A MICRO-ECONOMETRIC ANALYSIS OF POVERTY: EVIDENCE FROM TUNISIA

Amal Jmaii

▶ **To cite this version:**

Amal Jmaii. A MICRO-ECONOMETRIC ANALYSIS OF POVERTY: EVIDENCE FROM TUNISIA. Statistics [stat]. University Tunis El Manar, 2016. English. NNT : . tel-01443104

HAL Id: tel-01443104
https://theses.hal.science/tel-01443104

Submitted on 22 Jan 2017

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

PHD THESIS
University of Tunis El Manar

Speciality

Quantitative Methods

Doctoral School Economic and Management of Tunis

Defended by

AMAL JMAII

A thesis submitted for the degree of

DOCTOR of ECONOMIC SCIENCES, FACULTY OF ECONOMIC SCIENCES AND MANAGEMENT OF TUNIS

Subject of thesis :

A Micro-econometric Analysis of Poverty : Evidence from Tunisia

Presented publicly october, 14, 2016

Jury :

Professor Mohamed Ayadi	Reviewer/Chair	ISG Tunis
Professor Besma Belhadj	Advisor	FSEG Nabeul
Professor Mohamed Goaied	Reviewer	IHEC Carthage
Professor Rim Mouelhi Ben Ayed	Examinator	ISCAE Manouba
Professor Lamia Mokaddem	Examinator	FSEG Tunis

Vaincre la pauvreté, ce n'est pas un geste de charité; c'est un acte de justice

[Nelson Mandela]

Avant-propos

Cette thèse est le résultat d'un travail de longue souffrance et haleine, ayant profitée de la contribution de plusieurs personnes. Quand bien même je ne saurai citer tous ceux qui ont contribué à ce travail, j'aimerais souligner le rôle majeur joué par certaines personnes dans ma formation en général et dans l'accomplissement de cette œuvre en particulier.
Un sentiment de gratitude extrême envers ma directrice de recherches, Mme Belhadj Besma, qui m'a fait l'honneur de diriger ce travail de recherche. Je la remercie vivement pour la patience et la compréhension qu'elle a manifestée à mon égard face à mes difficultés.

Mes sincères remerciements vont à Pr. Rafik Baccouche qui en dehors des soutiens multiformes, m'a encouragé à poursuivre mes études jusqu'à ce niveau. Je remercie également mes collègues et ami(e)s Ben Marzouk Sonia, Soulaima Abdelli, Ines Sghir, Tendero Marjorie, Kevanci Goksel, Coisnon Thomas et Mbarek Marouene qui m'ont soutenu moralement et encouragé dans les moments critiques de mon parcoure.

Mes remerciements vont également au laboratoire français GRANEM (Agro campus Ouest) et l'université d'Angers, en particulier monsieur le professeur Damien Rousselière qui m'a invité, encouragé et m'a accompagné tout au long mes stages de recherches.

Je tiens aussi à remercier les professeurs, chercheurs et tout le personnel administratif de la faculté des sciences économiques et gestion de Tunis pour leurs diverses contributions à mes recherches et formation.

Finalement je remercie mon cher frère et mes sœurs pour tout ce qu'ils ont fait pour moi pour réussir et atteindre mon objectif. Une reconnaissance particulière à ma chère cousine Naili Sonia ainsi que son époux Naili Issam pour leur aide et soutien, financière que psychologique, pendant mes séjours en France.

Amal Jmaii

Acknowledgments

*Je dédie cette thèse au soleil de ma vie mes chers parents **Ali** et **Hayette** qui ont enduré mon éloignement durant ces années doctorales et qui m'ont supporté dans les moments de doutes et d'échec, je vous aime.*

Contents

List of Figures

List of Tables

List of Principal Equations

List of acronyms

AR	Auto-Regressive
EDE	Equally-Distributed Equivalent
EM	Expectation–maximization
EMB	Expectation-Maximization with Bootstrapping
FAO	Food and Agriculture Organization of the United Nations
FGT	Foster Greer Thorbecke
GCF	General Compensation Fund
GSD	Genuine State Dependence
INS	Tunisian National Institute of Statistics
JR	Jalan and Ravallion
MGD	Millennium Goals Development
OLS	Ordinary Least Squares
RIF	Recentered Influence Function
SAP	Structural Adjustment Plan
TLSS	Tunisian Living Standards Surveys
TSD	True State Dependence

Chapter 1

General Introduction

1.1 General context

For its socio-economic challenges, poverty is considered as a serious concern of public authorities. In fact, it is one of the biggest issues faced by various society in the current world. It's consequences vary depending on the region of the world, starting from social exclusion to malnutrition and death. Thus, poverty is different in France, in Tunisia or even in the United States. To give an exact definition to the phenomenon of poverty represents a difficult task. Indeed, poverty is a mixture of economic and social aspects (Patlagean (1977)) which must be studied simultaneously to find the efficient policy to fight against this scourge. Furthermore, although the reducing of poverty and especially the fight against inequality in the world remain major challenges, it is clear that the progress achieved to date is much lower than what would be necessary to attain those objectives, particularly in the poorest regions [1].

On the other side, the World Bank affirms that the number of people around the world living below the extreme poverty line (1.25 $ per day and per person) decreased from 1.9 to 1 billion between 1981 and 2011 (Figure1). This outstanding reduction is considered as a positive growth since the world population grew from 4.5 to 7 billion, at the same time [2]. Otherwise, the decrease in the level of poverty would be much less if we measured poverty in the poorest regions in the same way as in rich regions. If economic development provides higher income for a fraction of the population, in the vast majority of these countries, only a small fraction continues to capture a significant share of wealth.

Monetary poverty is often caused by weak income as a result of various causes, such as imbalances in labor market which generate unemployment and underemployment; limited access to agricultural inputs and markets (goods and services, credit) and to public utilities (water, electricity); the low level of education result in inadequate supply or lack of resources to finance training etc.

