variance explained by the model, the loading of the variable on the factor, the factor score coefficients for each variable and the test of model appropriateness.

As shown in Table 2-4, the communalities of the variables used to construct HCI range from 0.306 to 0.63. The amount of variance that is accounted for by the principal component is about 45.748%.The test of model fitness shows that the K-M-O value is 0.697 which is higher than the unacceptable value. Moreover, the Bartlett's test of sphericity is significant at 0.01 level. The factor loadings of the variables used to construct DGI range from 0.553 to 0.793. Equation 2-4 is applied to construct HCI based on the results reported in Table 2-4 as follow:

$$HCI = 0.243TD + 0.202TF + 0.236KIT + 0.289TT + 0.263SSM + 0.238LLN \qquad (2\text{-}6)$$

The factor was rescaled to range between zero and one and then multiplied by 100. Therefore, each individual is assigned a score of housing conditions index that lies between zero and 100.

Table 2-3: Definition of variables used to construct housing conditions index

Variable	Variable definition	Mean	S.D
TD	A dummy variable which takes the value 1 if the elderly live in a standard level of dwelling and 0 otherwise.	0.88	0.321
TF	A dummy variable which takes the value 1 if the elderly has a standard type of floor and 0 otherwise.	0.17	0.376
KIT	A dummy variable which takes the value 1 if the elderly have a separate kitchen and 0 otherwise.	0.91	0.291
TT	A dummy variable which takes the value 1 if the elderly has a standard type of toilet and 0 otherwise.	0.49	0.5
SSM	A dummy variable which takes the value 1 if the elderly has a standard sewerage system and 0 otherwise.	0.53	0.499
LLN	A dummy variable which takes the value 1 if the elderly has access to land line phone and 0 otherwise.	0.5	0.5

Table 2-4: Results of factor analysis of housing conditions index

Variables	Factor loading	Factor score	Communalities
TD	0.667	0.243	0.445
TF	0.553	0.202	0.306
KIT	0.647	0.236	0.418
TT	0.793	0.289	0.630
SSM	0.721	0.263	0.520
LLN	0.653	0.238	0.426
% of variance :			45.748
K-M-O test of sampling adequacy :			0.697
Bartlett's test of sphericity:			$\chi^2 = 3986.089, p = 0)$
Number of observations:			2102

2.3.2.3 Poverty index

Factor analysis is used to construct poverty index (PI). This index includes six items that represents poverty dimensions. The variables included are durable goods index, housing condition index, objective poverty which represents the status of the per capita expenditure whether below or above poverty line, subjective poverty which represents persons own perception about their economic status, and two variables to reflect the security dimensions that are measured by access to health insurance and coverage by pension scheme. The definitions of variables used to construct this index are presented in Table (2-5).

Table (2-6) indicates the results of constructing the poverty index including; the communalities, the proportion of the variance explained by the model, the loading of the variable on the factor, the factor score coefficients for each variable and the test of model appropriateness.

As shown in Table 2-6, the communalities of the variables used to construct PI range from 0.125 to 0.653. The amount of variance that is accounted for by the principal component is about 39.745%.The test of model fitness shows that the K-M-O value is 0.699 which is higher than the unacceptable value. Moreover, the Bartlett's test of sphericity is significant at 0.01 level. The factor loading of the variables used to construct PI ranges from 0.353 to 0.808. Equation 2-4 is applied to construct PI based on the results reported in Table 2-6 as follow:

$$PI = 0.312DGI + 0.339HCI + 0.148OP + 0.261HI + 0.276PC + 0.203SP \qquad (2\text{-}7)$$

The factor is rescaled to range between zero and one and then multiplied by 100. Therefore, each individual is assigned a score of poverty index that lies between zero and 100 where 100 means the poorest individual and 0 represents the richest.

Table 2-5: Definition of variables used to construct poverty index

Variable	Variable definition	Mean	S.D
DGI	A constructed index represent the ownership of durable goods ranges from 0 represents the poorest individual to 100 represents the richest	11.57	20.14
HCI	A constructed index represent the housing conditions and services available at the house ranges from 0 represents the poorest individual to 100 represents the richest	62.507	27.148
OPR	A dummy variable takes value 1 if the per capita expenditure is above poverty line and 0 otherwise	82.4	0.381
HI	A dummy variable which takes the value 1 if the elderly has access to health insurance scheme and 0 otherwise.	0.58	0.494
PC	A dummy variable which takes the value 1 if the elderly is pension beneficial and 0 otherwise.	0.56	0.497
SPR	A dummy variable which takes the value 1 if the elderly asses his status as not poor and 0 otherwise.	0.55	0.498

Table 2-6:Results of factor analysis of poverty index

Variables	Factor loading	Factor score	Communalities
DGI	0.743	0.312	0.553
HCI	0.808	0.339	0.653
OP	0.353	0.148	0.125
HI	0.622	0.261	0.386
PC	0.658	0.276	0.432
SP	0.485	0.203	0.235
% of variance :			39.745
K-M-O test of sampling adequacy :			0.699
Bartlett's test of sphericity :			$\chi^2 = 2244.921, p = 0)$
Number of observations:			2102

2.4 Older persons' characteristics by their Poverty index:

A total of 2102 heads of the household aged 60+ were successfully interviewed in the Egyptian Household Observatory Survey - Round 7, Egypt 2010 database (IDSC, 2010). The mean poverty for the sample is found to be 54.71%. This section presents poverty index of the respondents by their main characteristics. Studies on poverty among older people have identified age, gender, education, health status and place of residence, as the main correlates of poverty. Table (2-7) presents the distribution of the sample according to some selected characteristics. These are classified into individual demographic and socio-economic characteristics and governorate characteristics.

For the demographic characteristics, the results showed that, consistent with previous studies, age has a significant effect on poverty. Table (2-7) shows clearly that poverty declines as people age. The mean poverty is found to be 52.9% for the persons aged 60-64, increases to 53.76% for the age category 65-69, and reaches 57.7% for the oldest category. This means that the oldest category 70+ have around 3% higher in their poverty compared to the average poverty. As expected, consistent with previous studies (e.g, Masud et al, 2006), gender difference exists as well in favour of males. Table (2-7) shows that the mean poverty among males is 52.8%, while the correspondence percentage for females is 59.76% which means more than 5% higher than the the average poverty. This results stresses on the vulnerability of older females to face economic hardships.

Regarding the socio economic variables, the results showed that, educational attainment is one of the important significant correlates to poverty. Table (2-7) shows that mean poverty among illiterates is 66.27% which decreases to only 24.35% for those who hold a university degree or above. This result stresses on the importance of education to decrease poverty as holding a university degree or above was able to change the mean poverty for this group more than 30% lower than the average while mean poverty among illiterate is around 12% higher than the average. Consistent with previous studies, health status in terms of disability correlates to poverty as well (Zimmer, 2008). Table (2-7) indicated that the mean poverty for disabled is 62.82% which means more than 8% higher than the average poverty. However, having chronic disease does not show to have effect of increasing poverty as the mean poverty is found to be higher among the group who does not suffer from chronic disease. Regarding labour force participation, the mean poverty is found to be higher among working elderly. The results showed that the mean poverty among the working is 62.65% compared to 51.83% for their non-worker counterparts. This 7.94% higher mean poverty for the working persons than the average, in fact results due to the effect of poverty on forcing older persons to engage in the labour force as investigated in the following chapters.

For the governorate characteristic, Consistent with previous research (Gabr, 2009), the results showed that poverty differential is highly correlated with the place where the persons reside. Table (2-7) shows that Upper Egypt is the poorest region. For example, the mean poverty is found to be 68.87% in Asuit governorate, increased to 72.495% in Banisweif which means a higher mean poverty than the average by for 14.16% and 17.78% for Asuit and Baniswif respectively. While mean poverty decreases somehow for Lower Egypt governorate. For example, the mean poverty is found to be 42.66% for Ismaellia and 49.08% for Damitta which means a lower mean poverty than the average by for 14.16% and 17.78% for Ismaellia and Damitta respectively. The best situation is for Metropolitan governorates. The results showed that the mean poverty is 33.53% for Cairo and 40.64% for Alexandria means a lower mean poverty than the average by for 21.18% and 14.07% for Cairo and Alexandria respectively. There is a rural-urban difference in the mean poverty as well. Several studies showed that rural life is strongly associated to poverty due to older persons engagement in agricultural activities and lacking access to formal social security plans (khadr, 2004). The results showed that the mean poverty among rural residents is 66.84% compared to 43.12% among urban residents.

Table (2-7) Older persons' characteristics by their Poverty index

Variable name	Mean Poverty	Deviation from average poverty
Age (N=2102)		
Age category 60-64	52.94%	-1.77%
Age category 65-69	53.75%	-0.95%
Age category 70+	57.66%	2.95%
Gender (N=2102)		
Male	52.8%	-1.91%
Female	59.76%	5.05%
Education (N=2102)		
Illiterate	66.27%	11.56%
University+	24.35%	-30.36%

Variable name	Mean Poverty	Deviation from average poverty
Health (N=2102)		
Disabled	62.82%	8.11%
Having Chronic disease	53.55%	-1.16%
No health problem	55.94%	1.23%
Work Status (N=2102)		
Working	62.65%	7.94%
Non working	51.83%	-2.88%
Governorate (N=2102)		
Cairo	33.53%	-21.18%
Helwan	47.5%	-7.21%
Alexandria	40.64%	-14.07%
Portsaid	35.64%	-19.07%
Suez	45.32%	-9.39%
Damitta	49.08%	-5.63%
Daqahlya	55.42%	0.71%
Sharqya	61.82%	7.11%
Qalyobia	54.88%	0.17%
Kafr Alshekh	65.7%	10.99%

Variable name	Mean poverty	Deviation from average poverty
Gharbya	52.22%	-2.49%
menofia	57.41%	2.70%
Bhera	61.29%	6.58%
Ismaillia	42.66%	-12.05%
6th October	58.74%	4.03%
Giza	38.69%	-16.02%
Banisuif	72.49%	17.78%
Fayoum	63.99%	9.28%
Menia	64.62%	9.91%
Asuit	68.87%	14.16%
Sohag	66.27%	11.56%
Qina	66.07%	11.36%
Aswan	59.03%	4.32%
Luxor	65.45%	10.74%
Place of residence (N=2102)		
Rural	66.84%	12.13%
Urban	43.12%	-11.59%

2.5 Summary of findings

The first objective of the thesis is to construct an accurate measure of poverty in old age. In this chapter, a multidimensional measure of poverty is constructed using factor analysis. First I have applied factor analysis to construct an index of the durable goods owned by the household. Second, factor analysis is used to construct an index of the housing conditions of the household. The results obtained from these steps are the durable goods index and the housing condition index that are used as a variable in constructing the poverty index. Third, the two previously constructed indices along with other four variables that represent different dimensions of poverty are used to construct the poverty index. These variables include an objective poverty indicator represented by individual status of being below or above the poverty line, an indicator of subjective poverty presented by individual perception of their income and individual security which is measured by being covered by pension scheme and access to health insurance system. The factor is rescaled to range between zero and one and then multiplied by 100. Therefore, each individual is assigned a score of poverty index that lies between zero and 100 where a score of 100 indicates to the poorest individual and 0 indicates to the richest.

In the following chapters, the constructed poverty index is used as a dependent variable to model the determinants of elderly poverty and as independent variable in labour force participation models.

CHAPTER 3

THE ECONOMETRIC SINGLE-LEVEL MODELS

The main objective of this chapter is to identify the main determinants of both elderly poverty and their labour force participation using single-level models. In this chapter, two different modelling strategies are considered. Firstly, the traditional fixed effect model is carried out to investigate the determinants of both elderly poverty and labour force participation. Specifically, for the labour force participation determinants, a logistic regression model is carried out due to the binary nature of the dependent variable; being in/out of the labour force. For the poverty determinants, the ordinary least squares method (OLS) is implemented. Secondly, due to the expected endogeneity of labour force participation to poverty and vice versa, a simultaneous equation model is implemented and according to the results of the endogeneity tests, a correction for the endogeneity is carried out.

3.1 Logistic regression model

Logistic regression model is a special case of the generalized linear model where the outcome has a binomial distribution. According to this model, $p_r(Y_i)$ increases or decreases as an S-shaped function of Y as shown in figure 3-1.

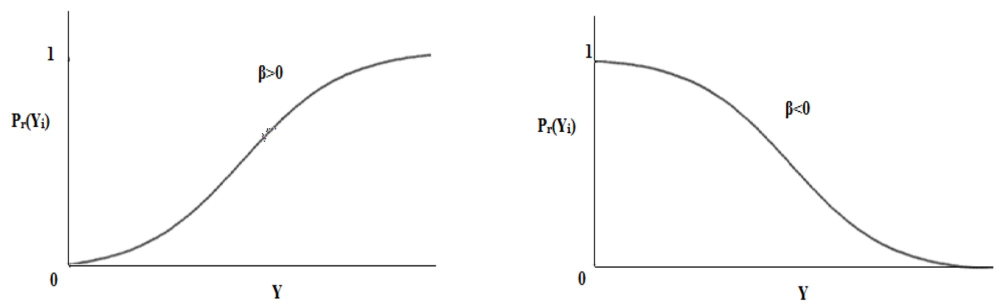

Figure 3-1: Logistic regression functions

This model is used to investigate the main determinants of elderly labour force participation. According to this model, the probability that the ith person is in labour force takes the form;

$$p_r(Y_i) = \frac{e^{(\alpha + \sum_{k=1}^{K} \beta_k x_{ik})}}{1 + e^{(\alpha + \sum_{k=1}^{K} \beta_k x_{ik})}} \tag{3-1}$$

where Y_i is a binary variable represents being in labour force, x_{ik} is the kth independent variable of the person i, β_k is the kth coefficient corresponding to the kth predictor, α is the intercept term.

Logistic regression does not rely on distributional assumptions. However, as with other forms of regression, multicollinearity among the predictors can lead to imprecise information about the unknown parameters and make it difficult to isolate the effect of each factor, for example, high standard errors and insignificant variables.

3.1.1 Logistic regression model results for labour force participation

Logistic regression model is applied to investigate the determinants of labour force participation. Considering the hypothesis testing presented in chapter 1, the candidate factors that are expected to affect labour force participation are grouped into two main categories. The first category represents variables measured at the individual-level including AGE1, AGE2, MALE, MRR, ILLTER, UNI+, DISB, CHR, DISBCHR, HHSUB, INCS, PI and RU. The second category represents variables measured at the governorate-level including UNEMP, PRIN and INEQUAL. Table 3-1 shows the logistic regression model results of the effect of these different variables on the log odds of being in labour force. It shows that most individual-level variables exert a significant effect on the log odds of being in labour force. Being 70 years old or above (AG2) decreases the log odds of being in labour force compared to being in the age category 60 to 64. Being male (MALE) increases the log odds of being in labour force. Married individual (MRR) are more likely to be in labour force compared to unmarried ones. Holding a university degree or above (UNI+) increases the log odds of being in labour force compared to those with less than university degree. However, being illiterate has no significant effect on the likelihood of being in labour force. Consistent with my prior expectation, the older people are motivated to work if they do not have enough potential supporters. This is asserted by the model result as increasing the household potential support ratio (HHSUP) decreases the log odds of being in labour force. According with literature, health has an important role in determining the elderly ability to engage in labour force. All health indicators including having chronic disease (CHR), disability (DISB) or both (DISBCHR) are found to decrease the log odds of being in labour force. Receiving other sources of income is found to diminish the older persons need to work. The results showed that it decreases the log odds of being in labour force significantly. Poverty index (PI) showed a highly significant positive effect on the log odds of being in labour force. Results do not support hypotheses H19, H23, H32.

Regarding governorate-level variables, two out of three variables are found to have a significant effect on the log odds of being in labour force. Living in a governorate with high rates of income inequality (INEQUAL) has a negative effect on the log odds of being in labour force. Increasing the percentage of population in labour force (PRIN) within the governorate decreases the log odds of being in labour force. Unexpectedly, unemployment rate does not exert a significant effect on log odds of being in labour force.

Table 3-1: Logistic regression results for determinants of labour force participation

Variables	Coefficients	Std.Err	Prior expectations	Results
Intercept	1.457**	.736		
AG1	-.191	.151	-	Not sig
AG2	-1.099***	.165	-	-
MALE	.587**	.286	+	+
MRR	.575**	.254	?	+
ILLTER	.119	.158	+	Not sig
UNI+	.480**	.244	+	+
HHSUP	-.162**	.075	-	-
CHR	-.618***	.129	-	-
DISB	-2.21***	.828	-	-
DISBCHR	-2.243***	.621	-	-
INCS	-2.643***	.165	-	-
PI	.023***	.005	?	+
RU	.156	.161	+	Not sig
INEQUAL	-3.538***	1.354	?	-
UNEMP	-.002	.013	-	Not sig
PRIN	-.033***	.013	-	-
Dependent variable: INLAB		**N**=2102		
AIC:2434.9		**Null deviance:**2434.9	**Residual deviance:**1679.5	

*** denotes that the estimated coefficient is Significant at .01 ** denotes that the estimated coefficient is Significant at .05 * denotes that the estimated coefficient is Significant at .1

3.2 Ordinary least squares regression model

Ordinary least squares model (OLS) is one of the most commonly used models in econometric work. In this model the dependent variable is expressed as a linear function of the explanatory variables as follow

$$Y_i = \beta_0 + \sum_{q=1}^{Q} \beta_q x_{qi} + U_i \tag{3-2}$$

where, Y_i is the poverty index for individual i, x_{qi} is the q$^{\text{th}}$ predictor for individual i, β_q is the q$^{\text{th}}$ parameter corresponding to the q$^{\text{th}}$ predictor, β_0 is the intercept term and U_i is the error term which follows $N(0,\sigma^2)$. The model assumes that the observations are iid. It also assumes that there is no multicollinearity among the predictors. The errors are assumed to be uncorrelated; i.e. $\text{cov}(U_i, U_j) = 0$ for all $i \neq j$. This assumption might be violated in the context of data with dependencies such as time series and hierarchical data. Another important assumption is the exogeneity of the predictors, i.e. $E(U_i / X_i) = 0$. The violation of this assumption may lead to biased and inconsistent results.

3.2.1 OLS model for poverty

OLS method is applied to investigate the determinants of poverty. Considering the hypothesis testing presented in chapter 1, the candidate factors that are expected to affect poverty are grouped into two main categories. The first category represents variables measured at the individual-level including AGE1, AGE2, MALE, MRR, ILLTER, UNI+, DISB, CHR, DISBCHR, HHSUB, INCS, INLAB and RU. The second category represents variables measured at the governorate-level including UNEMP, PRIN and INEQUAL. Table 3-2 shows the linear regression model results of the effect of these different variables on poverty. It shows that most individual-level variables exert a significant effect on poverty. The results showed that Being 70 years old or above (AG1) increases poverty Index compared to being in the age category 60 to 64. Consistent with the beliefs about women's vulnerability, the results showed that males are less likely to be poor than females. Education is one of the key correlates to poverty; the results showed that being illiterates (ILLTER) increases poverty index compared to other educated groups. Moreover, holding a university degree or above (UNI+) is found to have a significant impact in reducing poverty. Increasing the number of household potential supporters (HHSUP) decreases poverty significantly. Health status measured by having disability only (DISB) or having both disability and chronic disease (DISBCHR) are positively associated with poverty. The results showed also that having other sources of income than work (INCS) exerts a significant effect on decreasing poverty. Regarding the effect of labour force participation on poverty (INLAB), the main focus of this study, the results showed a positive effect of being in labour force participation on poverty. That is, the working elderly are more likely to be poor than non-working counterparts. This may be, in part, attributed to the poor individual need to work until their old age. Rural life is stongly associated with poverty due to the engagement in agricultural activities and lacking the access to formal social security plans. The results accord with this fact since living in rural areas (RU) shows a significant effect on increasing poverty index. Other individual-level variables that are tested by the hypothesis H_1, H_4, H_8 are not supported by the results.

All governorate-level variables have a significant effect on poverty. Income inequality (INEQUAL) is found to affect poverty negatively. Living in a governorate that has high percentage of population in labour force (PRIN) decrease poverty significantly. The results showed also that increasing in unemployment rate (UNEMP) within governorate exerts a negative effect on poverty. All these significant effects of governorate-level variables are not necessarily true and might be attributed to disaggregating governorate-level variable to the individual level which affects the standard errors of the estimated coefficient.

Table 3-2: OLS regression results for determinants of poverty

Variables	Coefficients	Std.Err	Prior expectations	Results
Intercept	71.989***	3.290		
AG1	-.045	.769	+	Not. Sig
AG2	2.228***	.761	+	+
MALE	-4.377***	1.203	-	-
MRR	-.547	1.118	-	-
ILLTER	13.028***	.699	+	+
UNI+	-16.684***	1.080	-	-
HHSUP	-1.269***	.365	-	-
CHR	.217	.662	+	+
DISB	6.458**	2.623	+	+
DISBCHR	4.093**	1.978	+	+
INCS	-7.231***	.966	-	-
INLAB	4.099***	.848	?	+
RU	12.798***	.735	+	+
INEQUAL	-42.665***	6.203	?	-
UNEMP	-.215***	.060	+	-
PRIN	-.230***	.063	-	-
Dependent variable: PI			**N**=2102	
R^2:0.5945	**F statistic**s: 132.5		**P value**= 0	

*** denotes that the estimated coefficient is Significant at .01 ** denotes that the estimated coefficient is Significant at .05 * denotes that the estimated coefficient is Significant at .1

3.3 Simultaneous-equations model

The two models mentioned above are single-equation regression models. In these models, the relationship between the dependent and the independent variables are unidirectional determined (Gujarati, 2010). However, Poverty and elderly labour force participation are often interlinked (Costa, 1996) and it is expected to find a simultaneous relationship between them. From one point of view, I expect that being poor forces the elderly to engage in labour force as a coping strategy to overcome their poverty which means a positive relationship between these two variables. On the other point of view, poverty might be diminished in response to engagement in labour force which means a negative relationship between these two variables. If this expected simultaneous relationship holds, labour force participation might be endogenous to poverty. The simultaneous relationship among variables is an important issue that should be taken into consideration whenever it exists; otherwise it causes inconsistent results for the effect of key variables (Chang and Yen, 2011).

Endogenous variables are the variables that can be determined from inside the model while exogenous variable refers to the variables that are determined from outside the model. There are different sources of endogeneity. It can arise due to simultaneity between the dependent variable and one or more of the independent variables. Endogeneity can also arise when the regressor is subject to measurement error. This is happen, for instance, when the measures is aggregated incorrectly from different data sources. It can also occurred when measuring variables like individual perceptions and beliefs. Omission of variables that are correlated with a regressor is another important source of endogeneity. Other sources include omitted selection, common-method variance, and Lagged dependent variables (see Antonakis et al, 2010 for further discussion on these other sources).

To highlight the effect of simultaneity on the parameter estimation, consider for simplicity that we have this system of structural equations:

$$Y_i = \beta_0 + \beta_1 X_i + e_i \tag{3-3}$$

$$X_i = \gamma_0 + \gamma_1 Y_i + U_i \tag{3-4}$$

Solving (3-3) using OLS requires $\text{cov}(X_i, e_i) = 0$. However, due to the simultaneity between X and Y, this assumption is violated. To explain, let's solve these structural equations for X_i

$$X_i = \gamma_0 + \gamma_1(\beta_0 + \beta_1 X_i + e_i) + U_i \tag{3-5}$$

$$X_i = \frac{\gamma_0 + \gamma_1\beta_0}{1 - \beta_1\gamma_1} + \frac{\gamma_1 e_i + U_i}{1 - \beta_1\gamma_1} \tag{3-6}$$

Assuming U_i and e_i are uncorrelated, then $\operatorname{cov}(X_i, e_i) = \frac{\gamma_1}{1-\beta_1\gamma_1}\operatorname{var}(e_i) \neq 0$. This example shows clearly that, due to the simultaneity between X and Y, X varies as a function of e. Consequently, ignoring this simultaneity by fitting single equation model may result in inconsistent estimate of the effect of X on Y (Gujarati, 2010; Antonakis et al, 2010).

To proceed with the simultaneous equation models, I first set the structural equations. The relationship between poverty and labour force participation will be investigated according to two structural equations. The first equation (3-7) expresses poverty index (PI) as a left-hand side variable which is determined by the potentially endogenous variable $(INLAB)$ along with other exogenous variables include AG1, AG2, MALE, MRR, ILLTER, UNI+, DISB, DISBCHR, HHSUP, INCS, RU, UNEMP, PRIN and INEQUAL. The second equation (3-8) is the labour force participation equation. It has being in labour force $(INLAB)$ as a left-hand side variable which is determined by the potentially endogenous variable (PI) along with other exogenous variables include AG1, AG2, MALE, MRR, ILLTER, UNI+, DISB, CHR, DISBCHR, HHSUP, INCS, RU, PRIN and INEQUAL.

$$PI = f_1(INLAB, \underline{X}_1) \tag{3-7}$$

$$INLAB = f_2(PI, \underline{X}_2) \tag{3-8}$$

where $\underline{X}_1$ and $\underline{X}_2$ are vectors of exogenous variables determine (PI) and $(INLAB)$ respectively.

Second, I set the reduced form equations. These equations represent the potentially endogenous variables as a function of all the exogenous variables in the structural equations. Accordingly, the reduced form equation for poverty, which is fitted using OLS model, is expressed as follow:

$$\begin{aligned} PI = f_1(&AGE1, AGE2, M, MRR, ILLTER, UNI+, DISB, DISBCHR, HHSUB, INCS, RU, \\ &UNEMP, PRIN, INEQUAL) \end{aligned} \tag{3-9}$$

and the reduced form equation for being in labour force, which is fitted using Logistic model, is expressed as follow:

$$\begin{aligned} INLAB = f_2(&AGE1, AGE2, M, MRR, ILLTER, UNI+, DISB, CHR, DISBCHR, \\ &HHSUB, INCS, RU, UNEMP, PRIN, INEQUAL) \end{aligned} \tag{3-10}$$

Reduced form equation results are used to obtain the predicted values of poverty and the predicted group membership of labour force participation, $\widehat{PI}$ and $\widehat{\mathrm{INLAB}}$ respectively. The predictions of these variables are in turn used to test for the exogeneity of poverty and labour force participation. The results from the reduced form models for poverty and labour force participation are presented in Table 3-3. Based on the results from the reduced form model, the predicted values of each potentially endogenous variable is calculated to be used in both the exogeneity test and in the simultaneous equation models if the variables were find to be endogenous.