1. All information are available on un.org/sustainabledevelopment/fr/poverty/ (last visit: June 23, 2015)
2. www.inegalites.fr/spip.php?article381

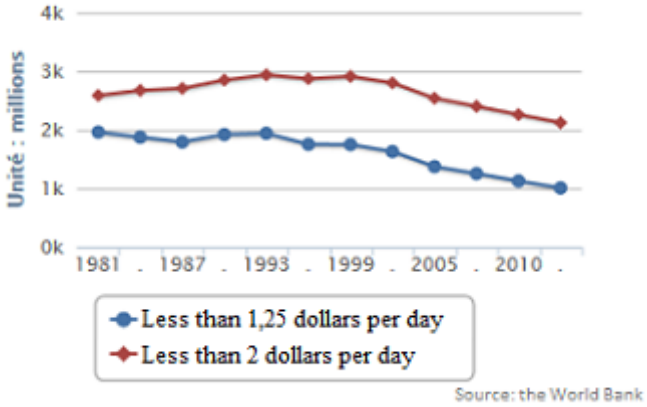


Figure 1.1 – Number of poors in the world according to the poverty line adjusted for inflation in 2005

One of the direct ways to improve the living conditions of the population and the fight against poverty is to promote a macroeconomic framework for growth, a framework to operate the market with an efficient manner that attracts investment, creates jobs and generates incomes . But this solution is not enough, especially because of the need for public goods (roads, dams, research and development,etc.) and the imperfection of some markets (Laderchi et al. (2003)).

Moreover, in theory, poverty was always linked to the country's political condition (Smith (2012)). They convincingly show that countries that succeeded to escape from poverty are those with appropriate economic institutions, especially private property and competition. In addition, they claim that countries are more likely to develop good institutions when they have a healthy pluralistic political system open to competition.

Another research path on poverty is the role of education. Economic and theoretical literature on poverty studies in the role of education in the fight against poverty. Education is a critical issue. Evidently, each country uses different measures to fight against this scourge, and those measures vary according to the importance given by a society to establish values such as equality and justice.

1.2 Poverty in Tunisia: A harmful eco-political context for the development and regional equality

Tunisia has long distinguished it self from the African continent by a strong growth through its opening to foreign trade and foreign investment in the "offshore" sector, but also better outcomes than its neighbors in health and poverty reduction. In fact, the growth model of the country from the creation of the statehood until the revolution of 2011 is often described as based on three main bases: 1) a strong state ensuring stability - but with a high cost in terms of civil and political freedoms and corruption; 2) an implicit social contract that includes an active social and educational policy, promoting the role of women in society and the development of infrastructure; and finally, 3) economic management based on broad openness to foreign trade and investment in certain sectors, however, the state keep controlling hand on strategic economic decisions (OECD (2015)).
However, the Tunisian development model also led to significant regional disparities, high unemployment rates among skilled workers and a significant government intervention in the economy which has hampered productivity. Moreover, the country has made remarkable progress in education compared to other emerging countries, but the quality of education remains a moot point. As a result, we emphasize an outstanding increase in graduates and inability of the labor market to absorb all of it. On the other hand ,skills unsuitability is one of the causes of persistently high unemployment, especially among young people. In fact, education system does not produce the skills required by the Tunisian labor market. Indeed, the lack of education may limit the opportunities for individuals to have a decent job. For example, the opportunity of a primary or secondary education diploma to get a job with higher salary is low compared to skilled workers with higher graduates education. Besides, the scarcity of teaching materials, teachers, support staff and well-trained managers in most business school is one of the causes of law performances. To achieve full employment the Tunisian government must improve the quality of basic education and vocational training (Morrisson (2002)).

The failure of the Tunisian economic systems

Tunisia, as a developing country, has implemented, since the statehood, several national programs to reduce poverty and promote employment. The country has shown some progress, but does not fully exploit its vast potential. The per capita income has rised,

public services are developed and health indicators are improved. In fact the country has opted for an open trade policy since the beginning of the 1990s. It is true that trade liberalization has led, over the last twenty years, to an increase in growth and income in developing countries, however, the gains from free trade are not equally distributed within the population and trade liberalization has a negative influence on some individuals. In addition, this strategy was preceded by the implementation of a Structural Adjustment Plan (SAP). However, economic restructuring, globalization of capital markets and structural adjustment are synonymous of drawdown of the permanent workers number, subcontracting with resort to temporary and seasonal work and reduced costs through deregulation of the labor market. Moreover, the environment, such as climate change and water scarcity problems threaten the sustainability of growth, while the aggravation of current account deficit is a vulnerable point at the macroeconomic level. To reduce the negative effects of trade liberalization on the poor population, mainly rural and vulnerable, the government continued to subsidize some basic food products through the General Compensation Fund (GCF) established since 1970, but it was not enough to respond to the feeling of inequality and injustice of some regions especially the rural ones.

All this factors led to an extremely high proportion of unemployed. Income disparities remain very high, the average educational outcomes are weak and highly unequal, while the failures of public services and corruption are growing. Production increases slowly relative to most other middle-income economies.

Regional disparities

The deterioration of living conditions of the rural population, the increase in the unemployment rate and the increase in general level of prices of basic goods has provoked the uprising of the people in the interior regions which was the main cause of the Tunisian revolution. Indeed, after the revolution, Tunisia is boldly emerging from the recession, the longest period of economic downturn ever, since the establishment of statehood. We highlight the failure of agricultural, trade and social policies and the exhaustion of the measures taken to deal with the vulnerability of the rural population.

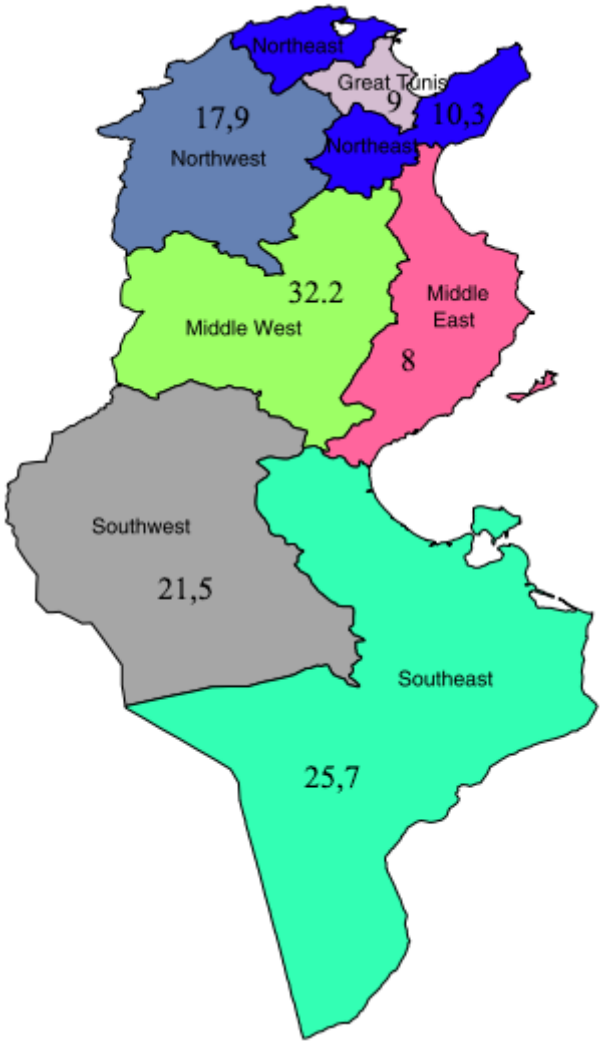


Figure 1.2 – Poverty rate per region - Tunisia 2010

In fact, the main cause of this revolution resides in the widening of economic and social disparities between the coastal and interior regions of the country. As we know, these regions have experienced deterioration in quality of life, a decrease in the purchasing power mainly for basic food products and more generally a social injustice (compared to other coastal areas). These regions have been marginalized under the previous regime and have suffered from the deterioration of their social situation. From figure1, we can highlight a potential gap between coastal regions and parts of the interior, where the rate of poverty reachs 32% (middle west).

In addition, the weakness of infrastructure in these areas, such as roads and communication, may limit poor people to have access to information or to labor markets. Furthermore, all these factors can be the cause of a persistent poverty and the inability of an individual to

get out of the trap of poverty. Currently, the rate of poverty in Tunisia is around 15.5%. This rate has increased especially in the western regions because of the observed protest movements of the residents who claim the improvement of their living conditions, the promotion of social services and improvement of infrastructures (INS). The number of unemployed is currently estimated to 700 000 individuals of which 69% are under the age of 30, while the number of unemployed among higher education graduates is estimated at 170,000 of total graduates according to data released by the national institute of statistics (INS) [3].

1.3 Poverty: different approaches and varying dimensions

According to the existing literature, we can distinguish three main forms of poverty. First of all, the monetary poverty which results from a lack of resources and leads to insufficient consumption. This approach is related to the economy of welfare since the monetary indicators define poverty according to an income deficiency or a too low consumption which reflect a lower standard of living (Townsend (1985)). It is a widely used concept of classifying individuals according to their monetary resources. The poor are those individuals or households whose income or consumption is below a given threshold (Ravallion (1998)). There are two methods to set the threshold, which generates two monetary poverty concepts. In absolute conception, the poverty line is a minimum subsistence reflecting the consumption of a basket of goods and services considered as essential to achieve a minimum standard of living. We must therefore define a list of goods considered as essential (food, housing, clothing) with a value that represents the minimum budget for a given type of family. Then the threshold changes each year depending on the general index of the cost of living. It is absolute in the sense that it is fixed without taking into account the distribution of resources among the population (Ravallion (1998)). In the relative logic, being poor means being at the bottom of the income scale. According to this logic, we identify a poor person by its position relative to other households. Poverty lines are then based on characteristics of the resources distribution (half median, half average, etc.)(Sen (1985)).

Regarding the second concept of poverty, poverty of living conditions, which was initiated by Townsend (1979), the poverty line is determined throught a multidimensional index. In

3. The entire data sets are available on http://www.ins.nat.tn/indexfr.php (last visit: August 1, 2015)

fact, this approach focuses on consumption patterns and takes into account the exclusion of individuals with respect to a dominant lifestyle. To determine the criteria for this exclusion, the author implements partial deprivation indicators about food regime, working conditions, level of education, etc, then he builds a multiple deprivation index. The analysis of poverty according to this logic is to build an overall score of living conditions: those who enjoy a good living conditions have a high score while those who suffer from privations have a low score. Households with the lowest overall score will be considered as poor. This approach corresponds to the logic of Sen (1985) with his concept on individual capacities. This approach supports the idea that poverty reflects a lack of basic functional capabilities (ie. the impossibility of eventually achieving a potentiality that would assist to work better in life).

Finally we evoke the concept of subjective poverty. Among the first authors who are interested in this concept we cite Van Praag (1971). This author is attached to the school of Leiden [4]. The approach of this school is based on the individuals perceptions. This implies that the utility or well-being is directly measured. In fact, this approach proposes to uses the views of the population on the problems of poverty and income distribution in order to measure poverty with the help of two hypotheses. The first one is that individuals are able to assess the income in general, as well as their own income in terms of "good", "sufficient", "bad" etc. The second assumption is that these verbal terms can be translated into numerical evaluation in the interval (0,1). The well being is then measured on the interval [0, 1]. Apart from this approach proposed by the Leiden school, we can distinguish two alternative approaches. The first method, based on the issue of minimum income, was initiated by Kapteyn et al. (1988). They proposed that households should qualify their standard of living (high or low) and estimate the minimum income required for an identical household. This approach assumes that an individual is able to estimate the minimum income level below which he is poor. In the second method, the approach of poverty according to a subjective scale corresponds to the individual assessment of their level of well being. Each individual are asked to place themselves on a scale of several levels ranging from poor to wealthy. In fact, it is a form of increasing scale ranging from the lowest to the highest (Ravallion and Lokshin (2002)). Indeed, this approach is similar to the method of the Leiden school with the assumption that individuals are able to assess their situations and that their individual responses are similar.