It is worth mentioning in this context that, it is necessary to exclude at least one predictor from each equation. This restriction is important for the equations to be identified and to be able to obtain consistent estimators (Bollen et al, 1995). Thus to satisfy the identification condition, I have excluded the variables (CHR) from poverty equation and (UNEMP) from labour force participation equation.

Table3-3: Reduced form models for poverty and labour force participation

	Poverty model		labour force participation model	
variables	Coefficients	Std.Err	Coefficient	Std.Err
Intercept	67.064^{***}	3.197	3.079^{***}	0.664
AG1	-0.165	0.772	-0.198	0.149
AG2	1.725^{**}	0.758	-1.041^{***}	0.165
MALE	-4.177^{***}	1.209	$.485^{*}$	0.284
MRR	-0.255	1.122	$.553^{**}$	0.252
ILLTER	13.251^{***}	0.701	$.440^{***}$	0.145
UNI+	-16.67^{***}	1.086	0.077	0.227
HHSUP	-1.367^{***}	0.366	$-.189^{**}$	0.074
CHR	-0.140	0.661	$-.608^{***}$	0.128
DISB	5.580^{**}	2.63	-2.115^{**}	0.847
DISBCHR	3.237	1.980	-2.088^{***}	0.614
INCS	-9.48^{***}	0.851	-2.822^{***}	0.163
RU	13.033^{***}	0.738	$.443^{***}$	0.150
INEQUAL	-44.786^{***}	6.221	-4.319^{***}	1.329
UNEMP	$-.218^{***}$	0.060	-0.007	0.013
PRIN	$-.250^{***}$	0.064	$-.037^{***}$	0.012
(N=2102 **)**	**Dependent variable:** PI **R^2:** 0.5933 **F statistics:** 126.2 **P value: 0**		**Dependent variable:** INLAB **AIC:**2434.9 **Null deviance:**2434.9 **Residual deviance:** 1679.2	

*** denotes that the estimated coefficient is Significant at .01 ** denotes that the estimated coefficient is Significant at .05 * denotes that the estimated coefficient is Significant at .1

3.3.1 The identification problem

In order to obtain consistent estimators, the estimation method must satisfy two identification conditions (Gujarati, 2010). The first necessary but insufficient condition is “order condition”. According to this condition, we must satisfy that $K-k \geq m-1$ for each equation in the structural equations, where m is the number of endogenous variables in the model, K is the number of the exogenous variables in the model, and k is the number of the exogenous variables in that equation. In other word, at least one exogenous variable should be excluded from each equation. The second necessary and sufficient condition is “rank condition”. According to this condition, each exogenous variable excluded from one equation must appear in at least one of the other m-1 equations.

The excluded variables must satisfy two conditions. The first condition is existence of a zero covariance between the excluded variable and the error term of that equation. The second condition is the existence of a non-zero covariance between the excluded variable and the endogenous independent variable represented in that equation. These two conditions are satisfied for the structural equation for poverty by excluding the variable that represents having chronic disease (CHR) from equation (3-7). Similarly, For the structural equation of labour force participation the variable represented by unemployment rate (UNEMP) satisfies these two conditions and consequently this variable is excluded from equation (3-8).

3.3.2 Endogeneity test

To apply simultaneous equation model on the structural equations presented by (3-7) and (3-8), I should first investigate whether poverty (PI) and labour force participation $(INLAB)$ are endogenous or not.

Different methods can be applied to test for the endogeneity. Hausman (1978) suggests that the endogeneity of the variable can be checked by comparing the estimate of the potentially endogenous variable based on OLS procedures with the estimates after correcting of endogeneity. If the difference was found to be significant, then the variable is said to be endogenous. Another method depends on obtaining the estimated residuals of the potentially endogenous variables. Then, each left-hand side is regressed on the other endogenous variable, its estimated residuals, and other exogenous variables in the structural equation. If the estimated residuals are found to be significant, the associated variable is said to be endogenous to the left hand side variable. I applied this method to examine the endogeneity of poverty and labour force participation. According to this method the reduced form models for (PI) and $(INLAB)$ are obtained. Then I have estimated the following models

$$PI = h_1(INLAB, \widehat{\mathrm{INLAB}}, \underline{X}_1) \tag{3-11}$$

$$INLAB = h_2(PI, \widehat{\mathrm{PI}}, \underline{X}_2) \tag{3-12}$$

Where (PI) and $(INLAB)$ are the original values of poverty index and labour force participation respectively, residual (PI) and residual (INLAB) are the estimated residuals of (PI) and $(INLAB)$ respectively, $\underline{X}_1$ and $\underline{X}_2$ are vectors of exogenous variables included in (3-9) and (3-10) respectively. If residual (PI) is significant, poverty is said to be endogenous to labour force participation. If residual (INLAB) is significant, labour force participation is said to be endogenous to poverty.

Based on the results of the endogeneity tests, there are two possibilities. First, both residual (PI) and residual (INLAB) might be insignificant. In this case, they should be estimated using single-equation models. Second, either residual (PI) and residual (INLAB) or both might be significant which means that they are endogenous. In this case, two stage least squares method is applied to adjust for the endogenous variable(s).

The results of the endogeneity tests are presented in Table 3-4. For poverty model, the residuals of labour force participation is highly significant which implies that labour force participation is endogenous to poverty. This further suggests using simultaneous equation to model the determinants of poverty is appropriate. Regarding labour force participation model, Table 3-4 shows that the residuals of poverty is insignificant. This implies that labour force participation can be modelled using single-equation.

Table 3-4**:** Endogeneity test for poverty and labour force participation

N=2102	Poverty model		labour force participation model	
variables	Coefficients	Std.Err	Coefficient	Std.Err
Intercept	12.60	16.973	11.182***	2.42
PI	—	—	-0.033	0.059
Residual (PI)	—	—	0.001	0.059
INLAB	7.456	6.424	—	—
Residual (INLAB)	-4.724*	2.611	—	—
AG1	0.378	0.790	-0.189	0.151
AG2	-0.850	1.083	-1.116***	0.192
MALE	3.721***	1.257	0.629	0.386
MRR	-0.211	1.194	.577**	0.254
ILLTER	-13.628***	0.775	-0.014	0.797
UNI+	-16.608***	1.080	0.646	0.997
HHSUP	1.496***	0.383	-0.149	0.111
CHR	—	—	-.616***	0.129
DISB	-4.547*	2.766	-2.266**	0.894
DISBCHR	-2.262	2.142	-2.275***	0.658
INCS	12.227***	2.925	-2.549***	0.576
RU	-13.410***	0.810	0.025	0.804
INEQUAL	48.185***	6.925	-3.091	3.256
UNEMP	0.222***	0.06	—	—
PRIN	0.276***	0.068	-.031*	0.019

*** denotes that the estimated coefficient is Significant at .01 ** denotes that the estimated coefficient is Significant at .05 * denotes that the estimated coefficient is Significant at .1

3.3.3 The two-stage least squares method (2SLS)

The 2SLS method is one of the most useful methods to correct for endogeneity results from simultaneity (Antonakis et al, 2010). This method relies on removing the proportion of variance in the endogenous variable that correlates with the error term (Antonakis et al, 2010). According to this method, the analysis is done in two-stage estimation. First, the endogenous variable is estimated from the reduced form models. Second, the estimated values of the endogenous variable are used as a regressor in the structural equations form instead of the original variables and then estimated using the traditional methods described previously. Thus (3-7) and (3-8) will be estimated using $\widehat{\mathrm{PI}}$ and $\widehat{\mathrm{INLAB}}$ instead of (PI) and $(INLAB)$ on the right hand sides. Based on the results of the exogeneity test, labour force participation is found to be endogenous to poverty. Consequently, poverty index model is fitted in two stages. At the first stage, the labour force participation was fitted based on the reduced form model. At the second stage, poverty Index is estimated using the predicted values of the labour force participation instead of its original values.

The results of two-stage least squares method of poverty is reported in table 3-5. The estimates of the parameters are, in general, consistent with OLS model, except for DISBCHR and INLAB. After accounting for endogeneity, the effect of DISBCHR becomes insignificant and the predicted group membership of being in labour force has a highly significant negative effect on poverty. Regarding the effect of labour force participation on poverty, it becomes more logic after endogeneity is considered and so, engagement in labour force can now reduce poverty among the elderly. Similar to the result of OLS model, results of the effect of other factors indicate that, those whose age is 70+ (AG2), illiterate (ILLTER), disabled (DISB), rural residents (RU) have a significant effect on increasing poverty index. In addition, being male (MALE), holding university degree or above (UNI+), receiving other source of income (INCS) and increasing in household potential support ratio (HHSUP) have a significant effect on decreasing poverty.

All governorate-level variables show a significant negative effect on poverty. That is living in a governorate with high income inequality (INEQUAL), unemployment rate (UNEMP) and percentage of population in labour force (PRIN) reduce poverty index.

Table 3-5: Two stage least squares model for poverty

variables	Coefficient	Std.Err	Prior expectations	Results
Intercept	82.612***	4.062		
AG1	-0.316	0.772	+	Not sig
AG2	1.459*	0.758	+	+
MALE	-4.032***	1.205	-	-
MRR	-0.115	1.121	-	Not sig
ILLTER	13.437***	0.702	+	+
UNI+	-16.567***	1.085	-	-
HHSUP	-1.409***	0.366	-	-
DISB	5.202***	2.601	+	+
DISBCHR	2.85	1.941	+	Not sig
INCS	-15.076***	2.303	-	-
$\widehat{\text{INLAB}}$	-6.2***	2.376	?	-
RU	13.123***	0.736	+	+
INEQUAL	-46.845***	6.248	?	-
UNEMP	-0.218***	0.06	+	-
PRIN	-0.27***	0.064	-	-
Dependent variable: PI			**N=**2102	
R^2: 0 .5946		**F statistics:** 126.9	**P value:0**	

*** denotes that the estimated coefficient is Significant at .01 ** denotes that the estimated coefficient is Significant at .05 * denotes that the estimated coefficient is Significant at .1

3.3.4 Single-equation model of labour force participation

The results of the exogeneity test showed that poverty is not endogenous to labour force participation. Consequently, labour force participation is modelled using single-equation. The results are reported in Table 3-6. It shows that most individual-level variables have a significant effect on the log odds of being in labour force. Being 70 years old or above (AG2) decreases the log odds of being in labour force compared to being in the age category between 60 to 64. Being male (MALE) increases the log odds of being in labour force. Married individual (MRR) are more likely to be in labour force compared to unmarried. Holding a university degree or above (UNI+) increases the log odds of being in labour force compared to those with less than university degree. The results asserted the importance of the presence of supporter within the household since increasing the number of household potential supporters (HHSUP) has a significant effect on decreasing the log odds of being in labour force. According with literature, health has an important effect in determining the elderly ability to engage in labour force. Having chronic disease (CHR) or disability (DISB) or both (DISBCHR) decrease the log odds of being in labour force. Receiving other sources of income than work (INCS) decreases the log odds of being in labour force significantly. Poverty index (PI) showed a positive effect on the log odds of being in labour force that is, being poor motivate the elderly to continue their working life. Again, evidence from Table 3-6 do not support the hypotheses H_{19}, H_{23}, H_{32}.

The results showed also that all the governorate-level variables have a significant effect on decreasing the log odds of being in labour force.

Table 3-6: Single-equation model for determinants of labour force participation

Variables	Coefficient	Std.Err	Prior expectations	Results
Intercept	1.441**	.729		
AG1	-.191	.151	-	Not sig
AG2	-1.1***	.165	-	-
MALE	.585**	.286	+	+
MRR	.567**	.254	?	+
ILLTER	.119	.158	+	Not sig
UNI+	.482**	.243	+	+
HHSUP	-.163**	.075	-	-
CHR	-.618***	.129	-	-
DISB	-2.209***	.828	-	-
DISBCHR	-2.238***	.62	-	-
INCS	-2.642***	.165	-	-
PI	.023***	.005	?	+
RU	.159	.159	+	Not sig
INEQUAL	-3.596***	1.311	?	-
PRIN	-.033***	.729	-	-
Dependent variable: INLAB			**N**=2102	
AIC:1709.5	**Null deviance:**2434.9	**Residual deviance:** 1679.2		

*** denotes that the estimated coefficient is Significant at .01 ** denotes that the estimated coefficient is Significant at .05 * denotes that the estimated coefficient is Significant at .1

3.4 Summary of findings

In this chapter, two modelling strategies are applied to investigate the main determinants of poverty and labour force participation. First, I have performed traditional models as an initial step. Specifically, I have applied OLS model to investigate poverty determinants and Logistic regression model to investigate labour force participation determinants. Second, I have considered the simultaneity between poverty and labour force participation by applying simultaneous equations model. The results of the traditional models showed that being in labour force is positively associated with poverty. Furthermore, increasing in poverty exerts a positive effect on the log odds of being in labour force according to the results of logistic regression model. However, accounting for the simultaneity between these two variables showed contradiction results regarding the relationship between poverty and labour force participation. While being in labour force was found to have a positive relationship with poverty based on OLS model, it shows a significant negative relationship with poverty once correction for the endogeneity is made. In this chapter, the hierarchical structure of the data is ignored and the data is analysed as one group. Ignoring this hierarchical structure results in different methodological problems. In the following chapter, the problems associated with the hierarchical structure of the data is investigated. Moreover, the determinants of both poverty and labour force participation are investigated based on the multilevel models.

CHAPTER 4

THE ECONOMETRIC MULTILEVEL MODEL

In the preceding chapter, I have used single-level models to identify the main determinants of the two issues of concern. These models assume that the observations are independent and consider only one source of variability in the dependent variable. However, due to the nesting nature of the data (i.e. individual nested within governorate) , other sources of variability exist that reflect the differences between governorates in the dependent variable and the differences between governorates in the effect of some independent variables on the response. Consequently, a more developed model that reflects these sources of variability is required. The main objective of this chapter is to develop a multilevel model to identify the main determinants of both elderly poverty and their labour force participation. Specifically, for the labour force participation determinants, a multilevel logistic regression model is carried out due to the binary nature of the dependent variable; being in/out of the labour force. For the poverty determinants, the multilevel linear regression model is implemented due to its continuous scale.

4.1 Why multilevel model is needed?

Multilevel model is a statistical method used to analyse the data that has complex pattern of variability. In this study, the sample survey structure is a hierarchical one as it involves households nested within governorates. This hierarchical structure results in certain degree of dependency among households within the same governorates. Consequently, the OLS assumption of the independence of observations is violated. Ignoring this problem by using fixed-effect models results in imprecise statistical inference due to the lower estimate of the standard error which might yield unrealistic significant results. In this case, it is recommended to implement multilevel analysis which allows examining the effect of variables measured at both individual and governorates level on the outcome variable (Steenbergen, 2002; Hox, 2002).

In addition to the problem of dependency among households, there are other problems results from ignoring the hierarchical structure of the data. Among these problems is the ecological fallacy. This problem results from interpreting aggregated data at the individual-level. For example, the correlation between the dependent variable and an independent variable might be very strong for the whole observations but if the observations are clustered into homogeneous groups, the correlation might be weak within each group (Robinson, 1950).

Simpson paradox is another related fallacy occurred when data from heterogeneous groups are collapsed and analysed assuming that they are one group (Hox, 2002; Jones, 2008). To illustrate this problem, I have considered the example presented in Jones' 2008 study. Figure 4-1 shows a scatter plot for the relationship between X and. The estimated relationship differs according to the employed method. As shown in figure 4-2, the estimated regression line using OLS shows that the relationship is negative. However, as shown in figure 4-3, when the multilevel model is applied, the estimated regression line for the whole observations is consistent with the positive relationship between X and Y in each group.

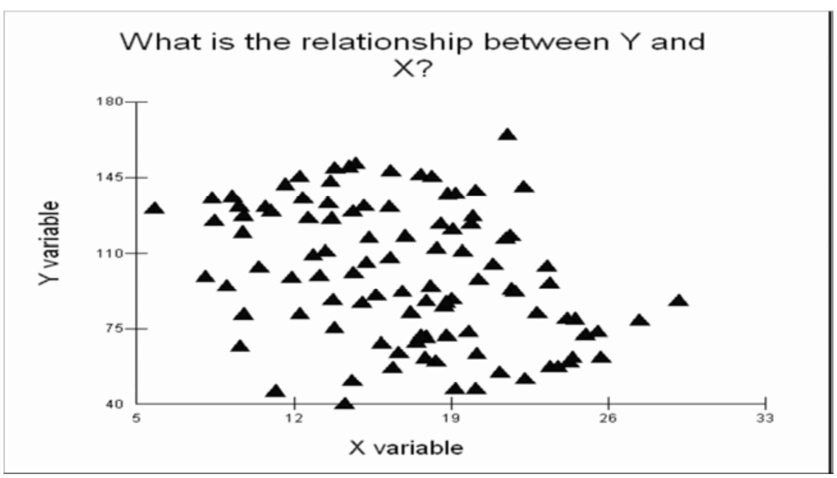

Figure 4-1: Scatter plot for the relationship between X and Y
(Source: Jones, 2008)

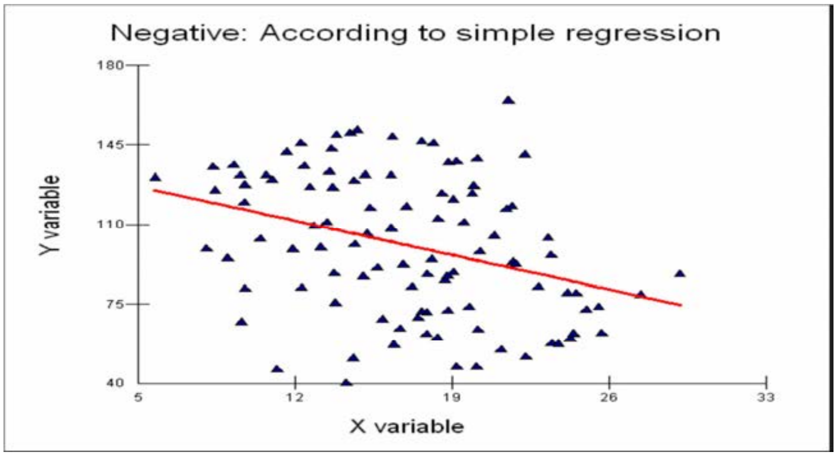

Figure 4-2: The OLS regression line for the relationship between X and Y (Source: Jones, 2008)

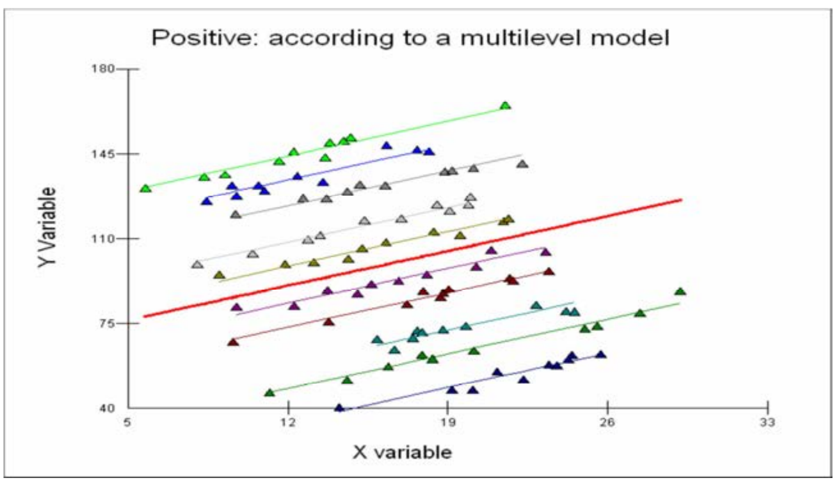

Figure 4-3: The multilevel model for the relationship between X and Y (Source: Jones, 2008)

The advantage of the multilevel model over the OLS model is that it allows examining the variation in the dependent variable at each level of data hierarchy. Figure 4-4 explains the importance of using the multilevel model. For illustration, let's assume that we have four groups and the interest is to examine the relationship between X and Y, we can consider four types of relationships. First the relationship between x and y might have the same intercept and the same slope in the four governorates as shown in part (a). In this case we do not need to perform the multilevel model as there will be only one error term describes the variability in y. Second, the relationship between x and y might have same intercept and four different slopes as shown in part (b). In this case another error term that reflects the variation in slopes should be included which can be done using multilevel model. Third, the relationship between X and Y might have same slopes but different intercepts as shown in part (c) and in this case another error term should be included to reflect the variability in these intercepts. The fourth and the more complex case is explained in part (d). In this case both intercepts and slopes differ among governorates and three sources of variability exist. These sources of variability cannot be captured by using OLS models and thus the multilevel model is desirable.

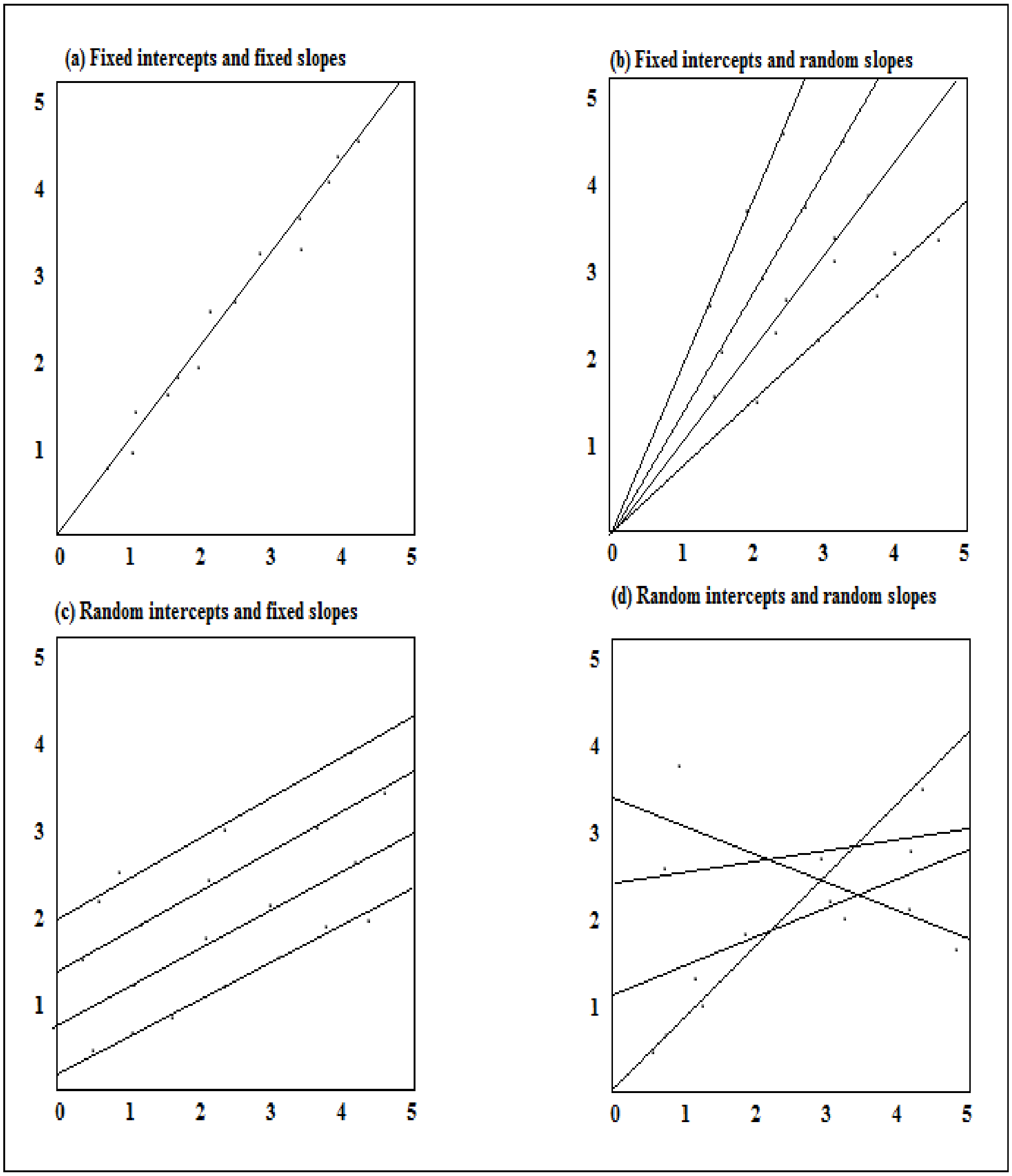

Figure 4-4: Relationships between x and y in hierarchical structure data

4.2 The multilevel logistic regression model for labour force participation

The multilevel logistic model for the dependent variable (INLAB) is set as a two-level model. The first level is a function of individual-level variables. These variables include AG1, AG2, MALE, MRR, ILLITER, UNI+, HHSUP, DISB, CHR, DISBCHR, INCS, PI, and RU. Since the dependent variable is binary, the individual level model can be expressed using the logit link function

$$\eta_{ij} = \beta^{*}_{0,j} + \sum_{q=1}^{13}\beta^{*}_{q,j}X_{qij} \qquad \text{for i=1, 2,……..2102 and j=1,2,…..24} \qquad (4\text{-}1)$$

where, η_{ij} is the predicted log odds resulting from the regression equation linked by the logistic transformation $\log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right)$ of the odds of being in labour force versus out labour force, π_{ij} is the probability of being in labour force, X_{qij} is the q^{th} predictor for individual i (nested) in governorate j, $\beta^{*}_{q,j}$ is the q^{th} coefficient associated with the q^{th} predictor for governorate j and $\beta^{*}_{0,j}$ is the intercept of governorate j.

The next step is to identify the governorate-level model. In this model, the variation of the overall intercept is assumed to be random and a function of governorate-level predictors that include UNEMP, INEQUAL, and PRIN. Thus,

$$\beta^*_{0,j} = \gamma^*_{0,0} + \sum_{h=1}^{3} \gamma^*_{0,h} Z_{h,j} + V_{0j} \tag{4-2}$$

where $\gamma^*_{0,0}$ is the overall intercept term, $Z_{h,j}$ is the h^{th} governorate-level predictor of governorate j, $\gamma^*_{0,h}$ is the h^{th} coefficient associated with $Z_{h,j}$, V_{0j} is the governorate-level error term. I assume that the slopes $\beta^*_{q,j}$ are fixed across governorates and denote it by letting j=0 because there is no variation across governorates in the effect of the predictors on labour force participation. Thus, $\beta^*_{q,j}=\gamma^*_{q,0}$ for q=1, 2,…13. Accordingly, the single equation version of the multilevel model is given by,

$$\eta_{ij} = \gamma^*_{0,0} + \sum_{q=1}^{13} \gamma^*_{q,0} X_{qij} + \sum_{h=1}^{3} \gamma^*_{0,h} Z_{h,j} + V_{0j} \tag{4-3}$$

To investigate the necessity of the multilevel model, I have examined the existence of variation across governorate. To do so, a null model that does not include any predictors is set up, and I test the significance of level-2 residual variance. At the individual-level, the null model is expressed as

$$\eta_{ij} = \beta^*_{0,j} \tag{4-4}$$

And the level-2 model is

$$\beta^*_{0,j} = \gamma^*_{0,0} + V_{0j} \tag{4-5}$$

Thus the single equation version of the null model is

$$\eta_{ij} = \gamma^{*}_{0,0} + V_{0j} \tag{4-6}$$

There are two parameters to be estimated from (4-6), one is the fixed effect for governorate-level intercept and the other is the random residual error term. Existence of a significant effect of governorate-level residual variance indicates a variation across governorates (Hox, 2002). Consequently, the assumption of IID residuals is invalid and ignoring this variation might bias the results.

In order to obtain a better understanding of the importance of considering the hierarchical structure of the data, I have examined the variance partition coefficient. This coefficient explains the proportion of variance due to the grouping structure. It is given by:

$$VPC = \frac{\tau_{00}}{\tau_{00} + \sigma^2} \tag{4-7}$$

where τ_{00} is the variance of the governorate-level residual and σ^2 is the variance of individual level residual. In logistic distribution the variance with scale factor 1 is approximately 3.29 (Hox, 2010; Heck, 2012). So the variance partition coefficient can be estimated as follow:

$$VPC = \frac{\tau_{00}}{\tau_{00} + 3.29} \tag{4-8}$$

4.2.1 The multilevel null model for labour force participation

Table 4-1 summarizes the null model results for labour force participation model. The variance component shows a significant variability in intercept among governorates which suggest the need to use the multilevel model. Moreover, the variance partition coefficient was estimated suggesting that 6.83% of the variability in labour force participation lies between governorates. These results violate the assumption of the independence of error terms. Ignoring this source of variation could result in erroneous statistical inference about the determinants of elderly labour force participation.

Table 4-1: The Null Model result of multilevel-logistic labour force participation

Dependent variable: INLAB (N=2102)		
Parameter	Estimate	Std.Err
Fixed effect		
Intercept	-1.045^{***}	0.111
Variance component		
τ_{00}	$.241^{**}$	.097
Variance partition coefficient	6.83%	

*** denotes that the estimated coefficient is Significant at .01 ** denotes that the estimated coefficient is Significant at .05

* denotes that the estimated coefficient is Significant at .1

4.2.2 The multilevel model for labour force participation

Table (4-2) shows the determinants of labour force participation based on the multilevel modelling. The fixed part includes the slopes of all the individual-level and governorate-level variables while the random part includes the variance of governorate-level residuals.

For the fixed part, the results of individual-level predictors showed that most variables exert a significant effect on the log odds of being in labour force. Being 70+ years old (AG2), having health problems (CHR, DISB, DISBCHR) , increasing the ratio of household potential supporters to the elderly (HHSUP) and having other sources of income (INCS) decreases the likelihood of being in labour force. The results showed also that being married (MRR), holding university degree or above (UNI+) are positively related to the likelihood of being in labour force. As expected, increasing in poverty index has a positive effect on the log odds of being in labour force. Other individual-level variables represented by age 65-69, illiterate and reside in rural area showed insignificant effect on the log odds of being in labour force.

The results of the effect of governorate-level predictors show that, both income inequality (INEQUAL) and percentage of population in the labour force (PRIN) are negatively related to the log odds of being in labour force. Unlike most existent literature, the results showed insignificant effect of governorate unemployment rate (UNEMP) on the log odds of being working.

The result of the random part shows that the variance of the intercepts becomes not significant after accounting for the hierarchical structure of the data. Moreover the variance partition coefficient decreased from 6.38% to 1.79 % which means that the model is able to explain most of the variability between governorates.

Table 4-2 : Multilevel model results for determinants of labour force participation

Fixed part	(dependent variable: INLAB)	(N=2102)		
Variables	Coefficient	Std.Err	Prior expectations	Results
Intercept	1.566***	.573		
AG1	-.194	.167	-	Not sig
AG2	-1.104***	.178	-	-
MALE	.601**	.247	+	+
MRR	.553**	.226	?	+
ILLTER	.123	.142	+	Not sig
UNI	.462*	.24	+	+
HHSUP	-0.168**	.068	-	-
CHR	-.606***	.145	-	-
DISB	-2.195***	.663	-	-
DISBCHR	-2.231***	.624	-	-
INCS	-2.668***	.148	-	-
PI	.022***	.004	?	+
RU	0.146	.19	+	Not sig
INEQUAL	-3.813***	1.177	?	-
UNEMP	-.002	.01	-	Not sig
PRIN	-.032***	.012	-	-
Random Part	**B**	**Std.Err**		
τ_{00}	.06	.051		
VPC	1.79%			

*** denotes that the estimated coefficient is Significant at .01 ** denotes that the estimated coefficient is Significant at .05 * denotes that the estimated coefficient

4.3 The multilevel linear model for poverty

The multilevel linear model of poverty index (PI) is set as a two-level model. The individual-level variables include AG1, AG2, MALE, MRR, ILLTER, UNI+, DISB, CHR, DISBCHR, HHSUP, INCS, INLAB and RU. Since the dependent variable is continuous, the individual-level model can be expressed using the linear model.

$$PI_{ij} = \beta_{0,j} + \beta_{1,j} ILLTER_{ij} + \beta_{2,j} INCS_{ij} + B_{3,j} INLAB_{ij} + \sum_{q=4}^{13} \beta_{q,j} X_{qij} + \varepsilon_{ij} \tag{4-9}$$

Where, PI_{ij} is the poverty index, X_{qij} is the q[th] predictor for individual i (nested) in governorate j, $\beta_{q,j}$ is the q[th] coefficient corresponding to the q[th] predictor for individual i (nested) in governorate j, $\beta_{0,j}$ is the intercept term of governorate j, and ε_{ij} is the error term of the individual-level.

At governorate-level, $\beta_{0,j}$ is assumed to be random. Moreover, the effect of being illiterate (ILLTER) and receiving other sources of incomes (INCS) vary significantly among governorates. Correspondingly, I construct the following three sets of equations to capture this variation by introducing random terms to $\beta_{0,j}$, $\beta_{1,j}$, $\beta_{2,j}$

$$\beta_{0,j} = \gamma_{0,0} + \sum_{h=1}^{3} \gamma_{0,h} Z_{h,j} + U_{0j} \tag{4-10}$$

$$\beta_{1,j} = \gamma_{1,0} + \sum_{h=1}^{3}\gamma_{1,h} Z_{h,j} + U_{1j} \tag{4-11}$$

$$\beta_{2,j} = \gamma_{2,0} + \sum_{h=1}^{3}\gamma_{2,h} Z_{h,j} + U_{2j} \tag{4-12}$$

Other slopes parameters are assumed to be fixed across governorates so we let j=0 because there is no variation between governorates in the effect of the predictors on poverty index i.e, $\beta^{*}_{q,j}=\gamma^{*}_{q,0}$ for q=3, 4,…13. .

Combining equations (4-9) to (4-12), the single equation for the multilevel linear model is given by

$$PI_{ij} = \gamma_{0,0} + \sum_{h=1}^{3}\gamma_{0,h} Z_{h,j} + (\gamma_{1,0} + \sum_{h=1}^{3}\gamma_{1,h} Z_{h,j})\ ILLTER_{ij} + (\gamma_{2,0} + \sum_{h=1}^{3}\gamma_{2,h} Z_{h,j}) INCS_{ij} + \gamma_{3,0} INLAB_{ij} +$$
$$\sum_{q=4}^{13}\gamma_{q,0} X_{qij} + \{\ \varepsilon_{ij} + U_{0j} + U_{1j} ILLTER_{ij} + U_{2j} INCS_{ij}\} \tag{4-13}$$

4.3.1 The multilevel null model results for poverty

To examine the existence of variation across governorates, I set up a a null model and test the significance of governorate-level variance of intercepts.

At individual-level, the null model can be expressed as :

$$PI_{ij} = \beta_{0,j} + \ \varepsilon_{ij} \tag{4-14}$$

and the governorate-level model will be:

$$\beta_{0,j} = \gamma_{0,0} + U_{0j} \tag{4-15}$$

Thus the single equation version of the null model will be

$$PI_{ij} = \gamma_{0,0} + \varepsilon_{ij} + U_{0j} \tag{4-16}$$

There are three parameters to be estimated in (4-16), the first one is the fixed effect for governorate-level intercept $\gamma_{0,0}$, the second one is the individual-level residual variance of ε_{ij} and the third one is governorate-level residual variance of U_{0j}. Existence of a significant effect of governorate-level residual variance indicates a variation across governorates.

A follow up step, in order to obtain a better understanding of the importance of considering the hierarchical structure of the data, is to examine the variance partition coefficient which explains the proportion of variance explained by the grouping structure. It is given by:

$$VPC = \frac{\tau_{00}}{\tau_{00} + \sigma^2} \tag{4-17}$$

where τ_{00} is the variance of the governorate-level residual and $\sigma^2$is the variance of individual level residual.

This model assumes that $U_{0j,}U_{1j}$ and U_{2j} are normally distributed with mean 0 and variance covariance matrix $\Sigma = \begin{bmatrix} \tau_{00} & \tau_{01} & \tau_{02} \\ \tau_{01} & \tau_{11} & \tau_{12} \\ \tau_{02} & \tau_{12} & \tau_{22} \end{bmatrix}$. The individual-level disturbances are assumed to follow $N(0,\sigma^2)$. The individual-level disturbances are assumed to be independent from the disturbance of governorate-level intercept and slopes, i.e; $\text{cov}(U_{0j,}\varepsilon_{ij}) = \text{cov}(U_{1j,}\varepsilon_{ij}) = \text{cov}(U_{2j,}\varepsilon_{ij}) = 0$ (Steenbergen and Jones, 2002).

In order to examine the determinants of poverty using traditional models, I assumed that the observations are independent. However, in this study, due to the hierarchical nature of the data, it is expected to violate this assumption. To test for the violation of this assumption, the extent of variability of the outcome variable across governorate-level units should be examined .Table 4-3 summarizes the null model results for poverty model. The variance component shows a significant variability in intercepts among governorates which suggest the need to use the multilevel model. Moreover, the variance partition coefficient was estimated suggesting that 27.2% of the variability in poverty index lies between governorates. These results violate the assumption of the independence of error terms. Ignoring this source of variation could result in erroneous statistical inference about elderly poverty. Consequently, a two-level model is required.

Table 4-3: The Null Model of poverty

Dependent variable: PI	**(N**=2102)	
Parameter	Estimate	Std.Err
Fixed effect		
Intercept	55.325***	2.295
Variance component		
τ_{00}	122.235***	37.19
σ^2	328.51***	10.19
variance partition coefficient	27.12%	

*** denotes that the estimated coefficient is Significant at .01 ** denotes that the estimated coefficient is Significant at .05 * denotes that the estimated coefficient is Significant at .1

4.3.2 The multilevel model for Poverty

Table (4-4) shows the determinants of elderly poverty based on the multilevel modelling. The fixed part includes the slopes of all the individual-level, governorate-level variables and cross-level interactions while the random part include the variance of governorate intercepts and variance of the slopes of being illiterate (ILLTER) and receiving other sources of income (INCS). For the fixed part, the results of individual-level predictors showed that being 70 years old or above (AG2) increases poverty compared to the age group 60 to 64. The findings reveals also that, being male (MALE), holding university degree or above (UNI+) and increasing in household potential support ratio (HHSUB) has a significant effect on decreasing poverty. Health is found to be a significant correlate with poverty as well. The results showed that having disability (DISB) or both chronic disease and disability (CHRDISB) are positively related to poverty. Moreover, living in rural areas is found to have a significant effect on increasing poverty.

Regarding the effect of labour force participation on poverty; the main focus in this study, the results of the multilevel model accords with the traditional model and contradicts the results of two stages least squares model. It shows a positive association between being in labour force participation and poverty. That is, the working elderly are more likely to be poor than non-working counterparts. This may be, in part, attributed to the poor individual need to work until their old age.

Other individual level-variables which tested the hypotheses H1, H_4, H_5, H_8, H_{13} showed insignificant effect on poverty index. The results reveal also that, while being illiterate and receiving other sources of income have insignificant effect on poverty; the interaction of these variables with some of governorate-level variable shows a significant effect on poverty. These interactions are examined due to the significance of the variation in the slopes of the individual-level variables (ILLTER and INCS) across the governorates. The results showed that, income inequality and unemployment rate are unrelated to the relationship between being illiterate and poverty. Thus, the interpretation of their main effect will be considered separately at their respective levels of the data hierarchy which showed that income inequality and unemployment rate exert insignificant effect on poverty. The interaction between illiterate and percentage of population in labour force shows a positive significant effect on poverty index which indicates that being illiterate reduces the effect of living in a governorate with high percentage of population in labour force in decreasing poverty. Receiving other sources of income showed insignificant interaction with unemployment rate and percentage of population in labour force. However, the interaction with income inequality showed a highly negative significant effect on poverty. It shows receiving other source of income in governorates with high income inequality have a significant effect on decreasing poverty. Among all other governorate-level variables, only percentage of population in labour force exerts a significant negative effect on poverty.

The results of the random part showed that the variance intercept decreases substantially from 55.325 to only 7.959 representing variance partition coefficient of about 4.16%. Thus implementing a multilevel modelling diminishes the variance partition coefficient from 27.12% to only 4.16%.

Table4-4: Multilevel model results for determinants of poverty

Dependent variable: PI		**N**=2102		
Variables	Coefficient	Std.Err	Prior expectantion	Results
Intercept	69.38***	10.26		
Demographic variables				
AG1	-0.179	.74	+	Not sig
AG2	2.03***	0.738	+	+
MALE	-4.07***	1.16	-	-
MRR	-.43	1.081	-	Not sig
Socio-economic variables				
ILLTER	-8.348	7.82	+	Not sig
UNI+	-16.097***	1.07	-	-
HHSUP	-1.335***	.353	-	-
CHR	. 593	0.645	+	Not sig
DISB	6.35**	2.53	+	+
DISBCHR	3.17*	1.91	+	+
INCS	14.57	8.64	-	Not sig
INLAB	3.15***	.823	?	+
RU	11.793***	.753	+	+
Governorate-level variables				
INEQUAL	-9.74	22.22	?	-
UNEMP	-.128	.219	+	Not sig
PRIN	-.405*	.236	-	-
Cross-level interactions				
ILLTER*INEQUAL	24.59	16.42	?	Not sig
ILLTER*UNEMP	-.065	.163	?	Not sig
ILLTER*PRIN	.511***	.178	?	+

Table4-4 (cont): Multilevel model results for determinants of poverty				
	Coefficient	Std.Err	Prior expectantion	Results
INCS*INEQUAL	-62.09***	19.07	?	-
INCS*UNEMP	-.011	.189	?	Not sig
INCS*PRIN	-.21	.199	?	Not sig
Ranodm Part	B	Std.Err		
τ_{00}	7.959	6.304	?	Not sig
τ_{11}	4.185	2.79	?	Not sig
τ_{22}	4.816	3.931	?	
σ^2	174.36***	5.48		
Variance partition coefficient	4.16%			

*** denotes that the estimated coefficient is Significant at .01 ** denotes that the estimated coefficient is Significant at .05 * denotes that the estimated coefficient is Significant at .1

4.4 Summary of findings

This chapter considers the hierarchical structure of the data set when modelling poverty and labour force participation. The results showed that 27.12% of differences in poverty and 6.83% of differences in labour force participation is due to the variability among governorates. This hierarchical structure results in low estimate of the standard error of the effect of the variables measured at the governorate-level if the parameters were estimated using single-level models that was presented in chapter three. Accordingly, in this chapter, I have performed a multilevel linear model to investigate the main determinants of poverty and a multilevel logistic model to investigate the main determinants of labour force participation. Furthermore, two variables were found to have different effect on poverty among governorates. In each governorate, the effect of being illiterate and receiving other sources of income have different effect on individual's poverty. The results showed that considering the hierarchical structure of the data when modelling poverty has significantly decreased the variance partition coefficient from 27.12% to only 4.16%. While for labour force participation, the model was able to decrease the variance partition coefficient from 6.83% to be only 1.79%. In the following chapter, a more complex econometric model that considers simultaneously the two key issues mentioned in chapter three and four; endogeneity and hierarchical structure of the data is introduced. Thus, a multilevel simultaneous equations model is developed in the following chapter to investigate the relationship between elderly poverty and their labour force participation.

CHAPTER 5
THE MULTILEVEL SIMULTANEOUS EQUATIONS MODEL

The empirical results mentioned in the previous chapters stress on two main statistical issues in determining the relationship between elderly poverty and their labour force participation. The first key issue is the endogeniety of labour force participation to poverty. I have developed a 2SLS regression model for poverty to correct for this endogeneity. Based on the result of this model I found that the positive association between poverty and labour force participation based on the traditional model is reversed to be negative after accounting for the endogeneity. The second key issue is the hierarchical structure of the dataset. This issue is taken into consideration by developing a multilevel model for both poverty and labour force participation. I found that multilevel model is very important to be considered since ignoring the hierarchical structure results in under-estimation of the standard errors of the variables measured at the governorate-level which yield unrealistic significant results if traditional models are applied. These interesting findings need further investigation to answer my research question: Does elderly participation in labour force reduce their poverty levels?

This chapter is based on developing a more complex statistical model that will consider, simultaneously, the two key issues mentioned above; endogeneity and hierarchical structure. Since the standard multilevel model assumes that the regressors in the model are independent of the random effects, it cannot produce consistent estimates when applied to model with an endogenous regressor.

5.1 Endogeneity in Multilevel models

In multilevel model, there is at least one random disturbance term at each level of the data hierarchy. These random disturbance terms reflect the nesting structure in the data. Consequently, endogeneity problem can concern error term at any level. In this study, there are two levels of the data (individual nested within governorates). Therefore, there is random error at each level and the explanatory variable (INLAB) can be correlated with the error term at any of these two levels.

The topic of endogeneity in fixed effect models has received a great interest among researchers (eg; Hausman, 1978; Bollen, 1995). In the last few years, researchers have paid some attention to the problem of endogeneity in the hierarchical random-effect model (eg; Ebbes et al; 2004; steele et al, 2009).

Empirical results of these studies showed that the presence of even a modest correlation between the regressor and the random disturbance affects the unbiasedness and the consistency of the regression parameter (Ebbes et al, 2004). In their study, they distinguished between three types of endogeneity in a two-level hierarchical data. Simulation is used to examine the consequence of ignoring endogeneity on the unbiasedness of the regression parameter. The first type of endogeneity considered in their study is modest level-2 endogeneity in which level-1 regressor is assumed to have a 0.3 correlation with level-2 disturbance term. They found that applying random-effect model in this case bias the parameter estimate of the endogenous variable upward while using fixed effect estimation yield unbiased estimate of the regression parameter. The second type of endogeneity is modest level-1 endogeneity in which level-1 regressor is assumed to have a .3 correlation with level-1 disturbance term. In this case, using either random-effect model or fixed effect model yield biased estimate of the regression parameter. The last type of endogeneity reflects endogeneity at both levels in which level-1 regressor is assumed to have a 0.3 correlation with each of level-1 and level-2 disturbances. In this case, both fixed effect and random effect models yield biased estimate of the regression parameter. Moreover, the estimate using random effect model yields larger bias.

Other researchers have used real data set to address the problem of endogeneity in hierarchical model. Dee (1998) was interested in the omitted variables and simultaneity problems as a source of endogeneity in examining the effect of the competition from private schools on the quality of public schools. The unit of observation in his data was school district which is nested in state nested in county. However, the study adopted an assumption- free approach to account for within group dependencies in the error structure rather than hierarchical model technique. He stressed on the importance of paying attention to simultaneity between the two variables of concern by comparing OLS estimates with 2SLS estimates and found that the former highly underestimates the effect of private school competition.

Steele et al (2007) were interested in the endogeneity results from the selection bias of the school resources on the pupil attainment taking into consideration the intra-school correlations in pupil responses. To consider these two methodological problems, they developed a two multilevel simultaneous equations model. The first equation is a three-level equation for the pupil attainment nested within school nested within the local education authorities while the second equation is a two-level equation for the school resources nested within the local education authorities. These simultaneous equations are framed as a multilevel bivariate response model and are estimated as a single equation by defining response indicator that take the value 1 if the response denotes to the pupil attainment and a value of zero if the response denotes to the school resources. This equation is then estimated using reweighted iterative generalised least squares method.

More recently, Steele et al (2009) have identified two-level simultaneous equations to model the relationship between child educational transition and family disruption. The first equation is a two-level proportional hazard model for marital disruption and the second one is a two-level probit model for child educational transition. They assumed a non-zero covariance between level-2 disturbances terms in both equations which suggests an endogeneity problem and followed the same procedure suggested in steele et al (2007). They showed evidence of the importance of tackling this problem since ignoring it over-estimate the effect of family disruption on the children outcome.

In 2013, Steele et al have considered a multilevel framework to examine the simultaneous influence of the individuals within the same social group based on a longitudinal data set. They focused on the reciprocal parent-child effects and sibling effects by setting two multilevel simultaneous equations autoregressive cross lagged model for the parent and child responses. The first equation is a two-level equation represents the parent response, with repeated measure (level-1) within family (level-2). It contains two error terms that capture the parent effect and occasion-specific residual. The second equation is a three-level equation to allow for multiple children per family. It represents the child responses, with repeated measures (level 1) within children (level-2) within family (level-3). This equation contains three error terms that capture the family effect, the child effect and occasion-specific residual. They assume that the endogeneity arise here due to the correlation of the error terms at the family-level and also the occasion-specific error terms across parent and child and between siblings while all other error terms are assumed to be independent.

In econometrics, a widely used approach to overcome the endogeneity problems in fixed-effect models is to construct instrumental variable that is correlated with the endogenous regressor but not with the random term. This constructed instrument is regressed on the dependent variable instead of the original endogenous variable. In multilevel modelling, Spencer (1998) has suggested such approach to overcome the problem of the endogeneity of a lagged version of the dependent variable that is used as a regressor. This approach is used by Spencer and Fielding (2000) as well. They have constructed instruments to overcome level-1 endogeneity in their study on the effect of the score of baseline tests on the score of current test. The instruments were constructed based on regressors assumed exogenous and independent of the random part. They have developed multilevel models with random intercept and fixed slopes to obtain these instruments and their predictions. A comparison between the estimates with and without the instruments showed a little difference in the coefficient and a higher estimated standard error using the instruments. The study emphasized on the ability of the constructed instruments to provide consistent estimates.

Ignoring level-2 endogeneity yields inconsistent estimates of the parameter as well. To obtain consistent estimates, Rice et al (1998) have recommended removing group variables and specifying dummy variables for each group, then using OLS for parameter estimation. However, according to this approach, we will not be able to estimate group-level variables and the estimation is not fully efficient compared to random-effects model.

5.2 Multilevel simultaneous equation models

To account for both the problem of endogeneity of labour force participation to poverty and the hierarchical structure of the data, I have developed a multilevel simultaneous equations model. To proceed with this model, I set the structural equations for both poverty and labour force participation. Each structural equation represents a two-level model of the dependent variable. The individual-level examines the effect of individual's characteristics on the dependent variable while governorate-level considers the effect of governorate's characteristics on the dependent variable.

The structural equation for labour force participation is set up by using a multilevel logistic model. The individual-level variables are mainly demographic and socio-economic variables that include AG1, AG2, MALE, MRR, ILLTER, UNI+, DISB, CHR, DISBCHR, HHSUP, INCS, RU and PI. Considering the dependent variable is categorical, the log odds of being in labour force at individual-level can be expressed using the following logit link function

$$\eta_{ij} = \beta^{*}_{0,j} + \beta^{*}_{1,j}\mathrm{PI}_{ij} + \sum_{q=2}^{13}\beta^{*}_{q,j}X_{qij} \qquad \text{for i=1, 2,……..2102 and j=1,2,…..24} \qquad (5\text{-}1)$$

Where, η_{ij} is the predicted log odds resulting from the regression equation linked by the logistic transformation $\log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right)$ of the odds of being in labour force versus out labour force, π_{ij} is the probability of being in labour force, X_{qij} is the qth predictor for individual i (nested) in governorate j, $\beta^*_{q,j}$ is the qth parameter associated with the qth predictor for governorate j, $\beta^*_{0,j}$ is the intercept of governorate j, PI_{ij} is the poverty index.