4. Leiden poverty line has been built using the issue of income assessment by a research group at the University of Leiden in the seventies

For many economists, the one-dimensional study may appear more limited, less complete and therefore less relevant than a multidimensional study, but this is not necessarily the case. Indeed, if we consider the available goods of the subject, for example, someone does not have a given good because of a simple personal choice and not because of the inability to obtain it. Personal preferences introduce therefore a bias difficult to correct (for example, a person who decides not to have a car because of his environmental convictions). A one-dimensional study escapes this problem since we assume that the chosen indicator reflects the level of well-being, irrespective of the choices that the individual can do. Univariate study would prove to be preferable as long as the income or consumption are good indicators of well-being, which is globally accepted.

Whatever approach we use, analysis poverty requires the definition of a poverty line to determine who is poor and who is not. Generally, to measure poverty, we can choose many poverty lines. These choices are crucial because they determine subsequently the sample. According to the approaches of poverty, we can distinguishe two groups of poverty line. Firstly, scientific or conventional threshold, this perspective is based on two methods for setting a poverty line: either they are based on the standards of dietetics, or they resort to economic theory. The Food and Agriculture Organization of the United Nations (FAO) norms distinguishes undernutrition (1500 calories per day and per person) and malnutrition (1500-2500 calories per day and per person), while economic theory allows to assign an economic value to the poverty line. Therefore, we can distinguish two types, namely the objective thresholds such as the minima social legislation, and subjective thresholds inspired from the perception that people have of poverty. On the other hand, we discuss two other poverty thresholds; namely the absolute and the relative poverty line. We can consider the absolute poverty line as a constant threshold over time in terms of living standards, updated with price inflation only. It allows to link the evolution of poverty to fluctuations in the economic environment and changes in social protection (Ravallion (1994)).However, the relative threshold measures both the evolution of inequality as well as poverty. The most commonly used threshold is the half of the median (or mean) income (or expenditure) per unit of consumption and per equivalent adult. In addition, poverty measurement requires the comparison of the households living standard. Typically, we should use equivalence scale and define per equivalent adult income to take into account the different household compositions(Deaton (1997).

1.4 Research questions

Among all the possible policies in the fight against poverty, a government must look for the one that gives the best results (ie. the most efficient to reduces poverty). However, it is difficult to adequately measure poverty in a society and therefore to determine which policies involve a greater reduction. The measurement of poverty is therefore of great importance since it makes the evaluation of policies against poverty possible. In the literature, we observe that different poverty measures often involve different conclusions about the suitability of a policy. It is therefore necessary to measure poverty with implements which correctly reflect the values and the preferences of a given society. In fact, there is a consequent risk of wastage which may adversely affect the poorest people. Indeed conventional affirmation about poverty measurement admits two stages :

- The Identification of Poverty; ie. answer to the question "Who is poor? "
- Aggregation of poverty: ie answer to the question "How many poor people there are?"

The answer to these questions is done by analyzing an appropriate set of data, which is supposed to give us the necessary information about individuals.
Regarding the data, as poverty is a phenomena that affects individual's well-being in many areas, we use various statistics that reflect the living standards of poor people, for example, statistics about access to education and health, available goods (car, appliances, type of housing, etc.), etc.

Furthermore, studying deeply regional disparities is very important to the assessment of poverty. In Tunisia, earlier studies have shown the importance of some variables in the fight against these social scourges (education, employment, etc.). However, despite the economic measures and the structural social reforms taken by the government to overcome poverty and inequality effects, the gap between urban and rural areas is still important.

Moreover, Poverty is fundamentally a dynamic phenomenon. The assessment of chronic poverty and transient poverty is necessary and has two advantages. First, it should enable more effective explanatory models of poverty that take into account the heterogeneity of poor individuals. It must allow in a second time a better specification of the contents of policies against poverty. Indeed, in the form of poverty, two distinct responses may be

considered. If poverty is essentially a transitory phenomenon, it will be necessary to set up a social protection system that helps individuals overcome their deprivation present: unemployment benefits, social assistance, etc. However, if poverty is chronic phenomenon, the implementation of structural policies will be more relevant (Hulme and Shepherd (2003)).
Research questions that we seek to answer are exposed as follows:

1. *What are the characteristics that make some households more vulnerable than other?*;
2. *What are the factors that explain the persistence of the gap between urban and rural areas?*;
3. *Why people fail to escape from the trap of poverty?*

1.5 Response strategy and plan

This PhD thesis seeks to understand the phenomenon of poverty in Tunisia, and better target the poor in various aspects using both static and dynamic measurements. To achieve this goal we propose a plan on three chapters.

The first chapter focuses on the determinants of household welfare in Tunisia. Welfare is measured by equivalent adult household expenditure (income). It will be devoted to the analysis of the relationship between poverty and the situation of household heads in relation to the labor market, region of residence and some household characteristics. The goal will be to measure the extent of poverty in Tunisia and to identify characteristic that influence households well-being. Using FGT indices and logit model, we measure poverty and analyze household welfare by selecting variables that would influence the well-being of these households. Therefore, we define an equivalence scale for the country, estimate the poverty lines and test the robustness of our results. Morever, we propose a new approach based on fuzzy set approach (Zadeh (1975), Betti et al. (2006), Belhadj (2011b)) by building a membership function based on the logistic function enable a comparison between logit model and fuzzy approach. This study aims to illustrate that, in contrast to fuzzy approach, ordinary logistic regression can not provide ideal assumptions.
Computing the three methods exposed previously, this chapter shows a higher disparities between rural and urban regions. In addition to these results, we find that some character-

istics, such as educational level, may improve households' well-being.