Then, I set up the governorate-level model by assuming random intercept and fixed slopes. At this level, the governorate-level variables include INEQUAL and PRIN while UNEMP is not considered to achieve the identification conditions. Thus the intercept term $\beta^*_{0,j}$ which represents the log odds of being in labour force in governorate j while all the predictors equal zero is written as,

$$\beta^*_{0,j} = \gamma^*_{0,0} + \sum_{h=1}^{2} \gamma^*_{0,h} Z_{h,j} + V_{0j} \tag{5-2}$$

where $\gamma^*_{0,0}$ is the overall intercept term, $Z_{h,j}$ is the hth governorate-level predictor of governorate j, $\gamma^*_{0,h}$ is the hth parameter associated with $Z_{h,j}$, V_{0j} is the error term. I assume that the slopes $\beta^*_{q,j}$ are fixed across g

overnorates and denote it by letting j=0 because there is no variation across governorates in the effect of the predictors on labour force participation. Thus, $\beta^*_{q,j}$=$\gamma^*_{q,0}$ for q=1,2,…13. In this model, governorate-level predictors include the factors of inequality within the governorate (INEQUAL) and percentage of population in labour force (PRIN). Therefore equation 2 can be explicitly written as:

$$\beta^{*}_{0,j} = \gamma^{*}_{0,0} + \gamma^{*}_{0,\text{INEQUAL}}\ \text{INEQUAL}_{j} + \gamma^{*}_{0,\text{PRIN}}\text{PRIN}_{j} + \text{V}_{0j} \tag{5-3}$$

Putting (5-1) and (5-2) together, the structural multilevel logistic model can be written in a single equation as:

$$\eta_{ij} = \gamma^{*}_{0,0} + \gamma^{*}_{1,0}\text{PI}_{ij} + \sum_{q=2}^{13}\gamma^{*}_{q,0}\text{X}_{qij} + \sum_{h=1}^{2}\gamma^{*}_{0,h}\text{Z}_{h,j} + \text{V}_{0j} \tag{5-4}$$

Similarly, the structural equation for poverty is also based on the multilevel model. For this case, the individual-level variables include AG1, AG2, MALE, MRR, ILLTER, UNI+, DISB, DISBCHR, HHSUP, INCS, RU, and INLAB and interaction effects $INLAB_{ij} \times M$ and $\text{INCS}_{ij} \times RU_{ij}$. Considering that the dependent variable PI is on a continuous scale, individual-level model can be expressed as

$$\text{PI}_{ij} = \beta_{0,j} + \beta_{1,j}\text{ILLTER}_{ij} + \beta_{2,j}\text{INCS}_{ij} + \text{B}_{3,j}\text{INLAB}_{ij} + \sum_{q=4}^{14}\beta_{q,j}\text{X}_{qij} + \varepsilon_{ij} \tag{5-5}$$

where, PI_{ij} is the poverty index, X_{qij} is the qth predictor for an individual i nested in governorate j, $\beta_{q,j}$ is the qth parameter associated with X_{qij}, β_{0j} is the intercept term of governorate j, and ε_{ij} is the random error term at the individual level.

At governorate-level model, $\beta_{0,j}$ is assumed to be random. Moreover, the effect of being illiterate (ILLTER) and receiving other sources of incomes (INCS) vary significantly among governorates as shown in Figure 5-2. Correspondingly, I have constructed the following three sets of equations to capture this variation by introducing random terms to $\beta_{0,j}$, $\beta_{1,j}$, $\beta_{2,j}$:

$$\beta_{0,j} = \gamma_{0,0} + \sum_{h=1}^{3}\gamma_{0,h}Z_{h,j} + U_{0j} \tag{5-6}$$

$$\beta_{1,j} = \gamma_{1,0} + \sum_{h=1}^{3}\gamma_{1,h}Z_{h,j} + U_{1j} \tag{5-7}$$

$$\beta_{2,j} = \gamma_{2,0} + \sum_{h=1}^{3}\gamma_{2,h}Z_{h,j} + U_{2j} \tag{5-8}$$

Other slopes parameters are assumed to be fixed across governorates so I let j=0 because there is no variation between governorates in the effect of the predictors on poverty index i.e, $\beta^{*}_{q,j}=\gamma^{*}_{q,0}$ for q= 3,4,…14 .

Combining equations (5-5) to (5-8), the single equation for the multilevel linear model of poverty is given by

$$\begin{aligned} PI_{ij} &= \gamma_{0,0} + \sum_{h=1}^{3}\gamma_{0,h}Z_{h,j} + (\gamma_{1,0} + \sum_{h=1}^{3}\gamma_{1,h}Z_{h,j})\ ILLTER_{ij} + (\gamma_{2,0} + \sum_{h=1}^{3}\gamma_{2,h}Z_{h,j})INCS_{ij} \\ &+\gamma_{3,0}INLAB_{ij} + \sum_{q=4}^{14}\gamma_{q,0}X_{qij} + \{\ \varepsilon_{ij} + U_{0j} + U_{1j}ILLTER_{ij} + U_{2j}INCS_{ij}\} \end{aligned} \tag{5-9}$$

Thus the full sets of structural equations are:

$$\eta_{ij} = \gamma^{*}_{0,0} + \gamma^{*}_{1,0}PI_{ij} + \sum_{q=2}^{13}\gamma^{*}_{q,0}X_{qij} + \sum_{h=1}^{2}\gamma^{*}_{0,h}Z_{h,j} + V_{0j} \qquad \text{(5-4) repeated}$$

$$PI_{ij} = \gamma_{0,0} + \sum_{h=1}^{3}\gamma_{0,h}Z_{h,j} + (\gamma_{1,0} + \sum_{h=1}^{3}\gamma_{1,h}Z_{h,j})\ ILLTER_{ij} + (\gamma_{2,0} + \sum_{h=1}^{3}\gamma_{2,h}Z_{h,j})INCS_{ij}$$

$$+\gamma_{3,0}INLAB_{ij} + \sum_{q=4}^{14}\gamma_{q,0}X_{qij} + \{\ \varepsilon_{ij} + U_{0j} + U_{1j}ILLTER_{ij} + U_{2j}INCS_{ij}\} \qquad \text{(5-9) repeated}$$

It is worth noting that, as is the case of single-level simultaneous equation models presented in chapter three, at least one variable should be excluded from each structural equation. Moreover, the excluded variable from each equation should be included in the other equation. The excluded variables must satisfy the two conditions of a zero covariance between the excluded variable and the error term of that equation and a non-zero covariance between the excluded variable and the endogenous independent variable represented in that equation. These two conditions are satisfied for the structural equation for poverty by excluding the variable that represents having chronic disease (CHR) from equation (5-9). Similarly, For the structural equation of labour force participation the variable represented by unemployment rate (UNEMP) satisfies these two conditions and consequently this variable is excluded from equation (5-4).

To account for the endogeneity, I have constructed an instrument for the endogenous variable (INLAB) using regressors assumed exogenous and independent of the random part of model (5-9). Multilevel logistic model is used to construct this instrument. The individual-level exogenous variables include AG1, AG2, MALE, MRR, ILLTER, UNI+, DISB, CHR, DISBCHR, HHSUP, INCS, RU and governorate-level exogenous variables include UNEMP, PRIN and INEQUAL. Accordingly, the reduced form equation for the log odds of being in labour force, which is fitted using multilevel logistic model, is expressed as follow:

$$\eta_{ij}' = \gamma_{0,0}' + \sum_{q=1}^{12} \gamma_{q,0}' X_{qij} + \sum_{h=1}^{3} \gamma_{0,h}' Z_{h,j} + V_{0j}' \tag{5-10}$$

The reduced form equation estimates is then used to obtain the predicted values of labour force participation, $\widehat{\text{INLAB}_{ij}}$. Now, $\widehat{\text{INLAB}_{ij}}$ does not correlate with the error term in poverty model (5-9), and hence it does not suffer from the endogeneity problem as the original variable INLAB_{ij}. These predicted values $\widehat{\text{INLAB}_{ij}}$ are used as an instrument into the multilevel equation of poverty as follows:

$$\begin{aligned} \text{PI}_{ij} &= \gamma_{0,0} + \sum_{h=1}^{3} \gamma_{0,h} Z_{h,j} + (\gamma_{1,0} + \sum_{h=1}^{3} \gamma_{1,h} Z_{h,j})\ \text{ILLTER}_{ij} + (\gamma_{2,0} + \sum_{h=1}^{3} \gamma_{2,h} Z_{h,j})\text{INCS}_{ij} \\ &+ \gamma_{3,0} \widehat{\text{INLAB}_{ij}} + \sum_{q=4}^{14} \gamma_{q,0} X_{qij} + \{\ \varepsilon_{ij} + U_{0j} + U_{1j}\text{ILLTER}_{ij} + U_{2j}\text{INCS}_{ij}\} \end{aligned} \tag{5-11}$$

It is worth mentioning here that the reduced form model in this model is constructed based on a multilevel framework not by single-level model as introduced in chapter three. This yield more accurate results regarding the predicted values of INLAB since the multilevel reduced form model here explained another part of variability that is not accounted for by the single-level model.

5.3 The empirical results

To investigate the necessity of fitting a multilevel model to construct the instrument of the endogenous variable INLAB, I have examined the existence of variation across governorate. To do so, a null model that does not include any predictors is set up, and I test the significance of governorate-level residual variance. At the individual-level, the null model is expressed as

$$\eta'_{\mathrm{ij}} = \beta'_{0,j} \tag{5-12}$$

And the governorate-level model is

$$\beta'_{0,j} = \gamma'_{0,0} + \mathrm{V}'_{0\mathrm{j}} \tag{5-13}$$

Thus the single equation version of the model is

$$\eta'_{ij} = \gamma'_{0,0} + \mathrm{V}'_{0\mathrm{j}} \tag{5-14}$$

There are two parameters to be estimated from (5-14), one is the fixed effect for governorate-level intercept and the other is the random error term. Existence of a significant effect of governorate-level residual variance indicates a variation across governorates (Hox, 2002). I have also examined the proportion of variance explained by the grouping structure by computing the variance partition coefficient (VPC). The VPC is given by:

$$VPC = \frac{\tau'_{00}}{\tau'_{00} + \sigma'^2} \qquad (5\text{-}15)$$

where τ'_{00} is the variance of the governorate-level residual and σ'^2 is the variance of individual-level residual. In logistic distribution the variance with scale factor 1 is approximately 3.29 (Hox, 2010; Heck, 2012). So the variance partition coefficient can be estimated as follow:

$$VPC = \frac{\tau'_{00}}{\tau'_{00} + 3.29} \qquad (5\text{-}16)$$

Table 5-1 summarizes the null model results for the multilevel reduced form of labour force participation model. The variance component shows a significant variability in intercepts among governorates which suggest the need to use multilevel model. Moreover, the variance partition coefficient was estimated suggesting that 6.83% of the variability in labour force participation lies between governorates. Consequently, to obtain a reduced form model of labour force participation, a two-level hierarchical model is fitted.

Table 5-1: The Null reduced form model of labour force participation

Parameter	Estimate	Std.Err
Fixed effect		
Intercept	-1.045^{***}	0.111
Variance component		
τ_{00}	$.241^{**}$	.097
σ'^2	3.29	1
VPC	6.83%	

*** denotes that the estimated coefficient is Significant at .01 ** denotes that the estimated coefficient is Significant at .05 * denotes that the estimated coefficient is Significant at .1.

Table 5-2 shows the result of the multilevel reduced form model for labour force participation. The results show that the model is able to explain part of the variability in labour force participation between governorate since the variance partition coefficient is reduced by more than half . Moreover, the variance of the intercepts is now insignificant.

The reduced form equation results will be used to obtain the predicted values of labour force participation; $\widehat{\mathrm{INLAB}}_{ij}$. These predicted values will be used as an instrument in the multilevel model of poverty. Once the instrument is created, different approaches like

2SLS can be used to estimate the regression parameter (Ebbes, 2007). In this study, two stage least squares multilevel model of poverty is estimated.

Table 5-2: The result of the multilevel reduced form model for labour force participation.

Dependent variable: INLAB	**N**=2102	
variables	Coefficient	Std.Err
Intercept	3.174***	0.551
AG1	-0.205	0.162
AG2	-1.054***	0.178
MALE	.513**	0.236
MRR	.521**	0.228
ILLTER	.416***	0.118
UNI+	0.08	0.227
HHSUP	-.196***	0.066
CHR	-.590***	0.148
DISB	-2.102***	0.751
DISBCHR	-2.101***	0.616
INCS	-2.854***	0.161
RU	.394**	0.196
INEQUAL	-4.692***	1.214
UNEMP	-0.006	0.011
PRIN	-.035***	0.013
Random Part		
τ^{*}_{00}	.103	.067
VPC*		3.04%

*** denotes that the estimated coefficient is Significant at .01 ** denotes that the estimated coefficient is Significant at .05 * denotes that the estimated coefficient is Significant at .1

5.3. 1 The empirical result of multilevel two-stage least square model of poverty

Before I proceed with this model, I first examine the existence of variation across governorates by setting up the null model and testing the significance of level-2 residual variance. Table 5-3 summarizes the multilevel null model results for poverty. The variance component shows a significant variability in intercepts among governorates. The variance partition coefficient suggests that 27.12% of the variability in poverty can be attributed to differences between governorates.

Table 5-3: The Null Multilevel mod for poverty

Dependent variable: PI	**N**=2102	
Parameter	Estimate	Std.Err
Fixed effect		
Intercept	55.325^{***}	2.295
Variance component		
τ_{00}	$122.235.775^{***}$	37.19
σ^2	328.51^{***}	10.19
variance partition coefficient	27.12%	

*** denotes that the estimated coefficient is Significant at .01 ** denotes that the estimated coefficient is Significant at .05 * denotes that the estimated coefficient is Significant at .1

The overall mean poverty across governorates is estimated as 55.325. The mean poverty for governorate j is $55.325 + \hat{U}_{0j}$, the governorate with $\hat{U}_{0j} \succ 0$ has a mean poverty index higher than the average while the governorate with $\hat{U}_{0j} \prec 0$ has a mean poverty index that is lower than the average.

Figure 5-1 shows a caterpillar plot of the estimated governorate residuals with 95% confidence intervals. These residuals represent governorates departure from the overall mean of poverty. Based on this plot, the mean poverty of 18 governorates out of 24 were found to differ significantly from the average. Most of the cluster of governorates whose mean poverty is lowest than the average comprise the metropolitan areas in Egypt e.g; Cairo and Alexandria. At the other extreme, there is a cluster with above average mean poverty. Almost all the governorates with poverty index above the average comprise of Upper Egypt governorates e.g; Asuit and Bani-sweif .

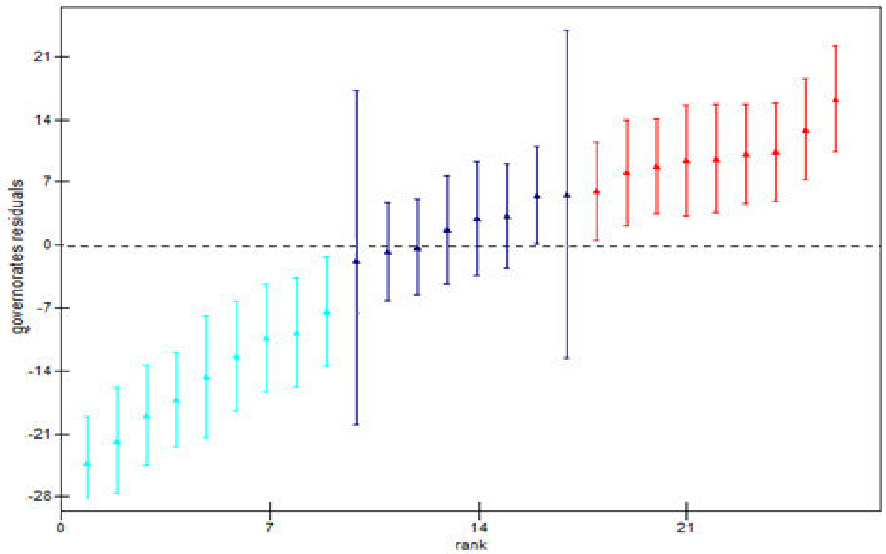

Figure 5-1: Caterpillar plot for governorates residuals with 95% confidence intervals for poverty

It is also important to examine whether the effect of the explanatory variables on poverty index varies across governorates. For each explanatory variable, the likelihood ratio test is used to test the null hypothesis $\sigma_{u_{0i}}$ for (i=1, 2,….14) are equal to zero. At the individual- level, two explanatory variables have different slopes across all governorates which means that the effect of these variables on poverty varies significantly across governorates. These variables include illiterate (ILLTER) and receiving other sources of income (INCS). Thus, the coefficients of these two regressors are set to have random components to allow their effect to vary across governorates.

Figure 5-2 shows the slopes of these variables across all governorates. The figure shows that the slopes of being illiterate have different strength among governorates. In particular, the Upper Egypt governorates have weaker effect of being illiterate on increasing poverty compared to other governorates. The figure shows also that for some governorates, receiving other sources of income has a strong effect on decreasing poverty while in other governorates; the effect of receiving other sources of income on decreasing poverty is weak or positive .

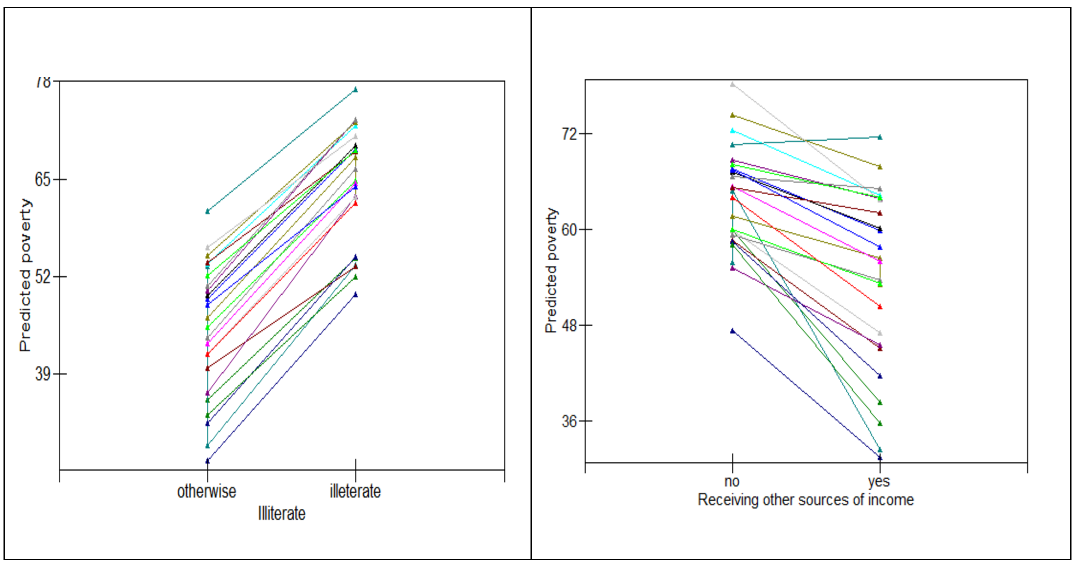

Figure 5-2: slopes of regressing being illiterate and receiving other sources of income on poverty in each governorate.

The huge differences in the effect of receiving other sources of income on poverty raise a question regarding the types of these sources. The results showed that the Metropolitan and Lower Egypt governorates have strong effect of receiving other sources of income on decreasing poverty while this effect is weaker in Upper Egypt governorates. This required further investigation on the reason behind these differences. Figure (5-3) shows the distribution of receiving other sources of income in these three main regions. It shows clearly that the most common sources of income other than work, in Metropolitan region, is retirement pensions while older persons who receive assistance either from relative or government consists of around 18%. In Lower Egypt, receiving assistance either from relative or from governorate is almost high compared to Metropolitan region since more than 38% of older people receive assistance as a source of income. The Situation is different in Upper Egypt region where more than half of the older people receive assistance from their relative or from government. These sources of income seems to be imperfect sources to decrease poverty compared to receiving pension which might justify the weakness of the slopes of this variable for Upper Egypt governorates.

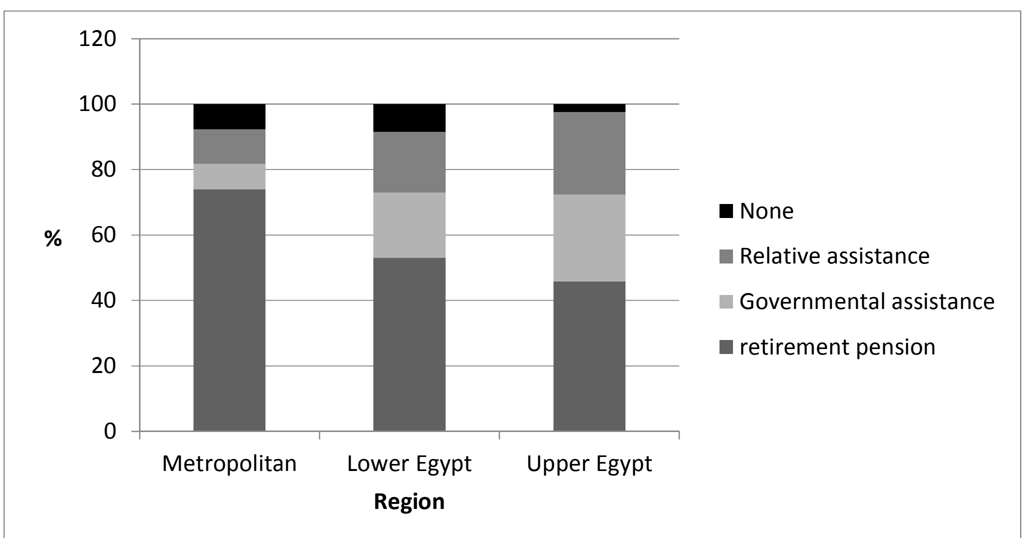

Figure 5-3: The distribution of receiving other sources of income by regions.

5.3. 2 Determinants of elderly poverty based on multilevel two-stage least square model.

In the previous subsection, I examined the existence of variation in mean poverty across governorates by setting up the null model and testing the significance of governorate-level residual variance. I also examined whether the effect of the explanatory variables on poverty index varies significantly across governorates or not. Based on the result of likelihood ratio test, I found that the effect of being illiterate (ILLTER) and receiving other sources of income (INCS) differ across governorate. Thus, according to this model, equation (5-11) consists of two-main components; the first component expresses the fixed effect part of the model which is divided into three effects:

1. Individual-level effect, represented by :

$$\gamma_{0,0} + \gamma_{1,0}\ \mathrm{ILLTER}_{ij} + \gamma_{2,0}\mathrm{INCS}_{ij} + \gamma_{3,0}\widehat{\mathrm{INLAB}}_{ij} + \sum_{q=4}^{14}\gamma_{q,0}X_{qij},$$

2. Governorate-level effect represented by : $(\sum_{h=1}^{3}\gamma_{0,h}Z_{h,j})$.

3. Cross-level interaction represented by: $(\sum_{h=1}^{3}\gamma_{1,h}Z_{h,j}\mathrm{ILLTER}_{ij} + \sum_{h=1}^{3}\gamma_{2,h}Z_{h,j}\mathrm{INCS}_{ij})$

The Second component expresses the random part of the model which is represented by:

1. Individual-level random part, represented by : ε_{ij}

2. Governorate-level random part $(U_{0j} + U_{1j}ILLTER_{ij} + U_{2j}INCS_{ij})$.

The modelling results of poverty determinants are shown in Table 5-4. The results of the fixed effects show that: For the individual-level variables, age, gender, health, education, labour force participation, and ratio of potential supports are the main determinants of poverty at the individual-level. Specifically, being 70 and older (AG2) and having disability (DISB) have a significant effect on increasing poverty index while being a male (MALE), holding a university degree or above (UNI+), increasing in household potential support ratio (HHSUP) and being in labour force ($\widehat{\text{INLAB}}$) decrease poverty index. Moreover, at the individual-level, there is a significant interaction effect between MALE and $\widehat{INLAB}$ which indicates that the effect of working on decreasing poverty is higher among females. This might be a reason behind the increase in the percentage of older females that are expected to engage to labour force. The UN projected an increase in the percentage of elderly working females through 2045-2050 by almost twice their percentage in 2007 compared to a dramatic decrease among their male counterparts by roughly 60% (Department of Economic and Social Affairs, Population Division, UN, 2007).

The results show also an interaction between receiving other sources of income and living in rural areas ($\text{INCS}_{ij} \times RU_{ij}$) which indicates that for those who are living in rural areas, receiving other sources of income does not help in decreasing poverty. This might due to the nature of these other sources of income which is mainly assistance from relative and governorates. The results showed that around 30% of older persons in rural areas receive governmental assistance and social security pensions and more than 23% receive assistance from relatives. While, beside income from work, the main sources of income in urban areas is pension. The results showed that 72.3% of urban residents receive pension compared to 38% of rural residents.

It is also of my concern to assess the effects of governorate-level variables on individual-level outcome and the extent to which they can explain the level-2 variance. In this model there are three governorate-level variables that are potential predictors of individual poverty index: governorates unemployment rate (UNEMP), governorates Gini coefficient for income inequality (INEQUAL), and percentage of population in labour force (PRIN). The results of the governorate-level predictors showed that, among the three considered variables, only higher percentage of population in labour force (PRIN) has a significant effect on poverty. The results showed that, living in a governorate with high percentage of population in labour force decreases the elderly poverty significantly.

As noted previously, due to the significance of the residual variance of the slopes of the individual-level variables (ILLTER) and (INCS), I assigned two random slopes for these two variables in the model. Furthermore, I considered whether the effect on poverty index of one of them depends on governorate-level variables. So, I considered the cross- level interaction between governorate–level variables and being illiterate (ILLTER) and receiving other sources of income (INCS). The results showed that, although they do not individually exert a significant effect on poverty, the interactions of these variables with some of governorate-level variables do. The results showed that the interaction between illiterate and percentage of population in labour force ($\mathrm{ILTER}_{ij} \times PRIN_j$) exerts a positive significant effect on poverty index which indicates that being illiterate reduces the effect of percentage of population in labour force on decreasing poverty. The results also show that for the governorate with high income inequality, receiving other sources of income decreases poverty significantly.

The random factor is concerned as well to examine the ability of multilevel two-stage least squares model to explain the variability in poverty index between governorates.

Assuming random intercept and two random slopes the governorate-level variance =

$$\begin{aligned}
&var\left(\mathrm{U}_{0j}+\mathrm{U}_{1j}\mathrm{ILLTER}_{ij}+\mathrm{U}_{2j}\mathrm{INCS}_{ij}\right)=var\left(\mathrm{U}_{0j}\right)+(\mathrm{ILLTER}_{ij})^2\,var\left(\mathrm{U}_{1j}\right)+\\
&(\mathrm{INCS}_{ij})^2\,var\left(\mathrm{U}_{2j}\right)+2cov\left(\mathrm{U}_{0j},\mathrm{U}_{1j}\right)+2cov\left(\mathrm{U}_{0j},\mathrm{U}_{2j}\right)+2cov\left(\mathrm{U}_{1j},\mathrm{U}_{2j}\right)=\\
&\tau_{00}+\tau_{11}+\tau_{22}+2\tau_{01}+2\tau_{02}++2\tau_{12}
\end{aligned} \tag{5-17}$$

Results suggest that governorate-level variance decreases substantially from 116.775 to 5.78. Accordingly, the variance partition coefficient is 3.24%. Thus, implementing a multilevel simultaneous equation model decreases the variance partition coefficient from 27.12% to only 3.24%.

5.3. 3 Comparison between the implemented models

In the previous chapters, three different modelling strategies are considered to investigate the relationship between elderly participation in labour force and its effect on their poverty status.

The first set of models is traditional OLS and logistic model. Based on these models I have identified the main determinants of elderly poverty and their labour force participation. These two models ignore both the endogeneity problem and the hierarchical structure of the data.

The second set of models is simultaneous-equation models. More specifically, I set two structural equations one for poverty determinants and the other one for labour force participation determinants. Based on these two equations, I have identified the determinants of elderly poverty and their labour force participation simultaneously. Simultaneous equation model is used due to the endogeneity of labour force participation to poverty. However, this type of model does not account for the hierarchical structure of the data.

The third set of models is the multilevel models. More specifically, I set a multilevel linear model to identify the main determinants of poverty and the multilevel logistic model to identify the main determinants of labour force participation. These models are used to account for the hierarchical structure of the data. However, it ignores the simultaneity between poverty and labour force participation.

In this chapter, I developed a multilevel- two stage least squares model (M2SLS) that takes into consideration the hierarchical structure of the data and the endogeneity of labour force participation to poverty. In order to be able to compare between this proposed model and these three different strategies, I have repeated these models using same variables and interactions that are identified based on the developed model (M2SLS).

The results of all different estimations are reported in Table 5-4. The factors that are candidates to determine poverty are classified into individual-level variables, governorate-level variables and cross-level interactions.

The individual-level variables include both demographic and socio-economic variables. For the demographic variables, the results of the effect of being 70 years or older showed that the direction and significance of their effect are the same across all models. However, the significant effect of gender appears only in two-stage models (i.e. 2SLS and M2SLS). This might be attributed to the fact that these two models considered the determinants of labour force participation and poverty simultaneously. Accordingly, the effect of gender on poverty is due to its effect on labour force participation. In labour force participation models, males were found to be more likely to work than females. This in turn affects their poverty where being males is found to decrease poverty significantly.

Regarding the socio-economic variables, the results showed that the direction and significance of the effect of most of these variables are the same across all models. The exceptions are for the health variables (DISB and DISBCHR) which showed a less significant effect on increasing poverty based on two-stage models (2SLS and M2SLS). Moreover, the results show that the significant effect of having disability and chronic disease (DISBCHR) on increasing poverty become insignificant after accounting for both the endogeneity and the hierarchical structure. In addition, living in rural areas showed only a significant effect on increasing poverty based on 2SLS model.

There are two main differences regarding the effect of being in labour force (INLAB) which is the variable of my main interest in this study. All models except the multilevel model show that this variable has a significant effect on poverty. However, it has different signs among models. While this variable has a significant effect on increasing poverty based on OLS model, applying 2SLS has changed it to have a negative effect. When a correction for both endogeneity and hierarchical structure are made using the M2SLS model, the variable of being in labour force (INLAB) exerts a significant effect on decreasing poverty. Furthermore, the interaction effect ($\mathrm{INLAB}_{ij} \times MALE_{ij}$) exerts a significant effect only when accounting for endogeneity whether using 2SLS or M2SLS.

At the governorate-level, the main difference among the four models is in the standard error of the estimated parameter. Although accounting for endogeneity, either by 2SLS model in comparison to OLS model or by M2SLS model in comparison to ML model, showed higher standard errors at the individual-level, it showed lower standard error for governorate-level variables. For example, the estimated parameter for the percentage of population in labour force (PRIN) showed a standard error of 0.17 in 2SLS model compared to 0.373 for OLS model. For multilevel case, the results showed that the standard error for M2SLS model is 0.369 compared to 0.378 for ML model. Moreover, the results showed that unemployment rate (UNEMP) exerts a significant effect on poverty in 2SLS model only. However, this effect is not highly significant.

With respect to the cross-level interactions, a comparison between these models shows similar results among models regarding the direction and the significance of the cross-level interactions except for the interactions between inequality and being illiterate $(\mathrm{ILLTER}_{\mathrm{ij}} \times INEQUAL_j)$.

The results showed that when a correction for the hierarchical structure is made by either multilevel or multilevel 2SLS, the significant effect of this interaction become insignificant. It is also obvious from the results that the multilevel models (ML and M2SLS) have higher standard errors of the estimated parameter than single-level models (OLS and 2SLS). This is due to the fact that single-levels models violated the independence assumption due to disaggregating the variable measured at the governorate-level to individual-level which yield low standard errors of the estimated parameters.

It is well known that one of the drawbacks of fitting a single-level model (e.g. OLS, 2SLS) with predictors defined at the group-level (INEQUAL, UNEMP and PRIN in this study) is that the standard error of the coefficients of these predictors may be underestimated. Accordingly, it is of importance to compare the results of these variables between a single-level model (OLS or 2SLS) and a multilevel model (ML or M2SLS). In this comparison, I focus on M2SLS model rather than the multilevel model since its results should be more consistent because it accounts for endogeneity. Similarly, with respect to single-level models, I focus on 2SLS model as a base for comparison as it accounts for endogeneity. As shown in Table 5-4, for the governorate-level variables, all the 2SLS standard errors are lower than its M2SLS counterparts. Furthermore, due to the low standard errors in 2SLS model in comparison to M2SLS, the 2SLS model shows more significant effects compared to M2SLS. The results showed that 15 out of 23 variables exert a significant effect on poverty compared to 11 significant variables based on M2SLS model.

The difference from the perspective of the error term can also be observed. In general, governorate-level variance in multilevel models is simply represented by τ_{00} . However, in this study the governorate-level variance is calculated by setting a random intercept parameter and two random slopes parameters. Accordingly, the governorate-level variance is calculated as $\tau_{00} + 2\tau_{01} + \tau_{11} + 2\tau_{02} + \tau_{22} + 2\tau_{12}$. Results demonstrated that, the variance partition coefficient based on multilevel 2SLS is 3.24%. This means that accounting for the hierarchical structure decrease variance partition coefficients from 27.12% to 2.29% in multilevel model and to 3.24% in M2SLS model indicating that applying multilevel models accounts for more than 88% of the variability on poverty among governorate.

Table 5-4 : The results of OLS, 2SLS, Multilevel and Multilevel 2SLS models

Variables \ Model	OLS		2SLS		Multilevel		Multilevel 2SLS	
Fixed part	Coefficient	Std.Err	Coefficient	Std.Err	Coefficient	Std.Err	Coefficient	Std.Err
Intercept	69.429***	19.440	80.303***	8.303	79.120***	19.440	103.976***	21.057
Demographic variables								
AG1	-0.038	.760	-0.188	0.765	-0.162	0.735	-0.244	.738
AG2	2.307***	.751	1.712**	0.752	2.0715***	0.730	1.697**	0.730
MALE	-1.560	2.556	-4.460***	1.20	-2.802	2.486	-10.290***	3.402
MRR	-0.248	1.108	-0.032	1.111	-0.407	1.073	-.307	1.075
Socio-economic variable								
ILLTER	-7.037	6.637	-5.482	6.055	-8.134	7.875	-7.922	7.608
UNI	-16.527***	1.088	-16.444***	1.092	-16.190***	1.0665	-16.171***	1.068
HHSUP	-1.399***	.362	-1.403***	0.364	-1.453***	0.351	-1.44569***	.352
DISB	6.484***	2.567	5.639**	2.579	6.063***	2.481	5.592**	2.487
DISBCHR	3.674**	1.912	2.865*	1.923	2.735*	1.850	2.263	1.858
INCS	-0.534	8.44	0.798	8.050	-1.340	8.824	-4.555	9.167
INLAB	8.44**	3.703	-9.450**	3.690	5.086	3.616	-12.172**	6.372
MXINLAB	-2.577	2.007	6.592**	3.003	-1.193	1.956	6.127**	3.082
RU	-0.753	4.324	6.786***	1.967	-0.334	4.188	-1.532	4.187
INCSxRU	6.858***	1.877	7.140***	1.883	6.514***	1.817	7.058***	1.827
Governorate variables								
INEQUAL	-0.028	37.350	-24.484	16.786	-6.064	37.420	-8.596	36.865
UNEMP	-0.2351	0.356	-0.241*	0.161	-0.297	0.360	-.335	.352
PRIN	-0.516*	0.373	-0.332*	0.170	-0.609*	0.378	-.621**	.369

Table 5(cont) : The results of OLS, 2SLS, Multilevel and Multilevel 2SLS models

Model / Variables	OLS		2SLS		Multilevel		Multilevel 2SLS	
Fixed part	Coefficient	Std.Err	Coefficient	Std.Err	Coefficient	Std.Err	Coefficient	Std.Err
Cross-level interaction								
ILLTER xINEQUAL	23.587*	12.499	22.991*	12.546	23.288	15.350	22.01	14.68
ILLTERxUNEMP	-0.078	0.1211	-0.074	0.122	-0.049	0.150	-.044	.144
ILLTERxPRIN	0.448***	0.132	0.431***	0.132	0.4876***	0.163	.483***	.156
INCSxINEQUAL	-43.802***	16.334	-41.769**	16.539	-42.196***	17.462	-40.965**	17.741
INCSxUNEMP	0.090	0.156	0.104	0.157	0.104	0.168	.118	.1685
INCSxPRIN	-0.249	0.161	-0.255	0.161	-0.239	0.173	-.237	.174
Random part	Coefficient	Std.Err	Coefficient	Std.Err	Coefficient	Std.Err	Coefficient	Std.Err
τ_{00}	-----	-----	-----	-----	5.467***		.9205	
τ_{11}	-----	-----	-----	-----	5.311***		3.9804***	
τ_{22}	-----	-----	-----	-----	3.778**		3.853***	
τ_{01}	-----	-----	-----	-----	-5.387		-1.11	
τ_{02}	-----	-----	-----	-----	1.027		1.883	
τ_{12}	-----	-----	-----	-----	-0.903		-2.26	
σ^2	186.137***	13.64	187.541***	13.69	172.050***	13.117	172.8348***	13.1467

5.4 Summary of findings

In this chapter have introduced a multilevel simultaneous equations modelling approach to consider simultaneously the endogeneity problem that is presented in chapter three and the problem associated with the hierarchical structure of the data which is presented in chapter four . In this chapter I have also compared between the traditional model, the simultaneous equation model, the multilevel model and the multilevel simultaneous equation model. There are two main differences between the four implemented models. First, the effect of being in labour force showed different signs among these models. While this variable has a significant effect on increasing poverty based on OLS model, applying 2SLS has changed it to have a negative effect. When a correction for both endogeneity and hierarchical structure are made using the M2SLS model, the variable of being in labour force (INLAB) exerts a significant effect on decreasing poverty. Second, at the governorate-level, the main difference among the four models is in the standard error of the estimated parameter. Although accounting for endogeneity, either by 2SLS model in comparison to OLS model or by M2SLS model in comparison to ML model, showed higher standard errors at the individual-level, it showed lower standard error for governorate-level variables. In the following chapter a comparison between the four implemented models is introduced based on a simulated data to formally asses to what extent the endogeneity problem in the hierarchical data structure cannot be ignored. This is investigated by assuming different scenarios of endogeneity.

CHAPTER 6

SIMULATION STUDY

In this chapter I have performed a simulation study to compare different modelling strategies that I introduced in Chapters 3, 4 and 5 in order to formally asses to what extent the endogeneity problem in the hierarchical data structure cannot be ignored. I have focused mainly on the comparison between multilevel models. Specifically, I have made comparison between multilevel-model that does not correct for the endogeneity and the proposed model "multilevel two-stage least squares" that corrects for the endogeneity. Moreover, I have compared between the single-levels models (OLS and 2SLS) and multi-level models in terms of the standard errors of the estimated parameters of governorate-level variables since, based on the literature, single-levels models should have lower standard errors at this level.

As discussed in chapter 5, the structural equations of the model can be written as:

$$\mathrm{PI}_{ij} = \gamma_{00} + \sum_{h=1}^{3}\gamma_{0h}Z_{hj} + (\gamma_{10} + \sum_{h=1}^{3}\gamma_{1h}Z_{hj})\ \mathrm{ILLTER}_{ij} + (\gamma_{20} + \sum_{h=1}^{3}\gamma_{2h}Z_{hj})\mathrm{INCS}_{ij} + \\ + \sum_{q=3}^{14}\gamma_{q0}X_{qij} + \{\ \varepsilon_{ij} + U_{0j} + U_{1j}\mathrm{ILLTER}_{ij} + U_{2j}\mathrm{INCS}_{ij}\} \tag{6-1}$$

For practical purpose, the structural equation of labour force participation can be expressed in terms of probability of being in labour force.

$$P_r.INLAB = \frac{\exp(\gamma^*_{00} + \gamma^*_{10}\mathrm{PI}_{ij} + \sum_{q=2}^{13}\gamma^*_{q0}X_{qij} + \sum_{h=1}^{2}\gamma^*_{0h}Z_{hj} + V_{0j})}{1+\exp(\gamma^*_{00} + \gamma^*_{10}\mathrm{PI}_{ij} + \sum_{q=2}^{13}\gamma^*_{q0}X_{qij} + \sum_{h=1}^{2}\gamma^*_{0h}Z_{hj} + V_{0j})} \tag{6-2}$$

I have considered two main situations regarding endogeneity problem in these two structural equations. The first one is level-1 endogeneity which occurs due to the correlation between leve-1 error terms of poverty model (ε_{ij}) with the level-2 error term of $P_r.INLAB$ (V_{0j}). That is $cov(\varepsilon_{ij}, V_{0j},) \neq 0$. The second one is level-2 endogeneity which occurs due to the correlation between leve-2 error term of the intercept of poverty model (U_{0j}) with the level-2 error term of $P_r.INLAB$ (V_{0j}) i.e. $cov(U_{0j}, V_{0j},) \neq 0$.

For each situation I performed 1000, 5000, and 10000 rounds of simulation studies. Moreover, to examine stepwise effects of endogeneity on the results of the estimated coefficient; I considered three different scenarios of the correlations between the error terms that captured a weak correlation with magnitude of 0.1, a moderate correlation with magnitude of 0.5, and a strong correlation with magnitude of 0.9. The assessment of the four models was examined in terms of biasedness, standard errors, and mean-square errors in all scenarios.

6.1 The simulation procedure

To perform these simulations, I generated a sample of 2012 individuals nested in 24 governorates based on the data. In addition, I assigned each governorate different number of cases similar to the original distribution in the data set (see table 1-2 for details).

To generate the dependent variable (poverty index) of the first structural equation, I have to formulate the random part first. The random part of poverty index model consists of level-1 error term ε_{ij} and three error terms U_{0j}, U_{1j}, and U_{2j} at level-2.

Level-1 disturbance is assumed to follow $\mathrm{N}\left(0,\ \sigma^2\right)$. In the simulation, I considered a value that is closed to the estimated value of σ^2 so the generated level-1 disturbance of ε_{ij} is assumed to follow $\mathrm{N}\left(0, 170\right)$.

Level-2 disturbances U_{0j}, U_{1j}, and U_{2j} are assumed to be normally distributed with mean $\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$ and variance covariance matrix $\Sigma = \begin{bmatrix} \tau_{00} & \tau_{01} & \tau_{02} \\ \tau_{01} & \tau_{11} & \tau_{12} \\ \tau_{02} & \tau_{12} & \tau_{22} \end{bmatrix}$. Similarly, to generate these disturbances, I considered values that are closed to the estimated value of $\tau_{00}, \tau_{11},\ \tau_{22}$

, τ_{01}, τ_{02}, and τ_{12} . So the generated level-2 disturbances U_{0j}, U_{1j}, and U_{2j} are assumed to be normally distributed with mean 0 and variance covariance matrix $\Sigma = \begin{bmatrix} 1 & -1 & 2 \\ -1 & 4 & -2 \\ 2 & -2 & 4 \end{bmatrix}$

In addition, the level-1 disturbance is assumed to be independent from level-2 disturbances, i.e; $cov(u_{0j}, \varepsilon_{ij}) = cov(u_{1j}, \varepsilon_{ij}) = cov(u_{2j}, \varepsilon_{ij}) = 0$.

For the second dependent variable, $P_r.INLAB$, which is represented by the second structural equation (6-2), I calculated its estimated error term V_{0j} based on the results of the multilevel model of labour force participation and tested for its normality. I also calculated the predicted probability of being in labour force $(\widehat{P_r.INLAB})$ that will be used instead of $(P_r.INLAB)$ in case of endogeneity.

The generated random errors of poverty index model ε_{ij} , U_{0j} are then assumed to have different strength of correlation with the error term of the $P_r.INLAB$ model; V_{0j} . Specifically, at level-1 endogeneity where there exists a correlation between $(\varepsilon_{ij}, V_{0j})$, I assumed a weak correlation coefficient of 0.1, a moderate correlation coefficient of 0.5 and a strong correlation coefficient of 0.9. Similarly, at level-2 endogeneity where there exists a correlation between (U_{0j}, V_{0j}), the same strength of correlations are assumed.

The dependent variable poverty index is assigned arbitrary values for population parameter at level-1 $(\gamma_{q,0})$ where $q = 3,4,5,...14$. Similarly, arbitrary values for population parameter at level-2 $(\gamma_{0,h})$ and the cross level interaction parameters $(\gamma_{1,h})$ and $(\gamma_{2,h})$ where $h = 0,1,2,3$ are used in the simulation.

Finally, to get generated values for the dependent variable poverty index, I added each of the values of the original predictors, the coefficient of population parameter and the random errors from the above procedures together. These steps are repeated 1000, 5000, and 10000 times based on the assumed correlation coefficients while keeping the sample size, the original predictors, and the coefficient of population parameters fixed and varying only the error terms and hence the dependent variable of poverty index.

6.2 Simulation for Level-1 endogeneity scenarios

Level-1 endogeneity exists due to the correlation between leve-1 error term of poverty model (ε_{ij}) with the level-2 error term of labour force participation model $\left(V_{0j}\right)$. Three different values of correlation coefficient between the error terms are considered; a weak correlation of 0.1, a moderate correlation of 0.5 and a strong correlation of 0.9. I estimated the four models of concern (OLS, 2SLS, ML, M2SLS) for each generated sample. Then, for the results of each model, the average of the estimated coefficient $(\hat{\gamma}_{0,0})$, $(\hat{\gamma}_{0,h})$, $(\hat{\gamma}_{1,h})$,

($\hat{\gamma}_{2,h}$), ($\hat{\gamma}_{q,0}$) and the average of their standard errors are calculated for h=1,2,3 and q=3,4,5 ,…14.

In this section the results of the four models in case of level-1 endogeneity are reported. In addition, a comparison between these models in terms of bias and mean square errors particularly for the endogenous variable is presented.

6.2.1 Simulation results for weak level-1 endogeneity

Tables 6-1, 6-2 and 6-3 show respectively the results of 1000, 5000, 10000 simulations of the four models in case of the existence of endogeneity at level 1, where the correlation between random errors is weak (0.1). A comparison between ML model and M2SLS shows that M2SLS model have less bias for the coefficient of the endogenous variable $P_r.INLAB$ and its interaction with being male $MALE \times P_r.INLAB$. For example in 10000 simulations the bias for $P_r.INLAB$ is 1.1 for M2SLS model compared to 1.449 for the ML model. Moreover, the total bias for M2SLS model is lower than the ML model.

The MSE for the estimated parameters of the endogenous variable $P_r.INLAB$ in M2SLS model are (1.22, 1.18, and 1.21) and its interaction with being Male $M * P_r.INLAB$ are (0.199, 0.193, and 0.197) for 1000, 5000, and 10000 simulations respectively. These MSE are the lowest among the four models.

Figure 6-1 shows a comparison of 10000 simulations between the four models regarding the bias and mean square errors of the estimated parameter of the endogenous variable in case of weak level-1 endogeneity. The figure shows clearly that ignoring both the hierarchical structure and the endogeneity problem by performing OLS model yield the highest biased and the highest MSE. When a correction for the endogeneity is considered by applying 2SLS model, the bias has declined significantly. However, the MSE still higher than the ML and M2SLS. Applying ML model which ignores the endogeneity problem but considers the hierarchical structure has increased the bias again. However MSE value is less than single-level models. The results showed that, once a correction for weak level-endogeneity is made by applying M2SLS model, the means square error reached the lowest value among the four models. Moreover, the bias is lower than the bias in single-level models that ignores the endogeneity (i.e. OLS and ML models).

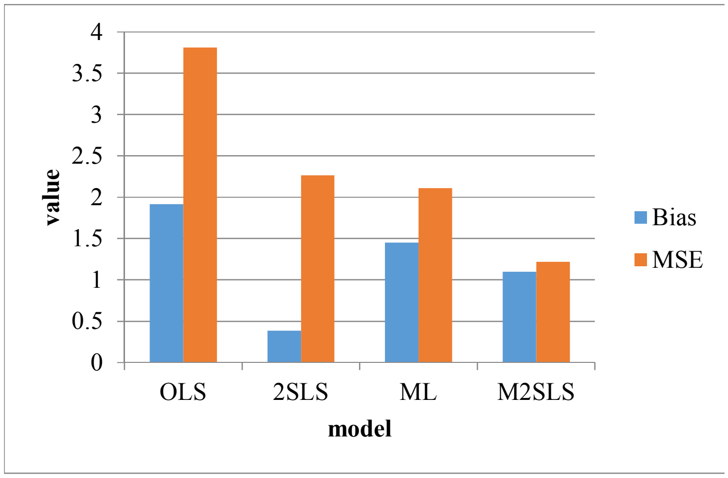

Figure 6-1: The bias and MSE of the endogenous variable associated parameter in case of weak level-1 endogeneity

It is well known from the literature that one of the draw backs of applying single-level models on hierarchical structured data is the low standard errors obtained for the variable measured at higher-levels which yield unrealistic significant effect of these variables on the dependent variable. This is confirmed in the simulation results reported in tables (6-1, 6-2 and 6-3). The reported results of the standard errors of the estimated parameters between single-levels models (OLS and 2SLS) and multi-levels models (ML and M2SLS) show that ML and M2SLS have the lowest standard errors of the estimated parameters for all variables except for the cross–level interactions variable and being illiterate(ILLTER). Although (ILLTER) is measured at the individual level, I assumed that its effects vary across governorates as well which might justify getting high standard errors for its estimated parameters.

6.2.2 Simulation results for moderate level-1 endogeneity

Tables 6-4, 6-5 and 6-6 show respectively the results of 1000, 5000, and 10000 simulations of the four models in case of the existence of endogeneity at level 1, where the correlation between random errors is set at the moderate level of 0.5. A comparison between ML model and M2SLS shows that the total bias for M2SLS model is lower than the ML model. Moreover, M2SLS model have less bias for the coefficient of the endogenous variable $P_r.INLAB$ and its interaction with being male $MALE \times P_r.INLAB$. For example, in 10000 simulations the bias for the coefficient of the endogenous variable in M2SLS model is 1.1 compared to 1.45 for the ML model.

The MSE for the estimated parameters of the endogenous variable $P_r.INLAB$ and its interaction with being Male $M * P_r.INLAB$ are the lowest in M2SLS Model. For example, in 10000 simulations the MSE for the coefficient of the endogenous variable in M2SLS model is 1.21 compared to 4.3, 2.29 and 2.01 for OLS, 2SLS, and ML respectively.

Figure 6-2 shows a comparison of 10000 simulations between the four models regarding the bias and mean square errors of the estimated parameter of the endogenous variable in case of moderate level-1 endogeneity. Similar to the case of weak level-1 endogeneity, the figure shows clearly that ignoring both the hierarchical structure and the endogeneity problem by performing OLS model yield the highest biased value and the highest MSE among the four models. When a correction for the endogeneity is considered by applying 2SLS model, the bias has declined significantly and approaches to be unbiased. On the other hand, MSE value is still higher than the ML and M2SLS. Applying ML model which ignores the endogeneity problem but considers the hierarchical structure has increased the bias again. However MSE value is less than single-level models. The results of M2SLS model showed that, once a correction for moderate level-endogeneity is made, the means square error reached the lowest value among the four models. Moreover, the bias is lower than the bias in single-level models that ignores the endogeneity (i.e. OLS and ML models). It is worth mentioning that increasing in the strength of the endogeneity from 0.1 to 0.5 showed a noticeable increase in the MSE based on OLS model meaning that when the strength of level-1 endogeneity increases, ignoring the hierarchical structure and the endogeneity problem become more sensitive.