In the second chapter, we examine the inequality gap of consumption in rural and urban areas. For this goal, welfare is measured by real per capita household expenditure (income). Our empirical analysis relies on the Tunisian Living Standards Surveys (TLSS)from 2010. This study makes two original empirical contributions to the literature compared to previous studies on the same topic in comparison to Hassine (2015), Fang and Sakellariou (2013), Chang (2012), Skoufias and Katayama (2011). First of all, in order to analyze the gap between the two regions, we apply a new counterfactual decompositions based on quantile regressions (Chernozhukov et al. (2013)), which encompas Machado-Mata decomposition (Machado and Mata (2005)) as a special case and enables to test the hypothesis of omitted variables. We also use censored and uncensored quantiles regressions for disaggregate consumption expenditures (Chernozhukov and Hong (2002), Chernozhukov et al. (2015)). This study offers another analysis of the sensitivity of some indicators such as health, food and especially education, with regional disparity in developing countries. It also examines the relationship between these indicators and development disparities across the two areas. We find that both covariate and return effects are larger at the higher quantile. Moreover, for poor households, the causes that make urban one better than rural households is essentially due to difference in characteristics, whereas for the non-poor households, the gap is rather due to the returns of their characteristics. Results of this modeling prove that the problem is not only about equality but also it is an equity issue. Such equity, implies that policy of fighting against poverty and inequality should be based on positive discrimination in favour of marginalized areas.

Finally, the third chapter proposes to focus on the dynamics of poverty. Unfortunately we are face to a lack of data as the case of many developed countries. To avoid this problem many economist used pseudo-panel or repeated cross data. This is important but not enough since these models allow only agregate analysis of poverty and don't take into account *within*-individuals poverty in the same cohort. Therefore, this study propose a new approach enables to execute a dynamic modeling of poverty by combining causal inference (Piesse et al. (2010), Rubin (1974), Gelman et al. (2014)) and multiple imputation approachs. Indeed, in a first step, we panelize our data sets using a Bayesian algorithm (Honaker et al. (2011), Blackwell et al. (2015)) in order to impute potential variables. For

the second step, we made a dynamic analysis of poverty through two methods. Firstly we use static decomposition of poverty using the Jalan-Ravallion approach (Ravallion (1998)) and the Equally-Distributed Equivalent (EDE) poverty gap approachs (Duclos et al. (2003)) since this statistic method allow us to work with a small size of data. On the other hand, we made an econometric modeling of poverty through a recursive bivariate probit model. The principal result of this study is that poverty in Tunisia is mainly a chronic phenomenon.

Chapter 2

The determinants of poverty in Tunisia

2.1 Background

There is a consensus on the need of poverty and inequalities reduction strategies, designed to facilate empowerment of poor or marginalized (Yeo and Moore (2003), Adams et al. (2004), Brinkerhoff and Goldsmith (2003), Basu (2006) and Blocker et al. (2013)). As poverty is a social complex phenomenon, in recent decades it has been the subject of many theoretical debates, often complementary. The interest of different approaches resides in the strict identification of poverty, a necessary condition to implement efficient policies against this scourge. After the construction and the analysis of poverty profiles, the study of its determinants is often a priority to develop good poverty reduction strategies. This literature offers several methods to model these determinants. On the one hand, the monetary approach of poverty, commonly called utilitarian approach (Arrow (1971)), conducts an essentially one-dimensional conceptualization of poverty based on the well-being (as measured by the utility). According to this approach, poverty is reducing to a simple lack of resources in terms of income necessary to achieve a minimum quality of life (Ravallion (1994)). Most monetary poverty studies [1] using consumption expenditure per capita as welfare indicator. Indeed, this approach was defended by several economists. Laderchi and House (2000) presents a set of methodologies to poverty measurement, based on poverty identification using a shortfall in monetary indicators. Belhadj (2011a), Belhadj and Matoussi (2007) used the fuzzy approach to propose a one-dimensional measure of poverty and distinguish three level of poverty.

On the other hand, in contrast to the monetary approach which is limited to one dimension, the non-monetary approach addresses poverty in a multidimensional way by integrating the basic conditions related to the existence of human being. The basic assumption of any multidimensional approach to welfare and poverty analysis, is that there are relevant dimensions of well-being that economic resources are not able to capture (Atkinson and Bourguignon (1982)). For several reasons, income and consumption are considered as only approximate measures of the quality of life. First of all, they are not able to completely describe what people can really achieve with those resources. In addition they can hide large differences and inequalities between individuals. And finally, because the quality of life is a wider concept than to consider it as a simple given amount of resources (Deaton and Zaidi (2002)). Alkire et al. (2014) propose multi-dimensional index to assess poverty dynamics in 108 countries. Ravallion (2011) argues that we should use multiple indices rather than

1. see previous chapter for more details

one multidimensional index. Ayadi et al. (2005) used a non-monetary composite index constructed by the factor analysis technique linked to the conditions of household lives. In addition, Ayadi et al. (2007) used a non-monetary approach to analyzing poverty and inequality in Tunisia between 1988 and 2002. Hamdène and Benhassen (2012) computed a composite index of well-being for each governorate, they found a significant disparity between regions and persistence of poverty in many governorates. On the other side, some economist have rather focused on the welfarist approach. The ability to pass from one perspective based on income to take into account the plurality constitutive of human life, has been widely advocated by theoretical debate on social protection and poverty. That considered a plurality of indicators to describe the quality of life of individuals and households. Health, longevity, education, social relations, etc., are constitutive elements of human life that should not be ignored if we are interested in evaluating the living standard of population. Aside from this discussion on the rough/smooth transition in the deprivation state, another line of research has addressed both one-dimensional and multidimensional povery. Sarangi et al. (2015) choose to deal with the two approachs to analysis poverty in arab counries.

In this chapter, we use the methodology of the monetary approach to build an equivalence scale for Tunisia, to define the poverty line and give, by region and some socio-economic characteristics of households, a meausrement of poverty. For these measurements, we use the FGT (Foster et al. (1984)) indicators, the logit model and we propose a new methodology using the fuzzy set approach. Finally, to test the robustness of our results we use two measures namely the stochastic dominance approach and the sensitivity test.

2.2 Welfare measures, equivalence scale and poverty line measurement

The measurement of poverty depends on three steps: The selection of an appropriate welfare indicator to represent individuals' well-being; the choice of z which identifies the lower part of the distribution; finally, the selection of some function of the level of well-being of 'poor' person relative to the poverty threshold ((Sen, 1976a)). Since, there is a difference between child and adult consumption, we use equivalence scale which takes into consideration the size of household and the eonomy scale.