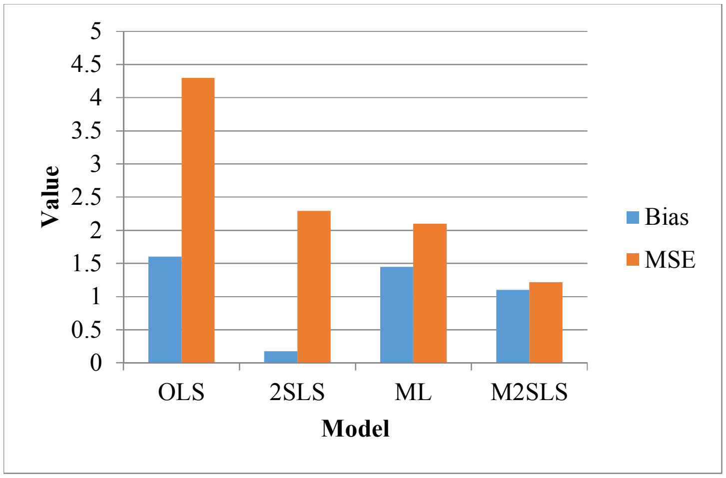

Figure 6-2: The bias and MSE of the endogenous variable associated parameter in case of moderate level-1 endogeneity

6.2.3 Simulation results for strong level-1 endogeneity

Tables 6-7, 6-8 and 6-9 present the results of 1000, 5000, and 10000 simulations of the four models respectively. These models are considered in case of the existence of endogeneity at level 1, where the correlation between random errors is strong (0.9). Similar to the case of weak and moderate level-1 endogeneity, the results showed that the total bias for M2SLS model is lower than the ML model. Moreover, M2SLS model have less bias for the coefficient of the endogenous variable $P_r.INLAB$ and its interaction with being male $MALE \times P_r.INLAB$. For example, in 10000 simulations the bias for the coefficient of the endogenous variable in M2SLS model is 1.09 compared to 1.45 for the

ML model. The correspondence figures for the coefficient of ($M * P_r.INLAB$) are 0.44 and 0.72 for M2SLS and ML model.

The MSE for the estimated parameters of the endogenous variable $P_r.INLAB$ and its interaction with being male ($M * P_r.INLAB$) are the lowest in M2SLS Model as in all level-1 endogeneity scenarios. For example, in 10000 simulations the MSE for the coefficient of the endogenous variable in M2SLS model is 1.2 compared to 5.39, 2.41 and 2.09 for OLS, 2SLS, and ML respectively.

Figure 6-3 shows a comparison of 10000 simulations between the four models regarding the bias and mean square errors of the estimated parameter of endogenous variable in case of strong level-1 endogeneity. Similar to the case of weak and moderate level-1 endogeneity, the figure shows clearly that ignoring both the hierarchical structure and the endogeneity problem by performing OLS model yield the highest biased and the highest MSE among the four models. When a correction for the endogeneity is considered by applying 2SLS model, the bias has declined significantly. However, the MSE still higher than the ML and M2SLS. Applying ML model which ignores the endogeneity problem but considers the hierarchical structure has increased the bias again. However MSE value is less than single-level models. Similar to all level-1 endogeneity scenarios, the results of M2SLS model suggest that, once a correction for strong level-endogeneity is made, the mean square errors reached the lowest value among the four models. Moreover, the bias is lower than the bias in single-level models that ignores the endogeneity (i.e.

OLS and ML models). It is worth mentioning that increasing in the strength of the endogeneity from 0.1 to 0.5 and again to 0.9 showed a noticeable increase in the MSE based on OLS model meaning that when the strength of level-1 endogeneity increases, ignoring the hierarchical structure and the endogeneity problem becomes more sensitive.

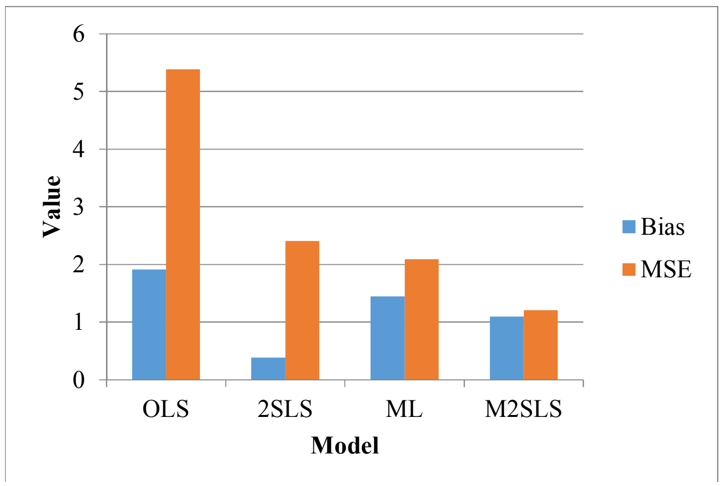

Figure 6-3: the bias and MSE of the endogenous variable associated parameter in case of strong level-1 endogeneity

A noteworthy finding from level-1 endogeneity scenarios is that the performance of the four models regarding the parameter associated with the endogenous variable is stable regardless of the strength of the correlation between $\left(V_{0j}\right)$ and (ε_{ij}). The results of all levels of endogeneity showed that 2SLS model has the lowest bias followed by M2SLS. Moreover, M2SLS has the lowest MSE in all level-1 endogeneity scenarios. While, as will be shown in the following scenarios of level-2 endogeneity, the performance of these models will differ according to the strength of the correlation between error terms.

6.3 Simulation for Level-2 endogeneity scenarios:

Level-2 endogeneity exists due to the correlation between leve-2 error term of poverty model (U_{0j}) with the level-2 error term of labour force participation model (V_{0j}). Three different values of correlation coefficient between the error terms are considered; a weak correlation of 0.1, a moderate correlation of 0.5 and a strong correlation of 0.9. I estimated the four models of interest, OLS, 2SLS, ML, M2SLS, for each generated sample based on 1000, 5000, 10000 simulations. Then, for the results of each model, the average of the estimated coefficient $(\hat{\gamma}_{0,0})$, $(\hat{\gamma}_{0,h})$, $(\hat{\gamma}_{1,h})$, $(\hat{\gamma}_{2,h})$, $(\hat{\gamma}_{q,0})$ and the average of their standard errors are calculated for h=1,2,3 and q=3,5 ,…14.

In this section the results of the four models in case of level-2 endogeneity are reported. In addition, a comparison between these models in terms of bias and mean square errors particularly for the endogenous variable is presented.

6.3.1 Simulation results for weak level-2 endogeneity

Tables 6-10, 6-11 and 6-12 show respectively the results of 1000, 5000,10000 simulations of the four models in case of the existence of endogeneity at level 2, where the correlation between random errors is weak (0.1). The results showed that the presence of level-2 endogeneity has more negative impact on the biasness and the accuracy of the estimates compared to the presence of level-1 endogeneity. A comparison between the effect of weak level-1 endogeneity and weak level-2 endogeneity shows that both bias and mean squares errors are higher in the latter case which stresses on the importance of considering the existence of the endogeneity at level-2.

For example, for 10000 simulations, the total absolute bias ranged from 31.8 to 33.5 in case of weak level-1 endogeneity compared to 57.9 and 59.6 in case of weak level-2 endogeneity.

A comparison between the multilevel models showed that M2SLS still performs better than ML regarding the total bias and the bias of the estimated parameter of the endogenous variable. For example, in the 10000 simulation, the absolute bias for the associated parameter of the endogenous variable is 3.63 for the M2SLS model compared to 4.38 for ML model. However, the MSE for M2SLS is the highest among all the models.

6.3.2 Simulation results for moderate level-2 endogeneity

Tables 6-13, 6-14 and 6-15 show respectively the results of 1000, 5000, and 10000 simulations of the four models in case of the existence of endogeneity at level 2, where the correlation between random errors is moderate (0.5). The results showed that the bias for estimated parameter of the endogenous variable is lower in M2SLS model compared to ML model. Moreover, the total absolute bias in M2SLS model is the lowest among the four models.

In case of moderate level-2 endogeneity, the accuracy of the estimated parameter of the endogenous variable and its interaction with being male started to be better in M2SLS than in ML. For example, in 10000 simulations, the MSE of the estimated parameter of the endogenous variable is 53.4 and 54.6 for M2SLS and ML respectively. The correspondence figures for the weak level-2 endogeneity are 51.3 and 50.

It is worth noting that the higher mean squares errors of the multilevel models (M2SLS and ML) are higher than single-level models. This is due to the higher MSE of the estimated parameter of the variables measured at level-2 such as (INEQUAL) or variables that has a cross-level interaction such as (ILLTERxINEQUAL) or variables measured at level-1 but are assumed to vary across level-2 units (ILLTER and INCS).

6.3.3 Simulation results for strong level-2 endogeneity

One of the interesting findings in this thesis is the performance of the proposed model (M2SLS) in the case of strong level-2 endogeneity. The results of 1000, 5000,10000 simulations of the four models in case of the existence of endogeneity at level 2, where the correlation between random errors is strong (0.9) are reported in Tables 6-16, 6-17 and 6-18 respectively.

In this case the M2SLS model yields the least total bias among all considered model. For example, in 10000 simulations, M2SLS yields a total bias of 60.17 compared to 76.14, 63.328 and 64.55 for OLS, 2SLS, and ML respectively. Figure 6-4 shows a comparison of the total bias among the four models according to different strength of level-2 endogeneity based on the result of 10000 simulations. The figure shows clearly that, two stages models (i.e. M2SLS and 2SLS models) have the lowest total bias among the four models in all endogeneity cases. Moreover, increasing in the strength of the endogeneity showed that M2SLS starts to give a better result regarding the total bias of the estimated parameter among all the four models even when the strength of level-2 endogeneity is moderate. The figure shows also that, for weak and moderate endogeneity, there is no noticeable difference between OLS and ML regarding the bias. However, increasing in the strength of the endogeneity at level-2 showed an increase in the gap between these two models. This means that, although both OLS and ML models ignore the endogeneity problem, ignoring strong level-2 endogeneity is worse in OLS model.

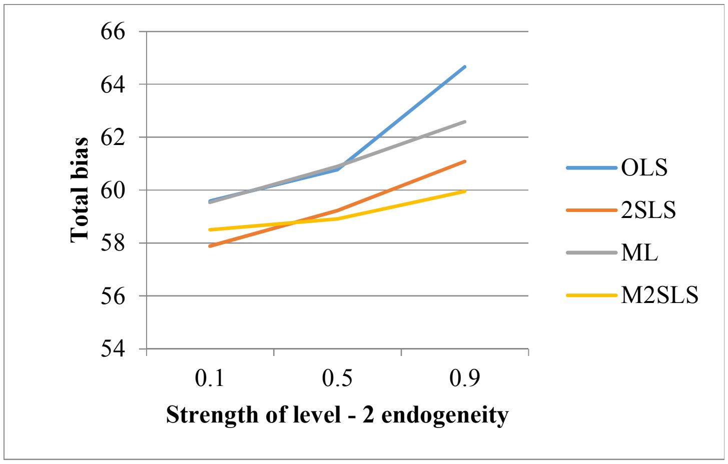

Figure 6-4: Results of the total bias in case of different level-2 endogeneity strength

Regarding the estimated parameter of the endogenous variable, M2SLS model yields the best results in terms of biasness and the accuracy of the estimates. For example, in case of 10000 simulations the bias of the coefficient of $P_r.INLAB$ is 4.82 for M2SLS model compared to 7.257, 5.39 and 6.2 for OLS, 2SLS, and ML models respectively. Figure 6-5shows a comparison of the bias of the estimated parameter of the endogenous variable among the four models according to different strength of level-2 endogeneity based on the result of 10000 simulations. The figure shows clearly that, two stages models (i.e. M2SLS and 2SLS models) have the lowest bias among the four models in all endogeneity cases. Moreover, increasing in the strength of the endogeneity showed that M2SLS starts to give a better result regarding the bias of the estimated parameter of the endogenous variable among all the four models. The figure shows also that, for weak endogeneity, there is no noticeable difference between OLS and ML regarding the bias. However, increasing in the strength of the endogeneity at level-2 showed an increase in the gap between these two models.

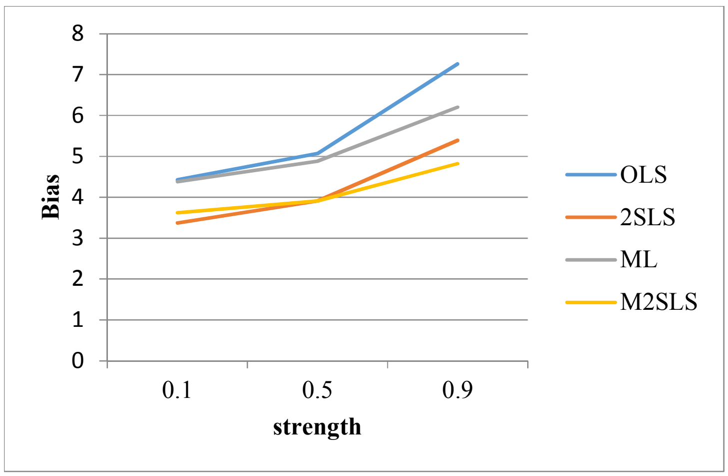

Figure 6-5: Results of the bias of the parameter associated with the endogenous variable in case of different level-2 endogeneity strength

The accuracy of estimating the associated parameter of the endogenous variable is the best for M2SLS model among other models. For example, in 10000 simulations, MSE in M2SLS model is 61.37 compared to 81.83, 67, and 69.31 for OLS, 2SLS, and ML respectively. Figure 6-6 shows a comparison of the MSE of the estimated parameter of the endogenous variable among the four models according to different strength of level-2 endogeneity based on the result of 10000 simulations. The figure shows clearly that for weak and moderate level-2 endogeneity, there is no noticeable difference between the four models regarding the accuracy of the estimated parameter of the endogenous variable. However, increasing in the strength of the endogeneity at level-2 showed an increase in the gap between these models. The figure shows that OLS model gives the worst result while M2SLS model shows the best result among all models.

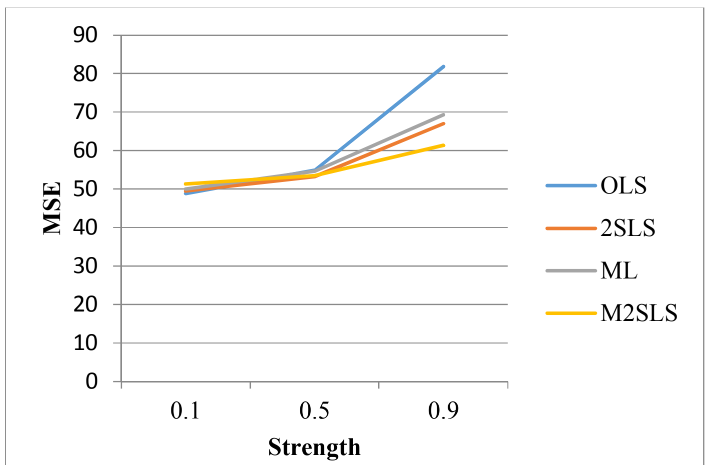

Figure 6-6: Results of the MSE of the parameter associated with the endogenous variable in case of different level-2 endogeneity strength

Table (6-1): Model results in case of level-1 endogeneity (e_{ij} with V_{0j},Rho=0.1), n=1000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr
Intercept	100	114.106***	1.21179	114.425***	1.23205	114.045***	0.399756	114.104***	0.40913
AG1	-1	-0.876***	0.12273	-0.93***	0.12614	-0.879***	0.00117	-0.888***	0.00307
AG2	2	1.758***	0.16753	1.616***	0.18345	1.758***	0.00172	1.73***	0.00459
MALE	-10	-8.786***	0.21765	-8.812***	0.22202	-8.791***	0.00204	-8.8***	0.00534
MRR	-1	-0.874***	0.18309	-0.819***	0.18729	-0.879***	0.00174	-0.871***	0.00453
ILLTER	-8	-7.174***	0.91525	-7.106***	0.92101	-7.155***	2.1464	-7.274***	2.16556
UNI+	-16	-14.08***	0.1646	-14.087***	0.16548	-14.066***	0.00157	-14.067***	0.00407
HHSUB	-2	-1.754***	0.05464	-1.748***	0.05498	-1.758***	0.00051	-1.756***	0.00132
DISB	6	5.282***	0.40394	5.157***	0.41124	5.275***	0.00383	5.26***	0.01003
DISBCHR	3	2.635***	0.30596	2.527***	0.31286	2.637***	0.00293	2.624***	0.00761
INCS	-5	-4.506***	1.13084	-4.597***	1.13691	-4.344***	0.79922	-4.111***	0.88968
RU	-2	-1.751***	0.30026	-1.738***	0.30215	-1.757***	0.00281	-1.745***	0.00799
$P_r.INLAB$	-12	-10.554***	1.31069	-11.904***	1.50196	-10.548***	0.01374	-10.896***	0.0376
$MALE \times P_r.INLAB$	6	5.256***	1.10723	6.084***	1.22076	5.274***	0.01088	5.555***	0.02987
INCSxRU	7	6.152***	0.28398	6.164***	0.28531	6.153***	0.00268	6.149***	0.00762
INEQUAL	-9	-8.236***	2.53555	-8.685***	2.5598	-8.085***	2.35938	-8.206***	2.38515
UNEMP	-1	-0.878***	0.02412	-0.878***	0.02424	-0.878***	0.02169	-0.877***	0.02195
PRIN	-1	-0.879***	0.02589	-0.881***	0.02606	-0.878***	0.01242	-0.879***	0.01263
ILLTERxINEQUAL	22	19.857***	1.88898	19.613***	1.899	19.714***	5.65391	19.838***	5.66201
ILLTER xUNEMP	-1	-0.882***	0.01838	-0.879***	0.01845	-0.881***	0.05802	-0.879***	0.05803
ILLTER xPRIN	1	0.88***	0.01989	0.88***	0.01998	0.88***	0.05008	0.883***	0.05048
INCSxINEQUAL	-40	-35.356***	2.46538	-35.173***	2.47857	-35.518***	4.71841	-35.631***	4.73134
INCSxUNEMP	1	0.882***	0.02361	0.882***	0.02372	0.88***	0.04339	0.878***	0.04363
INCSxPRIN	-1	-0.874***	0.02427	-0.873***	0.02439	-0.878***	0.02483	-0.884***	0.02636

Table (6-2): Model results in case of level -1 endogeneity(e_{ij} with V_{0j},Roh=0.1), n=5000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr
Intercept	100	114.051	1.214092	114.376	1.23469	114.088	0.39905	114.146	0.40862
AG1	-1	-0.883	0.12296	-0.937	0.12642	-0.88	0.00117	-0.889	0.00308
AgG2	2	1.755	0.16785	1.611	0.18386	1.76	0.00172	1.731	0.00459
MALE	-10	-8.803	0.21806	-8.831	0.2225	-8.801	0.00204	-8.81	0.00534
MRR	-1	-0.873	0.18345	-0.818	0.18771	-0.88	0.00174	-0.872	0.00454
ILLTER	-8	-6.913	0.91698	-6.843	0.92298	-6.99	2.13623	-7.104	2.1534
UNI+	-16	-14.086	0.16492	-14.093	0.16584	-14.082	0.00157	-14.083	0.00407
HHSUB	-2	-1.76	0.05474	-1.754	0.0551	-1.76	0.00051	-1.758	0.00133
DISB	6	5.264	0.4047	5.137	0.41213	5.281	0.00384	5.266	0.01005
DISBCHR	3	2.641	0.30654	2.531	0.31354	2.64	0.00293	2.627	0.00762
INCS	-5	-4.382	1.13298	-4.473	1.13934	-4.41	0.79771	-4.179	0.88686
RU	-2	-1.762	0.30083	-1.749	0.30279	-1.76	0.00281	-1.747	0.00799
$P_r.INLAB$	-12	-10.622	1.31317	-12.004	1.5053	-10.56	0.01375	-10.91	0.03765
$MALE \times P_r.INLAB$	6	5.316	1.10932	6.17	1.22344	5.28	0.01089	5.562	0.02991
INCSxRU	7	6.156	0.28452	6.169	0.28592	6.16	0.00269	6.156	0.00763
INEQUAL	-9	-7.894	2.54034	-8.348	2.56528	-7.892	2.35672	-8.012	2.38341
UNEMP	-1	-0.879	0.02417	-0.879	0.02429	-0.88	0.02162	-0.879	0.02189
PRIN	-1	-0.878	0.02594	-0.88	0.02612	-0.88	0.01242	-0.881	0.01265
ILLTER xINEQUAL	22	19.229	1.89255	18.983	1.90307	19.295	5.62015	19.414	5.62607
ILLTER xUNEMP	-1	-0.88	0.01842	-0.877	0.01849	-0.88	0.05761	-0.879	0.05761
ILLTER xPRIN	1	0.877	0.01992	0.877	0.02003	0.878	0.0498	0.881	0.05016
INCSxINEQUAL	-40	-35.23	2.47005	-35.047	2.48388	-35.152	4.71258	-35.259	4.72283
INCSxUNEMP	1	0.879	0.02366	0.879	0.02378	0.879	0.04324	0.876	0.04347
INCSxPRIN	-1	-0.88	0.02432	-0.878	0.02445	-0.88	0.02485	-0.885	0.02636

Table (6-3): Model results in case of level -1 endogeneity(eij with V0j,Rho =0.1), n=10000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**
Intercept	100	113.816	1.21341	114.198	1.23269	114.051	0.400572	114.1099	0.41019
AG2	-1	-0.858	0.12289	-0.919	0.12621	-0.879	0.00117	-0.888	0.00307
AG2	2	1.812	0.16775	1.649	0.18355	1.758	0.00172	1.73	0.00459
MALE	-10	-8.787	0.21794	-8.815	0.22214	-8.793	0.00204	-8.802	0.00534
MRR	-1	-0.91	0.18334	-0.842	0.18739	-0.879	0.00174	-0.871	0.00453
ILLTER	-8	-7.009	0.91647	-6.924	0.92149	-7.039	2.14593	-7.155	2.16105
UNI+	-16	-14.064	0.16482	-14.072	0.16557	-14.07	0.00157	-14.071	0.00407
HHSUB	-2	-1.76	0.05471	-1.753	0.05501	-1.758	0.00051	-1.756	0.00132
DISB	6	5.331	0.40447	5.185	0.41145	5.276	0.00383	5.261	0.01004
DISBCHR	3	2.684	0.30637	2.557	0.31302	2.638	0.00293	2.625	0.00761
INCS	-5	-4.405	1.13235	-4.5	1.1375	-4.407	0.80079	-4.175	0.88919
RU	-2	-1.767	0.30066	-1.745	0.3023	-1.758	0.00281	-1.745	0.00799
$P_r.INLAB$	-12	-10.086	1.31243	-11.616	1.50275	-10.551	0.01374	-10.9	0.03761
$MALE \times P_r.INLAB$	6	5.049	1.1087	5.963	1.2214	5.276	0.01088	5.557	0.02988
INCSxRU	7	6.156	0.28436	6.165	0.28546	6.155	0.00268	6.15	0.00762
INEQUAL	-9	-7.711	2.53892	-8.233	2.56114	-7.877	2.36438	-7.998	2.39155
UNEMP	-1	-0.877	0.02416	-0.877	0.02426	-0.879	0.02173	-0.878	0.02201
PRIN	-1	-0.877	0.02593	-0.879	0.02608	-0.879	0.01244	-0.88	0.01267
ILLTERxINEQUAL	22	19.379	1.89149	19.14	1.9	19.3	5.66223	19.421	5.66505
ILLTERxUNEMP	-1	-0.881	0.01841	-0.878	0.01846	-0.878	0.05806	-0.877	0.05802
ILLTERxPRIN	1	0.878	0.01991	0.878	0.02	0.879	0.05006	0.882	0.05036
INCSxINEQUAL	-40	-35.279	2.46866	-35.088	2.47987	-35.105	4.72818	-35.213	4.73765
INCSxUNEMP	1	0.88	0.02364	0.88	0.02374	0.879	0.04347	0.876	0.04369
INCSxPRIN	-1	-0.878	0.02431	-0.876	0.02441	-0.879	0.02489	-0.885	0.02639

Table (6-4): Model results in case of level -1 endogeneity (e_{ij} with V_{0j},Rho =0.5), n=1000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr
Intercept	100	113.762	1.21424	114.116	1.23398	113.902	0.4013	113.96	0.41
AG1	-1	-0.861	0.12298	-0.919	0.12634	-0.876	0.00118	-0.886	0.00306
AG2	2	1.792	0.16787	1.638	0.18375	1.755	0.00173	1.726	0.00458
MALE	-10	-8.775	0.21809	-8.805	0.22237	-8.773	0.00204	-8.782	0.00532
MRR	-1	-0.883	0.18348	-0.821	0.1876	-0.877	0.00175	-0.869	0.00452
ILLTER	-8	-6.872	0.9171	-6.794	0.92245	-6.94	2.14433	-7.058	2.15636
UNI+	-16	-14.04	0.16494	-14.047	0.16574	-14.037	0.00157	-14.039	0.00406
HHSUB	-2	-1.757	0.05475	-1.75	0.05506	-1.754	0.00051	-1.752	0.00132
DISB	6	5.288	0.40476	5.152	0.41189	5.264	0.00385	5.249	0.01001
DISBCHR	3	2.671	0.30658	2.553	0.31336	2.632	0.00294	2.619	0.00759
INCS	-5	-4.347	1.13313	-4.439	1.13869	-4.447	0.80259	-4.223	0.87849
RU	-2	-1.76	0.30087	-1.742	0.30262	-1.753	0.00291	-1.741	0.00796
$P_r.INLAB$	-12	-10.211	1.31334	-11.677	1.50444	-10.524	0.0138	-10.875	0.03751
$MALE \times P_r.INLAB$	6	5.074	1.10946	5.97	1.22274	5.263	0.0109	5.544	0.0298
INCSxRU	7	6.147	0.28456	6.158	0.28575	6.14	0.00278	6.136	0.00759
INEQUAL	-9	-7.518	2.54067	-8.006	2.56381	-7.711	2.36872	-7.841	2.39051
UNEMP	-1	-0.879	0.02417	-0.879	0.02428	-0.877	0.02177	-0.876	0.022
PRIN	-1	-0.875	0.02594	-0.877	0.02611	-0.877	0.01247	-0.878	0.01266
ILLTERxINEQUAL	22	18.834	1.8928	18.591	1.90197	19.064	5.66233	19.186	5.66605
ILTERLxUNEMP	-1	-0.872	0.01842	-0.869	0.01848	-0.875	0.05801	-0.874	0.058
ILLTERxPRIN	1	0.874	0.01993	0.874	0.02002	0.876	0.04998	0.878	0.05023
INCSxINEQUAL	-40	-34.763	2.47037	-34.578	2.48245	-34.747	4.73686	-34.851	4.74408
INCSxUNEMP	1	0.875	0.02366	0.875	0.02376	0.876	0.04354	0.873	0.04374
INCSxPRIN	-1	-0.881	0.02432	-0.879	0.02443	-0.878	0.02495	-0.883	0.02624