Welfare measures

Measuring welfare was the objective of several studies and theoretical foundations. Several approaches was developped to analyze welfare and can be classified according to Money Metric (Leibbrandt et al. (2010)) or Non-Money Metric approaches. In fact, most studies in social welfare typically use Money Metric measures such as income or consumption expenditures. Non-Money Metric approach depends on the different assets that a household has available. These measures often apply a multivariate analysis.
In this study we use consumption expenditure as an indicator of well-being. A brief summary of this variable is given in Table 2.1.

Table 2.1 – Descriptive Statistics of the variable Total annual Household Expenditure (2010)

Minimum	First Quantile	Median	Mean	Third Quantile	Maximum
259	5328	8486	10580	13230	197000

Household expenditures are further characterized by its stability over time compared to income fluctuations. They provide information about the degree of satisfaction that comes from the consumption of goods and services. This approach has been advocated in recent studies by Fang and Sakellariou (2013), Chamarbagwala (2010) or Pieters (2011). However, the generated data are not directly comparable because of the different households composition. Adult equivalence scale is a good tool enable to overcome this problem. In the next section we introduce the concept of equivalence scale to compare the household's living standard taking into account different size and composition.

2.2.1 Equivalence scale

The concept of equivalence scale is founded by the utility theory and individual preferences. It enables the estimation of relative weight for different individuals in the household to get finally the consumption (income) per capita (Bourguignon (1993)). Engel (1896) attempts to measure the level of household well-being by the share of food expenditure in its total consumption. In fact, the share of food expenditure is a welfare indicator that allow to adequately compare household with different size and composition [2]. According to Engel,

2. While Nicolson (1976) relativizes Engel method. For this author, the share of food expenditure is not a perfect indicator of household's welfare. In the context of developing countries, this argument seems to

two households with an identical share of food expenditure can be considered to have the same level of well-being. The relationship between food expenditure and total expenditure on the one hand, and the corresponding equivalence scale, on the other hand, can be estimated by an econometric method(Cutler and Katz (1992)) [3] as follows:

$$E = (N_a + \lambda N_c)^{\theta} \tag{2.1}$$

Where E is the adult equivalent number, N_a the number of adults andN_c the number of children. λ expresses the relative cost of a child compared to an adult and θ is the scale. Due to the specific needs of children and the demography of families, Lachaud (2000) proposes an extension of this model, for developing countries, taking into consideration specific needs of children and demographic characteristics of families, as follow:

$$EQ = (A + \lambda_{0-4}E + \lambda_{5-14}E)^{\theta} \tag{2.2}$$

Where EQ represent the value of equivalent scale, A and E, respectively, the number of adults and children in the household. λ_{0-4}, λ_{5-14}, equivalence coefficients between adult and children (respectively, from 0 to 4 and 5 to 14 old). While $(A + \lambda_{0-4}E + \lambda_{5-14}E)$ reflects the weight of the household equivalent adult and the coefficient θ converts these equivalent adult taking inro account effective household's resources [4]. An econometric procedure can then used to easy estimate λ and θ.

Following Deaton (1997) and Lachaud (2000) we consider the following equation:

$$E = c + \beta_1 ln(\frac{X}{n}) + \beta_2(1-\theta)ln(n_i) + \sum_{j=1}^{J}\sum_{i=1}^{n}\sigma_j n_i j + \epsilon \tag{2.3}$$

Equations 1 – Equivalence scale model

with, $\beta_1 = \beta_2(1-\theta)$, E represents the share of food expenditure of household i, X is the total household expenditure, n_i is the size of household and n_{ij} represent the percentage of individuals in household and which belongs to class J (adults, children aged 0-4 year

turn her relative, because food is the most important item of total household expenditure. In this regard consumption expenditures is considered as a good approximation of welfare

3. The use of Engel method was popularized from the work of Working (1943)

4. This coefficient is called elasticity size. It ranges between 0 and 1, $\theta = \frac{\frac{\delta\alpha}{\alpha}}{\frac{\alpha t}{t}}$, where α is the consumption expenditure and t represent the size of household

or 5-14 year). Estimating this equation enable to determine the scale parameter θ which corresponds to [1-(β_1 / β_2)].

Dependent variable is the share of food expenditure [5] in total household budget, and we define independent variables as follows:

1. The log value of total household consumption per capita;
2. The log of household size;
3. The proportion of individuals in the household, according to their ages, respectively, less than 5 years, between 5 and 14 years and over than 15;
4. Gender of household head, if a woman it is takes the value of 1 and 0 if it is a man;
5. Education of the household head, a value of 1 if it is not educated and 0 if not;
6. Marital status of the household head, a value of 1 if he is single and 0 if not.

Table 2.2 – Estimation of the Engel Curve Households by Least Squares −Tunisia 2010

variables	Coefficients	std dev
Intercept	−7225103	95392.21*
Log (Real Expenditure Per Capita)	576613	6172.524*
Log (household size)	191037.8	24971.46*
Education of Household Head	29012.36	9151.786*
(The individual is not Educated = 1)		
Demographic Variables		
Child under 5 years	11610.98	33082.2
Child 5 - 14 Years	-	-
CHILD aged 15 and over	−79211.58	24257.98*
Marital Status of Household Head		
Married	−38376.81	16465.34*
(the individual is not married = 1)		
Gender	29256.07	16137.36*
(Women = 1)		
Number of Observation	11281	
R2 adjust	0.54	

*variables are statistically significant at 1%

Table 2.2 shows results and gives rise to some interpretations. Firstly, we note that the factors taken into account in the model explain only about 54% of the variance. Besides, the coefficients for the standard living and household size are statistically significant and lead to an estimation of the scale parameter θ (0.67). Therefore, Tunisian equivalence scale is reduced to $n^{0.67}$ in 2010. However, coefficients associated with the proportion of children

5. In 2010, expenditure food remains the first post of household consumption according to the INS classification (see appendix A1)

in the household are not significant. Thus, it is not possible to evaluate the parameters λ_{0-4} and λ_{5-14}.

2.2.2 Choice and Measurement of Poverty Line

Poor individuals are those whose income (expenditure) falls below a poverty threshold. Once an aggregate consumption (income) or a non-monetary measure is defined at individual or household level, the next step is to define the poverty line. Poverty line is cut-off point separating the poor from the non-poor. The construction of this limit is the most difficult step in the practical measurement of poverty (Deaton (1997)). They can be two ways of setting poverty line—in a relative or absolute way.

Absolute poverty lines

These are anchored in some absolute standard of what individuals should be able to rely on in order to occur their basic needs. According to the monetary measures, absolute poverty line is often based on estimates the cost of nutritional basket, which considered minimal for the healthy survival of a typical household. For developing countries, many households survive with the bare minimum or less, it is often more pertinent to rely on an absolute rather than a relative poverty threshold. Different methods have been used to define absolute poverty line (Deaton (1997), Ravallion and Bidani (1994)).

- *The food-energy intake method*

  According to this method, poverty line is defined by finding the consumption expenditures (or income) level at which an individual's food energy intake is just sufficient to meet a predefined food energy requirement. If applied to different regions within the same country, the underlying food consumption pattern of the population group just consuming the necessary nutrient amounts will vary. This method can thus yield differentials in poverty line in excess of the cost-of-living differential facing the poor.

- *The Cost of Basic Needs method*

  This method values a bundle of foods typically consumed by poor individual at local prices first. To this, a specific allowance for nonfood goods, consistent with spending by the poor, is added. However defined, poverty line will always have a high arbitrary element.

Relative poverty lines

Relative poverty lines are defined in relation to the overall distribution of income or consumption in a country;

- *Relative poverty line determined by the statistical method:* According to this method, we must first of all classify individuals or household incomes in ascending order. Then the poverty line is the maximum income of the first $x\%$ of households. For example, the poverty line could be set at 50 percent of the country's mean income or consumption.

- *Relative poverty line as a percentage of the minimum wage:* In a country where we have a guaranteed minimum wage, we can use it as a reference to determining the poverty line.

An Axiomatic Approach to the Synthetic Measure of Poverty

Synthetic index were adopted to obtain some indicators of poverty that enable to examine whether a number of theoretical properties are really verified by a simple poverty rate. Poverty Headcount Ratio, Gap Measure, and Squared Gap of Poverty index are the most commonly used in the literature. These index belong to the family of measuring poverty developed by Foster-Greer-Thorbecke (Foster et al. (1984)). In fact, Traditional poverty approaches presents the individual poverty function as follows:

$$P_i = \begin{cases} 0 & \text{si} \quad y_i \geq z, \\ \frac{z-y_i}{z} & \text{si} \quad y_i < z. \end{cases} \tag{2.4}$$

Equations 2 – Individual poverty function

And aggregated function is represented by the folowing FGT index:

$$FGT_\alpha = f(x,z) = \frac{1}{n}\sum_{i}^{n}(P_i)^\alpha I(P_i > 0) \tag{2.5}$$

Equations 3 – Aggregate poverty function

i. *Symmetry Axiom:* Poverty measurement is unchanged by a permutation of initial allocations between individuals. This means that, if individuals A and B exchange

their initial endowments, the measured poverty does not change. Indeed, this property indicates that nominative knowledge of poor person does not change the assessment of poverty.

ii. *Monotonicity Axiom:* If the endowment yi of a poor person decreases, then the measurement of poverty increases. This property may seem obvious, however, a basic measure such as the incidence does not verify it.

- **Strong Axiom:** Every time when the income of poor rise poverty index should decrease.
- **Weak Axiom:** As long as the individual remain poor, every time when the income of poor rises, poverty index should decrease.

It is true that there is a very small difference, but we should distinguish the two cases;

iii. *Transfer Axiom:* This axiom is verified if,*Ceteris paribus*, a transfer from a poor to a less poor person should increase the level of poverty. Nevertheless it is not as simple, the partial transfer of a poor endowment may allow a less poor person to become "rich" (passing above the poverty line). In this case the intensity of poverty increase, but the incidence of poverty decreases. In fact, some authors have pointed out that this axiom should not be systematically checked as soon as we attach some importance to the incidence of poverty (Sen (1979));

- **Minimal axiom:** According to this axiom, poverty index increase (decline) after a regressive (progressive) transfer between two poor people's staying poor after this transfer [6];
- **Weak axiom:** Poverty index increase (decline) after a regressive (progressive) transfer from a person below or above poverty line in favor of a relatively poorer person (as well as the first axiom, we use same number of peoples before and after transfer);
- **Strong upward axiom:** According to this axiom, poverty index increase (decline) after a regressive (progressive) transfer when the poorest of the two persons is poor and remain poor after the transfer and the wealthier of the two person can be poor or non-poor depending to the result of the transfer;

6. using the same number of peoples before and after transfer

- **Strong downward axiom:** Poverty index increase (decline) after a regressive (progressive) transfer come from a relatively wealthier individual, who either be poor or not poor, to a poor individual who can become non-poor after this transfer.

iv. *Population Homogeneity's Axiom:* If two or more identical populations are clustered poverty index should not be changed;

v. *Axiom of decomposability:* A measure $P(y, z)$ is called decomposable if and only if for any partition of the distribution y with k classes $(y^1, y^2, ..., y^k)$, we have: $P(y, z) = \sum_{j=1}^{k} \frac{n_j}{n} P(y^j, z)$, where n_j is the size of the class j. For decomposable measures, poverty can be expressed as a weighted average of subgroup. If the sizes are constant, an increase in poverty of a sub-group increases global poverty. Thus, it is true that decomposable index verifies the consistency by sub-group, but this property have a false converse. These two properties of consistency and decomposability are generally considered desirable. In fact, we believe that these two principles are a necessity if the poverty analysis is based on a geographical, ethnic,(...) division. If this approach is not adopted, poverty measures remaining always valid;

vi. *Focus Axiom:* Poverty measurement does not depend on the endowment "y_i" of non-poor individuals.