Table (6-5): Model results in case of level -1 endogeneity (e_{ij} with V_{0j},Rho =0.5), n=5000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**
Intercept	100	113.919	1.21663	114.269	1.1759	114.048	0.400722	114.105	0.40932
AG1	-1	-0.868	0.12322	-0.926	0.1204	-0.879	0.00118	-0.888	0.00307
AG2	2	1.783	0.1682	1.631	0.1751	1.759	0.00173	1.73	0.00459
MALE	-10	-8.789	0.21852	-8.817	0.2119	-8.794	0.00205	-8.803	0.00534
MRR	-1	-0.892	0.18384	-0.831	0.17877	-0.879	0.00175	-0.871	0.00453
ILLTER	-8	-6.961	0.91891	-6.884	0.87904	-7.007	2.14759	-7.114	2.15937
UNI+	-16	-14.062	0.16526	-14.07	0.15794	-14.071	0.00158	-14.072	0.00407
HHSUB	-2	-1.758	0.05485	-1.752	0.05247	-1.758	0.00051	-1.756	0.00132
DISB	6	5.302	0.40555	5.167	0.3925	5.277	0.00386	5.262	0.01004
DISBCHR	3	2.657	0.30719	2.54	0.29861	2.638	0.00295	2.625	0.00761
INCS	-5	-4.416	1.13536	-4.508	1.08509	-4.402	0.80125	-4.18	0.87789
RU	-2	-1.762	0.30146	-1.745	0.28838	-1.757	0.00291	-1.745	0.00798
$P_r.INLAB$	-12	-10.322	1.31592	-11.768	1.43363	-10.549	0.01384	-10.901	0.03763
$MALE \times P_r.INLAB$	6	5.158	1.11164	6.037	1.16519	5.276	0.01093	5.558	0.02989
INCSxRU	7	6.153	0.28512	6.164	0.2723	6.154	0.00278	6.151	0.00761
INEQUAL	-9	-7.71	2.54567	-8.193	2.44314	-7.883	2.36547	-8.008	2.38667
UNEMP	-1	-0.878	0.02599	-0.879	0.02314	-0.879	0.02173	-0.878	0.02195
PRIN	-1	-0.879	0.02422	-0.88	0.02488	-0.879	0.01246	-0.88	0.01265
ILLTERxINEQUAL	22	19.324	1.89253	19.058	1.81245	19.375	5.6559	19.485	5.65663
ILLTERxUNEMP	-1	-0.879	0.01846	-0.876	0.01761	-0.878	0.05799	-0.877	0.05794
ILLTERxPRIN	1	0.876	0.01997	0.877	0.01907	0.878	0.05008	0.88	0.05031
INCSxINEQUAL	-40	-35.106	2.47523	-34.921	2.36561	-35.139	4.72968	-35.235	4.73817
INCSxUNEMP	1	0.879	0.0237	0.879	0.02264	0.879	0.04346	0.876	0.04366
INCSxPRIN	-1	-0.878	0.02437	-0.877	0.02328	-0.879	0.02492	-0.884	0.02622

Table (6-6): Model results in case of level -1 endogeneity (e_{ij} with V_{0j},Rho =0.5), n=10000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**		γ	$\hat{\gamma}$	**Std.rr**
Intercept	100	114.003	1.21407	114.346	1.23417	114.0662	0.40067	114.088	0.40682
AG1	-1	-0.873	0.12296	-0.93	0.12636	-0.879	0.00118	-0.888	0.00307
AG2	2	1.773	0.16784	1.623	0.18377	1.759	0.00174	1.73	0.00459
MALE	-10	-8.791	0.21806	-8.819	0.2224	-8.796	0.00205	-8.801	0.00534
MRR	-1	-0.884	0.18344	-0.824	0.18761	-0.879	0.00175	-0.871	0.00454
ILLTER	-8	-7.014	0.91697	-6.939	0.92259	-7.076	2.1511	-7.124	2.15698
UNI+	-16	-14.075	0.16491	-14.082	0.16576	-14.073	0.00158	-14.07	0.00407
HHSUB	-2	-1.758	0.05474	-1.752	0.05507	-1.759	0.00051	-1.756	0.00133
DISB	6	5.293	0.4047	5.16	0.41195	5.277	0.00386	5.261	0.01003
DISBCHR	3	2.654	0.30654	2.539	0.3134	2.639	0.00295	2.625	0.00762
INCS	-5	-4.383	1.13297	-4.475	1.13886	-4.381	0.80118	-4.175	0.84754
$P_r.INLAB$	-12	-10.396	1.31315	-11.824	1.50454	-10.551	0.01384	-10.899	0.03764
$M \times P_r.INLAB$	6	5.184	1.10931	6.055	1.22286	5.277	0.01093	5.556	0.0299
RU	-2	-1.762	0.30083	-1.746	0.30267	-1.758	0.00292	-1.745	0.00794
INCSxRU	7	6.152	0.28452	6.163	0.2858	6.155	0.00278	6.15	0.00757
INEQUAL	-9	-7.923	2.54032	-8.4	2.5642	-7.932	2.36479	-8.021	2.37109
UNEMP	-1	-0.878	0.02417	-0.878	0.02428	-0.879	0.02174	-0.878	0.02183
PRIN	-1	-0.879	0.02594	-0.88	0.02611	-0.879	0.01245	-0.88	0.01256
ILLTERxINEQUAL	22	19.324	1.89253	19.08	1.90227	19.462	5.66925	19.389	5.66352
ILLTERxUNEMP	-1	-0.88	0.01842	-0.876	0.01848	-0.88	0.05817	-0.877	0.05809
ILLTERxPRIN	1	0.878	0.01992	0.879	0.02002	0.879	0.05019	0.881	0.0503
INCSxINEQUAL	-40	-35.255	2.47002	-35.069	2.48284	-35.24	4.72842	-35.26	4.72799
INCSxUNEMP	1	0.879	0.02365	0.879	0.02377	0.88	0.04347	0.876	0.04358
INCSxPRIN	-1	-0.879	0.02432	-0.877	0.02444	-0.879	0.0249	-0.884	0.02563

Table(6-7): Model results in case of level-1 endogeneity (e_{ij} with V_{0j},Rho =0.9), n=1000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**		γ	$\hat{\gamma}$	**Std.rr**
Intercept	100	113.68	1.215358	114.055	1.234855	113.955	0.400529	114.012	0.40722
AG1	-1	-0.854	0.12309	-0.914	0.12643	-0.879	0.00119	-0.888	0.00308
AG2	2	1.812	0.16802	1.651	0.18388	1.759	0.00175	1.73	0.00459
MALE	-10	-8.787	0.21829	-8.816	0.22253	-8.792	0.00205	-8.801	0.00534
MRR	-1	-0.906	0.18364	-0.84	0.18773	-0.879	0.00176	-0.871	0.00454
ILLTER	-8	-6.804	0.91794	-6.72	0.92311	-6.914	2.14401	-7.025	2.15073
UNI+	-16	-14.057	0.16509	-14.065	0.16586	-14.068	0.00159	-14.07	0.00407
HHSUB	-2	-1.759	0.0548	-1.753	0.0551	-1.758	0.00051	-1.756	0.00133
DISB	6	5.33	0.40513	5.187	0.41218	5.275	0.0039	5.261	0.01003
DISBCHR	3	2.681	0.30686	2.557	0.31358	2.638	0.00296	2.625	0.00762
INCS	-5	-4.477	1.13417	-4.571	1.13949	-4.43	0.80875	-4.201	0.84634
$P_r.INLAB$	-12	-10.097	1.31454	-11.615	1.5055	-10.548	0.01394	-10.899	0.03765
$MALE \times P_r.INLAB$	6	5.051	1.11048	5.964	1.2236	5.275	0.01097	5.556	0.02991
RU	-2	-1.758	0.30114	-1.737	0.30283	-1.757	0.0031	-1.746	0.00794
INCSxRU	7	6.156	0.28482	6.166	0.28596	6.154	0.00296	6.15	0.00758
INEQUAL	-9	-7.633	2.54299	-8.146	2.56562	-7.902	2.36491	-8.023	2.37513
UNEMP	-1	-0.878	0.0242	-0.878	0.0243	-0.88	0.0217	-0.878	0.02181
PRIN	-1	-0.874	0.02597	-0.877	0.02612	-0.879	0.01247	-0.879	0.0126
ILLTERxINEQUAL	22	19.257	1.89453	19.017	1.90332	19.286	5.63742	19.402	5.63962
ILLTERxUNEMP	-1	-0.88	0.01844	-0.877	0.01849	-0.88	0.05782	-0.878	0.05782
ILLTERxPRIN	1	0.872	0.01994	0.872	0.02003	0.876	0.05	0.879	0.05014
INCSxINEQUAL	-40	-35.163	2.47262	-34.975	2.48421	-35.163	4.72544	-35.266	4.7294
INCSxUNEMP	1	0.879	0.02368	0.879	0.02378	0.879	0.04338	0.876	0.04349
INCSxPRIN	-1	-0.876	0.02434	-0.875	0.02445	-0.877	0.02505	-0.883	0.02569

Table (6-8) : Model results in case of level-1 endogeneity (e_{ij} with V_{0j},Rho =0.9), n=5000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr
Intercept	100	113.857	1.213864	114.222	1.23355	113.968	0.400866	114.026	0.40774
AG1	-1	-0.862	0.12294	-0.922	0.1263	-0.878	0.00119	-0.888	0.00307
AG2	2	1.797	0.16782	1.639	0.18369	1.758	0.00175	1.729	0.00459
MALE	-10	-8.78	0.21802	-8.808	0.22229	-8.79	0.00205	-8.798	0.00534
MRR	-1	-0.901	0.18342	-0.837	0.18753	-0.879	0.00176	-0.871	0.00453
ILLTER	-8	-6.997	0.91681	-6.916	0.92213	-6.984	2.14511	-7.099	2.15316
UNI+	-16	-14.063	0.16489	-14.071	0.16568	-14.063	0.00158	-14.065	0.00407
HHSUB	-2	-1.757	0.05473	-1.751	0.05504	-1.757	0.00051	-1.755	0.00132
DISB	6	5.32	0.40463	5.18	0.41175	5.273	0.0039	5.258	0.01002
DISBCHR	3	2.672	0.30649	2.55	0.31325	2.637	0.00296	2.624	0.00761
INCS	-5	-4.442	1.13277	-4.536	1.13829	-4.447	0.8094	-4.219	0.84723
$P_r.INLAB$	-12	-10.203	1.31292	-11.684	1.50392	-10.546	0.01393	-10.897	0.03762
$MALE \times P_r.INLAB$	6	5.099	1.10911	5.989	1.22232	5.274	0.01096	5.555	0.02989
RU	-2	-1.761	0.30077	-1.741	0.30252	-1.757	0.0031	-1.745	0.00794
INCSxRU	7	6.145	0.28447	6.156	0.28565	6.152	0.00296	6.148	0.00757
INEQUAL	-9	-7.766	2.53986	-8.268	2.56292	-7.868	2.36574	-7.993	2.37719
UNEMP	-1	-0.877	0.02417	-0.877	0.02427	-0.879	0.02175	-0.877	0.02187
PRIN	-1	-0.878	0.02594	-0.88	0.0261	-0.879	0.01245	-0.88	0.0126
ILLTERxINEQUAL	22	19.33	1.8922	19.09	1.90132	19.253	5.65595	19.372	5.65911
ILLTERxUNEMP	-1	-0.881	0.01841	-0.878	0.01847	-0.879	0.058	-0.878	0.058
ILLTERxPRIN	1	0.878	0.01992	0.878	0.02001	0.878	0.05003	0.881	0.0502
INCSxINEQUAL	-40	-35.088	2.46958	-34.9	2.4816	-35.094	4.72735	-35.199	4.73146
INCSxUNEMP	1	0.879	0.02365	0.879	0.02375	0.88	0.04347	0.877	0.04357
INCSxPRIN	-1	-0.878	0.02431	-0.876	0.02442	-0.878	0.02503	-0.883	0.02567

Table (6-9): Model results in case of level-1 endogeneity (e_{ij} with V_{0j},Rho =0.9), n=10000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**
Intercept	100	113.8163	1.21341	114.1982	1.232697	114.027	0.40074	114.084	0.40682
AG1	-1	-0.858	0.12289	-0.919	0.12621	-0.879	0.00119	-0.888	0.00307
AG2	2	1.812	0.16775	1.649	0.18355	1.759	0.00175	1.73	0.00459
MALE	-10	-8.787	0.21794	-8.815	0.22214	-8.795	0.00205	-8.804	0.00534
MRR	-1	-0.91	0.18334	-0.842	0.18739	-0.879	0.00176	-0.871	0.00454
ILLTER	-8	-7.009	0.91647	-6.924	0.92149	-7.04	2.14775	-7.153	2.15698
UNI+	-16	-14.064	0.16482	-14.072	0.16557	-14.072	0.00159	-14.074	0.00407
HHSUB	-2	-1.76	0.05471	-1.753	0.05501	-1.759	0.00051	-1.757	0.00133
DISB	6	5.331	0.40447	5.185	0.41145	5.277	0.0039	5.262	0.01003
DISBCHR	3	2.684	0.30637	2.557	0.31302	2.638	0.00296	2.626	0.00762
INCS	-5	-4.405	1.13235	-4.5	1.1375	-4.422	0.80825	-4.196	0.84754
$P_r.INLAB$	-12	-10.086	1.31243	-11.616	1.50275	-10.553	0.01394	-10.903	0.03764
$MALE \times P_r.INLAB$	6	5.049	1.1087	5.963	1.2214	5.277	0.01097	5.558	0.0299
RU	-2	-1.767	0.30066	-1.745	0.3023	-1.758	0.0031	-1.746	0.00794
INCSxRU	7	6.156	0.28436	6.165	0.28546	6.156	0.00296	6.152	0.00757
INEQUAL	-9	-7.711	2.53892	-8.233	2.56114	-7.938	2.36435	-8.063	2.37109
UNEMP	-1	-0.877	0.02416	-0.877	0.02426	-0.879	0.02175	-0.878	0.02183
PRIN	-1	-0.877	0.02593	-0.879	0.02608	-0.879	0.01244	-0.88	0.01256
ILLTERxINEQUAL	22	19.379	1.89149	19.14	1.9	19.384	5.65949	19.501	5.66352
ILLTERxUNEMP	-1	-0.881	0.01841	-0.878	0.01846	-0.88	0.05807	-0.878	0.05809
ILLTERxPRIN	1	0.878	0.01991	0.878	0.02	0.879	0.05011	0.882	0.0503
INCSxINEQUAL	-40	-35.279	2.46866	-35.088	2.47987	-35.248	4.72083	-35.351	4.72799
INCSxUNEMP	1	0.88	0.02364	0.88	0.02374	0.88	0.04345	0.878	0.04358
INCSxPRIN	-1	-0.878	0.02431	-0.876	0.02441	-0.878	0.02498	-0.884	0.02563

Table (6-10) : Model results in case of level-2 endogeneity (U_{0j} with V_{0j}, Rho =0.1), n=1000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**
Intercept	100	95.808	5.0183	97.025	5.0644	96.751	5.1602	96.704	5.1821
AG1	-1	-0.724	0.5082	-0.705	0.5185	-0.66	0.5052	-0.667	0.5127
AG2	2	1.166	0.6937	1.182	0.7541	1.292	0.7059	1.218	0.752
MALE	-10	-5.395	0.9013	-6.504	0.9126	-6.488	0.8895	-6.456	0.8994
MRR	-1	-0.279	0.7582	-0.587	0.7698	-0.631	0.7523	-0.597	0.76
ILLTER	-8	-6.032	3.7902	-5.121	3.7859	-5.173	4.2689	-5.085	4.2401
UNI+	-16	-10.285	0.6816	-10.37	0.6802	-10.355	0.6773	-10.316	0.6748
HHSUB	-2	-1.326	0.2262	-1.281	0.226	-1.286	0.2234	-1.281	0.2229
DISB	6	3.309	1.6727	3.738	1.6904	3.839	1.6577	3.809	1.6689
DISBCHR	3	1.417	1.267	1.842	1.286	1.933	1.2592	1.896	1.2721
INCS	-5	-2.242	4.683	-3.424	4.6734	-3.385	5.1329	-3.204	5.0951
$P_r.INLAB$	-12	0.622	5.4278	-8.874	6.174	-7.824	5.5617	-8.348	6.1659
$MALE \times P_r.INLAB$	6	-7.051	4.5852	4.51	5.0181	3.878	4.597	4.219	4.9772
RU	-2	-1.35	1.2434	-1.252	1.242	-1.259	1.2321	-1.234	1.2286
INCSxRU	7	4.866	1.176	4.5	1.1728	4.481	1.1723	4.471	1.1676
INEQUAL	-9	-5.677	10.5002	-6.46	10.5223	-5.964	10.7804	-5.6	10.7797
UNEMP	-1	-0.626	0.0999	-0.647	0.0996	-0.647	0.1025	-0.642	0.1021
PRIN	-1	-0.648	0.1072	-0.649	0.1071	-0.648	0.1103	-0.646	0.1099
ILLTERxINEQUAL	22	17.297	7.8226	14.202	7.806	14.242	8.8788	13.862	8.8099
ILLTERxUNEMP	-1	-0.656	0.0761	-0.645	0.0758	-0.646	0.0864	-0.642	0.0857
ILLTERxPRIN	1	0.65	0.0823	0.646	0.0821	0.647	0.0934	0.645	0.0927
INCSxINEQUAL	-40	-28.487	10.2096	-25.85	10.1884	-25.914	11.2346	-26.039	11.152
INCSxUNEMP	1	0.635	0.0977	0.649	0.0975	0.649	0.1077	0.643	0.1069
INCSxPRIN	-1	-0.657	0.1005	-0.643	0.1002	-0.643	0.1112	-0.64	0.1103

Table (6-11) : Model results in case of level -2 endogeneity(U_{0j} with V_{0j},Rho =0.1), n=5000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr
Intercept	100	96.624	4.9996	96.877	5.05868	96.618	5.1616	96.67	5.2057
AG1	-1	-0.637	0.5063	-0.679	0.5179	-0.637	0.5046	-0.676	0.5142
AG2	2	1.29	0.6912	1.179	0.7532	1.287	0.7048	1.232	0.7541
MALE	-10	-6.463	0.898	-6.483	0.9116	-6.463	0.8886	-6.45	0.902
MRR	-1	-0.647	0.7554	-0.603	0.769	-0.645	0.7514	-0.638	0.7623
ILLTER	-8	-5.196	3.7761	-5.141	3.7815	-5.178	4.2559	-5.102	4.2649
UNI+	-16	-10.336	0.6791	-10.341	0.6794	-10.336	0.6764	-10.368	0.677
HHSUB	-2	-1.286	0.2254	-1.281	0.2257	-1.286	0.2232	-1.293	0.2235
DISB	6	3.87	1.6665	3.772	1.6885	3.868	1.6557	3.848	1.6737
DISBCHR	3	1.93	1.2623	1.845	1.2845	1.927	1.2577	1.872	1.2758
INCS	-5	-3.178	4.6656	-3.247	4.668	-3.173	5.1296	-3.367	5.1317
$P_r.INLAB$	-12	-7.726	5.4076	-8.782	6.1669	-7.756	5.5524	-8.26	6.1828
$MALE \times P_r.INLAB$	6	3.833	4.5682	4.477	5.0123	3.849	4.5908	4.196	4.9913
RU	-2	-1.27	1.2388	-1.258	1.2406	-1.264	1.2311	-1.303	1.2324
INCSxRU	7	4.497	1.1716	4.506	1.1714	4.494	1.1713	4.529	1.1714
INEQUAL	-9	-5.64	10.4612	-5.992	10.5103	-5.625	10.788	-6.031	10.8314
UNEMP	-1	-0.644	0.0995	-0.644	0.0995	-0.645	0.1026	-0.644	0.1026
PRIN	-1	-0.646	0.1068	-0.648	0.107	-0.646	0.1103	-0.646	0.1104
ILLTERxINEQUAL	22	14.235	7.7936	14.054	7.7971	14.188	8.8514	14.177	8.8655
ILLTERxUNEMP	-1	-0.647	0.0758	-0.645	0.0757	-0.647	0.0862	-0.646	0.0862
ILLTERxPRIN	1	0.646	0.082	0.647	0.082	0.646	0.0931	0.645	0.0933
INCSxINEQUAL	-40	-25.989	10.1717	-25.851	10.1767	-25.989	11.2293	-25.542	11.234
INCSxUNEMP	1	0.645	0.0974	0.645	0.0974	0.645	0.1077	0.644	0.1077
INCSxPRIN	-1	-0.645	0.1001	-0.644	0.1001	-0.645	0.1111	-0.643	0.110

Table (6-12): Model results in case of level -2 endogeneity(U_{0j} with V_{0j},Rho =0.1), n=10000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr
Intercept	100	96.582	5.001	96.8361	5.06	96.599	5.1608	96.71	5.2039
AG1	-1	-0.641	0.5065	-0.683	0.518	-0.642	0.5047	-0.671	0.5139
AG2	2	1.306	0.6914	1.196	0.7534	1.301	0.7052	1.234	0.7537
MALE	-10	-6.471	0.8982	-6.49	0.9118	-6.472	0.8888	-6.477	0.9015
MRR	-1	-0.646	0.7556	-0.602	0.7692	-0.644	0.7516	-0.624	0.7618
ILLTER	-8	-5.14	3.7772	-5.085	3.7826	-5.144	4.2547	-5.068	4.2605
UNI+	-16	-10.339	0.6793	-10.344	0.6796	-10.337	0.6766	-10.32	0.6767
HHSUB	-2	-1.289	0.2255	-1.284	0.2258	-1.289	0.2233	-1.285	0.2234
DISB	6	3.889	1.667	3.79	1.6889	3.884	1.6563	3.818	1.6728
DISBCHR	3	1.97	1.2627	1.885	1.2849	1.963	1.2581	1.894	1.275
INCS	-5	-3.183	4.6669	-3.251	4.6693	-3.188	5.1316	-3.223	5.1282
$P_r.INLAB$	-12	-7.577	5.4091	-8.626	6.1685	-7.621	5.5556	-8.375	6.179
$MALE \times P_r.INLAB$	6	3.775	4.5695	4.411	5.0137	3.799	4.5928	4.293	4.9882
RU	-2	-1.309	1.2391	-1.297	1.2409	-1.306	1.2313	-1.298	1.2317
INCSxRU	7	4.528	1.172	4.536	1.1717	4.527	1.1716	4.544	1.1708
INEQUAL	-9	-5.841	10.4641	-6.193	10.5131	-5.841	10.7854	-6.064	10.8277
UNEMP	-1	-0.644	0.0995	-0.644	0.0995	-0.644	0.1026	-0.645	0.1026
PRIN	-1	-0.644	0.1068	-0.645	0.107	-0.644	0.1103	-0.644	0.1104
ILLTERxINEQUAL	22	14.228	7.7957	14.051	7.7992	14.217	8.8479	14.046	8.8549
ILLTERxUNEMP	-1	-0.647	0.0758	-0.645	0.0757	-0.647	0.0861	-0.644	0.0861
ILLTERxPRIN	1	0.645	0.082	0.645	0.082	0.645	0.0931	0.644	0.0931
INCSxINEQUAL	-40	-25.823	10.1745	-25.687	10.1795	-25.817	11.2336	-25.681	11.2262
INCSxUNEMP	1	0.645	0.0974	0.645	0.0974	0.645	0.1077	0.646	0.1076
INCSxPRIN	-1	-0.647	0.1001	-0.646	0.1002	-0.647	0.1112	-0.647	0.1111

Table (6-13): Model results in case of level -2 endogeneity (U_{0j} with V_{0j},Rho =0.5), n=1000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	**Std.rr**
Intercept	100	95.808	5.0183	96.886	5.0622	96.658	5.1578	96.643	5.1929
AG1	-1	-0.724	0.5082	-0.65	0.5183	-0.612	0.505	-0.657	0.5138
AG2	2	1.166	0.6937	1.269	0.7537	1.375	0.706	1.242	0.7535
MALE	-10	-5.395	0.9013	-6.482	0.9122	-6.469	0.8893	-6.445	0.9012
MRR	-1	-0.279	0.7582	-0.671	0.7695	-0.715	0.7521	-0.658	0.7616
ILLTER	-8	-6.032	3.7902	-5.221	3.7842	-5.301	4.2496	-5.331	4.2591
UNI+	-16	-10.285	0.6816	-10.332	0.6799	-10.324	0.6766	-10.326	0.6764
HHSUB	-2	-1.326	0.2262	-1.287	0.2259	-1.292	0.2234	-1.291	0.2234
DISB	6	3.309	1.6727	3.857	1.6897	3.947	1.6573	3.816	1.6722
DISBCHR	3	1.417	1.267	1.905	1.2854	1.987	1.2589	1.956	1.2746
INCS	-5	-2.242	4.683	-3.291	4.6713	-3.239	5.1035	-3.094	5.1221
$P_r.INLAB$	-12	0.622	5.4278	-8.064	6.1712	-7.094	5.5637	-8.127	6.1776
$MALE \times P_r.INLAB$	6	-7.051	4.5852	4.196	5.0158	3.64	4.5973	4.127	4.9868
RU	-2	-1.35	1.2434	-1.259	1.2414	-1.268	1.2318	-1.225	1.2311
INCSxRU	7	4.866	1.176	4.469	1.1722	4.457	1.1715	4.457	1.1704
INEQUAL	-9	-5.677	10.5002	-6.187	10.5176	-5.812	10.7773	-6.274	10.8021
UNEMP	-1	-0.626	0.0999	-0.641	0.0996	-0.642	0.1025	-0.64	0.1024
PRIN	-1	-0.648	0.1072	-0.65	0.1071	-0.65	0.1102	-0.643	0.1101
ILLTERxINEQUAL	22	17.297	7.8226	14.221	7.8025	14.352	8.8356	14.389	8.8514
ILLTERxUNEMP	-1	-0.656	0.0761	-0.647	0.0758	-0.648	0.0861	-0.647	0.0861
ILLTERxPRIN	1	0.65	0.0823	0.649	0.0821	0.649	0.093	0.65	0.0931
INCSxINEQUAL	-40	-28.487	10.2096	-25.775	10.1839	-25.898	11.1695	-25.66	11.2119
INCSxUNEMP	1	0.635	0.0977	0.642	0.0975	0.642	0.1071	0.64	0.1075
INCSxPRIN	-1	-0.657	0.1005	-0.642	0.1002	-0.643	0.1105	-0.649	0.1109

Table (6-14): Model results in case of level -2 endogeneity (U_{0j} with V_{0j},Rho =0.5), n=5000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**
Intercept	100	96.295	4.989	96.646	5.0545	96.399	5.1623	96.613	5.2077
AG1	-1	-0.613	0.5052	-0.671	0.5175	-0.631	0.5042	-0.652	0.5142
AG2	2	1.391	0.6897	1.229	0.7526	1.335	0.7046	1.255	0.7542
MALE	-10	-6.426	0.896	-6.446	0.9108	-6.434	0.8878	-6.461	0.9021
MRR	-1	-0.7	0.7538	-0.632	0.7683	-0.676	0.7508	-0.634	0.7623
ILLTER	-8	-5.206	3.7681	-5.083	3.7784	-5.121	4.2533	-5.091	4.263
UNI+	-16	-10.307	0.6777	-10.331	0.6789	-10.327	0.6759	-10.34	0.677
HHSUB	-2	-1.29	0.2249	-1.281	0.2255	-1.285	0.223	-1.294	0.2236
DISB	6	3.937	1.663	3.815	1.6871	3.906	1.6545	3.851	1.6738
DISBCHR	3	2.033	1.2596	1.894	1.2835	1.976	1.2568	1.895	1.2758
INCS	-5	-3.153	4.6557	-3.308	4.6642	-3.262	5.1252	-3.123	5.1338
$P_r.INLAB$	-12	-6.8	5.3961	-8.25	6.1618	-7.294	5.5508	-8.082	6.1832
$MALE \times P_r.INLAB$	6	3.368	4.5585	4.197	5.0082	3.641	4.5881	4.071	4.9914
RU	-2	-1.296	1.2362	-1.287	1.2395	-1.298	1.2301	-1.262	1.2325
INCSxRU	7	4.501	1.1691	4.521	1.1705	4.51	1.1703	4.5	1.1716
INEQUAL	-9	-5.422	10.4389	-5.737	10.5017	-5.359	10.7902	-5.577	10.8363
UNEMP	-1	-0.643	0.0993	-0.644	0.0994	-0.644	0.1026	-0.644	0.1027
PRIN	-1	-0.644	0.1066	-0.647	0.1069	-0.646	0.1103	-0.647	0.1105
ILLTERxINEQUAL	22	14.323	7.777	14.131	7.7907	14.218	8.8452	13.975	8.8602
ILLTERxUNEMP	-1	-0.647	0.0757	-0.643	0.0756	-0.644	0.0861	-0.643	0.0862
ILLTERxPRIN	1	0.644	0.0818	0.643	0.082	0.642	0.0931	0.645	0.0932
INCSxINEQUAL	-40	-26.172	10.15	-25.92	10.1684	-26.015	11.2194	-26.166	11.2389
INCSxUNEMP	1	0.645	0.0972	0.644	0.0973	0.643	0.1076	0.643	0.1077
INCSxPRIN	-1	-0.644	0.0999	-0.641	0.1001	-0.641	0.111	-0.645	0.1112

Table (6-15) : Model results in case of level -2 endogeneity (U_{0j} with V_{0j}, Rho =0.5), n=10000									
	True Value	**OLS**		**2SLS**		**Multilevel**		**Multilevel 2SLS**	
	γ	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**	$\hat{\gamma}$	**Std.rr**
Intercept	100	96.318	4.9907	96.651	5.05452	96.412	5.1557	96.721	5.2041
AG1	-1	-0.609	0.5054	-0.664	0.5175	-0.625	0.5042	-0.655	0.514
AG2	2	1.382	0.6899	1.256	0.7526	1.362	0.7045	1.262	0.7537
MALE	-10	-6.438	0.8964	-6.455	0.9108	-6.441	0.8879	-6.457	0.9016
MRR	-1	-0.696	0.754	-0.634	0.7683	-0.678	0.7508	-0.643	0.7619
ILLTER	-8	-5.182	3.7694	-5.089	3.7784	-5.15	4.2515	-5.097	4.2549
UNI+	-16	-10.311	0.6779	-10.34	0.6789	-10.334	0.6759	-10.325	0.6767
HHSUB	-2	-1.292	0.225	-1.284	0.2255	-1.288	0.223	-1.288	0.2234
DISB	6	3.984	1.6636	3.837	1.6871	3.927	1.6546	3.861	1.6729
DISBCHR	3	2.018	1.2601	1.904	1.2835	1.985	1.2568	1.917	1.2751
INCS	-5	-3.213	4.6573	-3.221	4.6642	-3.175	5.1243	-3.299	5.126
$P_r.INLAB$	-12	-6.932	5.398	-8.093	6.1618	-7.118	5.5508	-8.091	6.1794
$MALE \times P_r.INLAB$	6	3.48	4.5601	4.11	5.0082	3.535	4.5884	4.117	4.9887
RU	-2	-1.312	1.2366	-1.272	1.2395	-1.285	1.2301	-1.272	1.2319
INEQUAL	-9	-5.459	10.4425	-5.868	10.5016	-5.494	10.7749	-5.925	10.8287
UNEMP	-1	-0.644	0.0993	-0.643	0.0994	-0.643	0.1025	-0.644	0.1026
PRIN	-1	-0.644	0.1066	-0.646	0.1069	-0.645	0.1102	-0.647	0.1104
ILLTERxRU	1	0.632	0.9079	0.637	0.9093	0.63	0.9106	0.652	0.9116
ILLTERxINEQUAL	22	14.305	7.7796	14.005	7.7907	14.11	8.8415	14.113	8.8423
ILLTERxUNEMP	-1	-0.647	0.0757	-0.644	0.0756	-0.645	0.0861	-0.645	0.086
ILLTERxPRIN	1	0.644	0.0819	0.644	0.082	0.644	0.093	0.644	0.093
INCSxRU	7	4.515	1.1696	4.521	1.1704	4.509	1.1704	4.507	1.1709
INCSxINEQUAL	-40	-25.909	10.1535	-25.702	10.1684	-25.811	11.2177	-25.669	11.2212
INCSxUNEMP	1	0.645	0.0972	0.642	0.0973	0.642	0.1076	0.645	0.1076
INCSxPRIN	-1	-0.644	0.0999	-0.645	0.1001	-0.645	0.111	-0.644	0.111

Table (6-16): Model results in case of level-2 endogeneity (U_{0j} with V_{0j}, Rho =0.9), n=1000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr
Intercept	100	95.808	5.0183	95.785	5.034	95.622	5.1317	96.443	5.201
AG1	-1	-0.724	0.5082	-0.628	0.5154	-0.592	0.5023	-0.61	0.5131
AG2	2	1.166	0.6937	1.396	0.7495	1.496	0.7025	1.368	0.7527
MALE	-10	-5.395	0.9013	-6.388	0.9071	-6.388	0.8843	-6.376	0.9001
MRR	-1	-0.279	0.7582	-0.716	0.7652	-0.76	0.7479	-0.695	0.7607
ILLTER	-8	-6.032	3.7902	-5.157	3.7631	-5.27	4.2288	-5.264	4.2431
UNI+	-16	-10.285	0.6816	-10.26	0.6761	-10.263	0.6733	-10.289	0.6755
HHSUB	-2	-1.326	0.2262	-1.274	0.2246	-1.276	0.2221	-1.28	0.2231
DISB	6	3.309	1.6727	3.939	1.6803	4.014	1.6481	3.967	1.6702
DISBCHR	3	1.417	1.267	2.058	1.2783	2.131	1.2519	2.008	1.2731
INCS	-5	-2.242	4.683	-2.758	4.6453	-2.746	5.104	-3.214	5.1149
$P_r.INLAB$	-12	0.622	5.4278	-6.544	6.1368	-5.717	5.5352	-6.984	6.171
$MALE \times P_r.INLAB$	6	-7.051	4.5852	3.211	4.9879	2.768	4.5716	3.398	4.9811
RU	-2	-1.35	1.2434	-1.196	1.2345	-1.217	1.2248	-1.23	1.2299
INCSxRU	7	4.866	1.176	4.412	1.1657	4.397	1.1654	4.441	1.1688
INEQUAL	-9	-5.677	10.5002	-4.411	10.4591	-4.066	10.72	-5.67	10.8237
UNEMP	-1	-0.626	0.0999	-0.639	0.099	-0.64	0.102	-0.64	0.1026
PRIN	-1	-0.648	0.1072	-0.644	0.1065	-0.644	0.1096	-0.649	0.1104
ILLTERxINEQUAL	22	17.297	7.8226	13.924	7.7591	13.977	8.7882	14.749	8.8157
ILLTERxUNEMP	-1	-0.656	0.0761	-0.647	0.0753	-0.647	0.0856	-0.65	0.0858
ILLTERxPRIN	1	0.65	0.0823	0.646	0.0816	0.648	0.0925	0.643	0.0928
INCSxINEQUAL	-40	-28.487	10.2096	-26.75	10.1272	-26.885	11.1708	-25.98	11.1962
INCSxUNEMP	1	0.635	0.0977	0.641	0.0969	0.64	0.1071	0.641	0.1073
INCSxPRIN	-1	-0.657	0.1005	-0.648	0.0996	-0.646	0.1106	-0.641	0.1108

Table (6-17): Model results in case of level -2 endogeneity(U_{0j} with V_{0j},Rho =0.9), n=5000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr
Intercept	100	95.685	4.9967	96.193	5.0633	95.977	5.166	96.741	5.2046
AG1	-1	-0.51	0.506	-0.605	0.5184	-0.568	0.5052	-0.663	0.5142
AG2	2	1.648	0.6908	1.395	0.7539	1.496	0.7065	1.231	0.7577
MALE	-10	-6.387	0.8974	-6.44	0.9124	-6.445	0.8895	-6.45	0.9009
MRR	-1	-0.833	0.7549	-0.708	0.7697	-0.754	0.7523	-0.602	0.762
ILLTER	-8	-5.352	3.7739	-5.247	3.785	-5.319	4.2594	-5.151	4.2487
UNI+	-16	-10.316	0.6787	-10.339	0.68	-10.338	0.6771	-10.319	0.6785
HHSUB	-2	-1.295	0.2253	-1.288	0.2259	-1.291	0.2234	-1.286	0.2233
DISB	6	4.186	1.6656	4.027	1.69	4.109	1.6577	3.793	1.6732
DISBCHR	3	2.226	1.2616	2.021	1.2857	2.102	1.2592	1.86	1.2757
INCS	-5	-3.056	4.6629	-3.011	4.6723	-3.002	5.1276	-3.141	5.3045
$P_r.INLAB$	-12	-4.656	5.4045	-6.763	6.1725	-5.938	5.5666	-8.368	6.2149
$MALE \times P_r.INLAB$	6	2.247	4.5655	3.407	5.0169	2.986	4.5984	4.247	5.0009
RU	-2	-1.321	1.2381	-1.289	1.2417	-1.308	1.2322	-1.25	1.2285
INCSxRU	7	4.483	1.171	4.52	1.1725	4.5	1.1722	4.496	1.1677
INEQUAL	-9	-4.575	10.4551	-5.283	10.5199	-4.837	10.7949	-5.949	10.8006
UNEMP	-1	-0.641	0.0994	-0.644	0.0996	-0.646	0.1027	-0.641	0.1023
PRIN	-1	-0.642	0.1067	-0.645	0.1071	-0.644	0.1104	-0.645	0.1103
ILLTERxINEQUAL	22	14.576	7.789	14.568	7.8042	14.519	8.8552	14.145	8.781
ILLTERxUNEMP	-1	-0.651	0.0758	-0.651	0.0758	-0.649	0.0862	-0.644	0.0856
ILLTERxPRIN	1	0.645	0.082	0.646	0.0821	0.646	0.0932	0.646	0.0929
INCSxINEQUAL	-40	-26.263	10.1658	-26.362	10.1861	-26.482	11.2241	-25.91	11.5994
INCSxUNEMP	1	0.644	0.0973	0.647	0.0975	0.646	0.1076	0.643	0.1114
INCSxPRIN	-1	-0.645	0.1001	-0.649	0.1002	-0.648	0.1111	-0.644	0.1153

Table (6-18): Model results in case of level -2 endogeneity(U_{0j} with V_{0j},Rho =0.9), n=10000

	True Value	OLS		2SLS		Multilevel		Multilevel 2SLS	
	γ	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr	$\hat{\gamma}$	Std.rr
Intercept	100	95.582	4.993	96.276	5.05278	96.055	5.154	96.495	5.1972
AG1	-1	-0.515	0.5057	-0.595	0.5173	-0.558	0.5042	-0.617	0.5134
AG2	2	1.629	0.6903	1.415	0.7523	1.515	0.705	1.356	0.753
MALE	-10	-6.406	0.8968	-6.426	0.9105	-6.429	0.8876	-6.445	0.9005
MRR	-1	-0.81	0.7544	-0.712	0.7681	-0.76	0.7507	-0.677	0.761
ILLTER	-8	-5.264	3.7711	-5.192	3.7771	-5.252	4.2489	-5.214	4.2571
UNI+	-16	-10.283	0.6782	-10.295	0.6786	-10.291	0.6758	-10.3	0.6759
HHSUB	-2	-1.302	0.2251	-1.296	0.2254	-1.3	0.2229	-1.285	0.2232
DISB	6	4.199	1.6643	4.015	1.6865	4.098	1.6542	3.957	1.671
DISBCHR	3	2.247	1.2607	2.075	1.283	2.154	1.2566	2.008	1.2737
INCS	-5	-2.977	4.6595	-3.085	4.6626	-3.083	5.1201	-3.248	5.1202
$P_r.INLAB$	-12	-4.743	5.4005	-6.61	6.1597	-5.799	5.5552	-7.178	6.1739
$MALE \times P_r.INLAB$	6	2.313	4.5622	3.316	5.0065	2.907	4.5887	3.631	4.9835
RU	-2	-1.328	1.2372	-1.279	1.2391	-1.298	1.2295	-1.277	1.2303
INCSxRU	7	4.506	1.1701	4.522	1.17	4.506	1.1698	4.52	1.1694
INEQUAL	-9	-4.522	10.4474	-5.391	10.498	-4.954	10.7685	-5.694	10.813
UNEMP	-1	-0.642	0.0994	-0.641	0.0994	-0.643	0.1024	-0.642	0.1025
PRIN	-1	-0.638	0.1067	-0.645	0.1069	-0.643	0.1101	-0.647	0.1103
ILLTERxINEQUAL	22	14.543	7.7833	14.492	7.788	14.433	8.8324	14.46	8.8467
ILLTERxUNEMP	-1	-0.65	0.0757	-0.65	0.0756	-0.648	0.086	-0.649	0.086
ILLTERxPRIN	1	0.642	0.0819	0.644	0.0819	0.644	0.093	0.645	0.0931
INCSxINEQUAL	-40	-26.304	10.1583	-26.053	10.1649	-26.155	11.207	-25.81	11.2082
INCSxUNEMP	1	0.644	0.0973	0.645	0.0973	0.644	0.1075	0.644	0.1074
INCSxPRIN	-1	-0.648	0.1	-0.648	0.1	-0.646	0.1109	-0.644	0.1109

6.4 Summary of findings

This chapter is concerned with the effect of endogeneity problem in the hierarchical data structure based in a simulated data set. Based on this data, the four models for poverty determinants that are presented in chapters three, four and five are performed. I have considered the effect of the existence of level-1 endogeneity which occurs due to the correlation between leve-1 error term of poverty model (ε_{ij}) with the level-2 error term of labour force participation model i.e. the case where $cov\left(\varepsilon_{ij}, V_{0j}\right) \neq 0$. I have also considered level-2 endogeneity which occurs due to the correlation between leve-2 error term of the intercept of poverty model (U_{0j}) with the level-2 error term of labour force participation model i.e. the case where $cov\left(U_{0j}, V_{0j}\right) \neq 0$. For each situation I performed 1000, 5000, and 10000 simulation studies. Moreover, due to the importance of the assessment of to what extent such endogeneity affects the results of the estimated coefficient; I considered three different scenarios of the correlation between the error terms that captured a weak correlation of 0.1, a moderate correlation of 0.5, and a strong correlation of 0.9. The assessment of the four models was examined in terms of biasedness, standard errors, and mean-square errors in all scenarios.

The main significant findings from the simulation study regarding the parameter associated with the endogenous variable showed that M2SLS has the lowest MSE in all level-1 endogeneity scenarios. Moreover, this model shows less biased compared to OLS model and ML model. For level-2 endogeneity, M2SLS has the lowest bias and lowest MSE when the correlation between error terms is strong. The following chapter is the last chapter in the thesis in which the main finding of the thesis are presented. In addition, policy recommendations based on the findings and some suggested future work are introduced.

CHAPTER 7

CONCLUSION AND FUTURE RESEARCH

7.1 Concluding remarks

Egypt is currently going through a significant demographic change in which the population ageing is one of its main characteristics. This phenomenon requires researchers and policy makers to pay attention to the well-being of this most fast growing segment of population. In this study, my main interest was to investigate the relationship between elderly poverty and their labour force participation while accounting for two methodological problem that plague many of the existence researches, endogeneity and hierarchical structure of the data. The study used a nationally represented data set from the Egyptian Household Observatory Survey - Round 7 (IDSC, 2010).

The study adopted a multidimensional measure of poverty in old age. This measure captured different dimensions of poverty rather than depending on only money deprivation. Based on the review of literature on poverty measures that is provided in chapter two, I have constructed a poverty index that captured five broad dimensions of poverty using factor analysis. The first dimension is an objective poverty indicator represented by individual status of being below or above the poverty line. The second dimension is an indicator of wealth represented by an index of the ownership of durable goods. The third dimension reflects housing conditions. The fourth dimension is an indicator of subjective poverty presented by individual perception of their income. The last dimension reflects the individual security which is measured by being covered by pension scheme and access to health insurance system. The constructed poverty index is then used as a dependent variable to model the determinants of elderly poverty and as independent variable in labour force participation models.

To investigate the relationship between poverty and labour force participation and to identify other determinants as well, I have performed traditional models as an initial step. Specifically, I have applied OLS model to investigate poverty determinants and Logistic regression model to investigate labour force participation determinants. However, a review of the relevant literature on elderly poverty and their labour force participation, that is presented in chapter one showed that most existent researches on elderly poverty and their labour force participation ignored the simultaneous relationship between these two variables and the within governorate dependencies as well.

The first issue, simultaneity, is presented in chapter three. It concerns the endogeneity of labour force participation to poverty. This endogeneity exists due to the simultaneity between poverty and labour force participation. On one hand, increasing of poverty might force the elderly to engage in labour force and so the relationship between them is expected to be positive. On the other hand, engaging in labour force is expected to decrease poverty and consequently the relationship between them is expected to be negative. However, the results of OLS showed that being in labour force is positively associated with poverty. Furthermore, increasing in poverty exerts a positive effect on the log odds of being in labour force according to the results of logistic regression model.

Accordingly two simultaneous equations are considered. I have performed endogeneity test and confirms the endogeneity of labour force participation to poverty. Thus, a two-stage least squares method was applied to correct for this endogeneity when investigating the main determinants of poverty. The most important result is the contradiction among models regarding the relationship between poverty and labour force participation. While being in labour force was found to have a positive relationship with poverty based on OLS model, it shows a significant negative relationship with poverty once correction for the endogeneity is made. Moreover, according to labour force participation model, poverty was found to have a significant positive effect on the log odds of being in labour force.

The second key statistical issue is presented in chapter four. It concerns the hierarchical structure of the data which results in dependences among individuals within each governorate. In this study I found that 27.12% of differences in poverty and 6.83% of differences in labour force participation are due to variability among governorates.

This hierarchical structure results in low estimate of the standard error of the effect of the variables measured at the governorate-level if the parameters were estimated using single-level models. Accordingly, in chapter four, I have performed a multilevel linear model (ML) to investigate the main determinants of poverty and a multilevel logistic model to investigate the main determinants of labour force participation.

Comparing the results of poverty determinants based on OLS model and multilevel model showed clearly that, the standard error of the coefficients of governorate-level variables are much lower in OLS than multilevel model. Furthermore, two variables were found to have different effect on poverty among governorates. In each governorate, the effect of being illiterate and receiving other sources of income have different effect on individual's poverty. Considering the hierarchical structure of the data when modelling poverty has significantly decreased the variance partition coefficient from 27.12% to only 4.16%. While for labour force participation, the model was able to decrease the variance partition coefficient from 6.83% to be only 1.79%.

The study contributes to develop a more complex econometric model that considered simultaneously the two key issues mentioned above; endogeneity and hierarchical structure of the data. Thus, in chapter five, I developed a multilevel simultaneous equations model to investigate the relationship between elderly poverty and their labour force participation. As for ML model, I have introduced a more complex variance structure by allowing two of the regression coefficients to vary across governorate-level units. I modelled this variation as a function of governorate-level explanatory variables. In this chapter I have also compared between the traditional model, the simultaneous equation model, the multilevel model and the multilevel simultaneous equation model.

To formally asses to what extent the endogeneity problem in the hierarchical data structure cannot be ignored, I have performed a simulation study in chapter six to compare different modelling strategies that I introduced in chapters three, four and five. I have considered the effect of the existence of level-1 endogeneity which occurs due to the correlation between leve-1 error term of poverty model (ε_{ij}) with the level-2 error term of labour force participation model i.e. the case where $cov\left(\varepsilon_{ij}, V_{0j}\right) \neq 0$. I have also considered level-2 endogeneity which occurs due to the correlation between leve-2 error term of the intercept of poverty model (U_{0j}) with the level-2 error term of labour force participation model i.e. the case where $cov\left(U_{0j}, V_{0j}\right) \neq 0$. For each situation I performed 1000, 5000, and 10000 simulation studies. Moreover, due to the importance of the assessment of to what extent such endogeneity affects the results of the estimated coefficient; I considered three different scenarios of the correlation between the error terms that captured a weak correlation of 0.1, a moderate correlation of 0.5, and a strong correlation of 0.9.

The main significant findings from the simulation study regarding the parameter associated with the endogenous variable showed that M2SLS has the lowest MSE in all level-1 endogeneity scenarios. Moreover, this model shows less biased compared to OLS model and ML model. For level-2 endogeneity, M2SLS has the lowest bias and lowest MSE when the correlation between error terms is strong.

7.2 Policy Relevance

The study has both social and statistical implications regarding the relationship between poverty and labour force participation in old age. The social aspect of the study reveals that being in labour force has a significant effect on decreasing poverty. This would require a deep focus from policy makers to maintain elderly participation in labour market in particular with the expected decrease in the percentage of elderly labour force participation from 31.9% in 1980 to only 7.5% in 2020 (Department of Economic and Social Affairs, Population Division, UN, 2007). This can be done by different ways for example; supporting older people who are nearing retirement in making decisions by informing them with the advantage of continuing their work. Older people can be encouraged to work beyond their 60s by providing opportunities to them to extend their working life.

The social aspect of the study reveals also that those who are old and disabled and being female, have fewer potential supporters and those who are not working are more likely to be poor. This requires collaboration between governmental and non-governmental organizations and the private sector to strengthen various support systems for the elderly formally and informally, and particularly for those vulnerable groups. Social security systems and safety nets must be improved to secure the well-being and ensure adequate income for older people. This requires innovative approach from policy makers to reform the social support system in Egypt. Furthermore, health insurance and access to pension scheme should be available to all older people. In addition, poverty studies should consider specific indicators of poverty for older people to be able to represent their information accurately.

This study aims not only to provide empirical results on the relationship between poverty and labour force participation, but also to overcome two important methodological problems that plague many of the existent research on the topic of concern. The empirical results support the importance of using a multilevel model when the data structure is hierarchical. Endogeneity should be considered as usual whenever it exists. Existence of even a weak endogeneity at either level-1 or level-2 spoils the biasness and the accuracy of the parameters of interest. So both levels should be taken into account by applying particular statistical techniques to correct for this endogeneity.

7.3 Future research

In an ideal situation, I would like to use a dataset that allow me to monitor the change in poverty status before and after retirement as well as more factors that might affect elderly people's decision to work such as interrupted work history and type of the previous job, and the differences among different neighbourhoods within each governorate.

Within the broader debate of improving the welfare for the old people in Egypt, there is a calling to improve the modelling accuracies. Further research can be carried out in a number of areas. For instance, the study stresses on the differences among governorates in poverty and labour force participation. However, within each governorate there still exists heterogeneous groups. Also, another level of data hierarchy might be considered if data is available on the characteristics of the neighbourhoods within each governorate. Another important issue can be explored further is the gender differences. In Egypt, the percentage of the elderly males who are expected to participate in labour force will decrease dramatically. However, the elderly female participation rate is expected to increase. Thus, it might be useful to model the determinants of labour force participation separately for these two groups. Furthermore, poverty throughout the life span is important as well to differentiate between those who were poor before retirement and those who trapped in the cycle of poverty after leaving their work. This requires a longitudinal study to examine the factors associated with the transition from/to poverty circle. Once longitudinal data will be available, a more advanced modelling strategy on the relationship between poverty and labour force participation can be established.

In the future, I can also improve the model by considering other scenarios of endogeneity in multilevel models. For instance, model the endogeneity results from the association between random slopes at poverty model and random error in labour force participation model. Another possible extension is to consider the existence of endogeneity among all levels simultaneously. I can also explore the problem of endogeneity at higher than two- levels. For example, consider the case when the model has three-levels data structure. Another extension can be the impact of variance partition coefficient on the proposed M2SLS model results.

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