- **The standard axiom:** Consider two distributions of income with the same size, note that for the two cases the poor incomes are the same, we should have the same poverty index measure for the two distributions.
- **The generalized axiom:** Consider two distributions of income with different size, note that for the two cases the poor incomes are the same, we should have the same poverty index measure for the two distributions.

vii. *Axiom of consistency by subgroups*[7]*:* Consider a $\tilde{y}$ distribution obtained from the distribution y by changing the incomes of a subgroup j, the size n_j of this group remains the same. According to this axiom, if the subgroup j is poorer than initially, then total population is poorer. This criterion, which is a principle of consistency between the evolution of poverty in a community and the whole population, is generally

7. In the literature, this principle was first presented as a subgroup monotony axioms (Foster et al. (1984)).

considered desirable. The statement of this criterion, however, is conditional on some demographic configurations: stationary population and absence of migration between different subgroups. This precision enables to avoid any change in the measurement of poverty in a subgroup that would be due to migration.

2.3 Poverty measurement and analysis

Information on poverty is fundamental in understanding the politics of public policies. Collecting information about individuals and their economic status, one can distinguish who gains from public grants. On the other hand, these informations can simulate the impact of various policies. The more accurate measurement outcomes about poverty help policymakers better target resources at specific groups.

This section introduces to the measurement of poverty as defined previously. We select (qualitative and quantitative) socio-economic variables related to the household's head. Our choice is justified by the fact that the head of household is the main source of income, and plays the main role in asset and household resource management. Other variables for the entire household are included to take into account the other members and the place of residence. We use the 2010 national survey "Tunisian Living Standards Survey" as a data resource. This survey takes a representative sample of the Tunisian population of 11281 households with 50371 individuals. The variables that we will use in our analysis are as follow:

i Geographical Location:
- Urban-Rural decomposition;
- Administrative decomposition (seven areas: Greater Tunis, North East, North West, Middle East, Middle West, South East and South West).

ii Social Characteristics:;
- Age of Household Head (Three Intervals: 18 to 34 old, 25 to 60 old and more than 60 old);
- Household Size (Five Intervals per person: 1-2, 3-4, 5-6, 7-8, and more than 8);
- Gender of Household Head (man or women);
- Employment (Inactive, employed, unemployed, independent);
- Education (illiterate, primary level, secondary level and high level).

iii Money-Metric Measure

- Relative Poverty measurement: Relatively we consider poor households whose expenditures per equivalent adult are below the half median of total expenditures;
- Adult Equivalence scale.

2.3.1 Summary measures of the extent of poverty

Once the indicator and measures have been chosen, various characteristics of different poverty groups (poor/non-poor) can be assessed to shed light on the determinants of poverty. In this section, we use FGT index Foster et al. (1984) for a synthetic measure of poverty

The role of Education in Poverty Reduction :

Before analyzing the access to education in Tunisia, we will emphasize some facts about the Tunisian education system, largely based on the French model. After the statehood, education is considered as a high priority in Tunisia. The desire to develop the country and to provide a skilled labor has led the Tunisian authorities to promote access to education by eliminating registration fees for primary and secondary school.

With a budget representing approximately 17.34% of government expenditure in 2012 (6.7% of GDP), Tunisia is quite well endowed with education, compared to literacy, access to education system and infrastructures [8].

According to statistics from the Ministry of Education, in 2009, there were 4517 public primary schools that hosted 1.008600 students (484,198 girls) supervised by 58,567 teachers (32,109 female teachers) there had also 102 private schools that hosted 21,509 students supervised by 1619 teachers. Moreover, 2097 public preparatory schools hosted 485,860 pupils taught by 38,515 teachers. The enrollment rate for the age class of 6-11 years was 98.2% (98.5% for girls and 97.9% for boys) [9]. The success rate of the bachelor was 60.3% in 2009 and 55.5% in the June 2010.

The relationship between education and poverty is important because of the fundamental role played by education in reducing poverty and raising economic growth (Cremin and Nakabugo (2012), Tarabini and Jacovkis (2012), Tarabini (2010), Wedgwood (2007)). Better-educated individuals have higher incomes and thus there are less likely to be poor.

To analyze the effect of education and employment sector on poverty we perform an

8. according to the World bank report
9. the entire data sets are available on http://www.ins.nat.tn/indexfr.php (last visit: August 1, 2015)

estimation of poverty index [10] related to Tunisia. Individuals living in households with Illiterate household head are more likely to be poor, with a poverty rate (incidence of poverty) of 19% in 2010. With higher educational level, the likelihood of being poor decreases considerably. Raising educational level is a high priority enable to improve individuals living standards and reduce poverty.

According to the results presented in Table 2 [11], the illiterate have the highest poverty rates (51%).

The poverty rate differs by the level of education of household head. Ceteris paribus, as the level of education increases, the probability of being poor decreases significantly.

Employment and poverty :

The reduction of unemployment rate and the creation of decent and productive jobs for youth are one of the MGD targets. Unemployment and poverty are serious problem in Tunisia. Higher rate of unemployment and poverty are concentrated in rural areas especially in the Middle West (INS). In rural zone agriculture sector did not succeed to decrease the higher level of unemployment and poverty. For this reason, we observe an increase in internal migration [12]. In fact rural unemployment has caused significant population movement to urban centers, where conditions are often hard.

In fact, high levels of youth unemployment are linked to the search for a good job in the formal sector. As these employment opportunities became fewer, the length of the transition from school to work actually fell, with more young people accepting jobs in the informal sector (this is the reason why the probability of the first job being in the informal sector rose). On the other side, we have generated four socioeconomic groups to the employment sector: employees, independent inactive and unemployed. We find the highest incidence of poverty among households guided by an unemployed household head.

10. we have advanced three standard index: Headcount Ratio, Poverty Gap Measure and Squared Gap Measure Foster et al. (1984)

11. We compute absolute and relative contribution of poverty as folow:
Absolute contribution to national poverty (AC) = Percentage of Tunisians living in this area * Incidence of poverty in the region (%);
Relative contribution to national poverty (RC) = CA / National Poverty Rate.

12. unfortunately, data concerning internal migration are not available otherwise it can improve this study

Table 2.3 – Poverty Measurement by Education and Employment Status - Tunisia 2010

	Headcount Ratio			Poverty Gap Measure			Squared Gap Measure		
	P0	AC	RC	P1	AC	RC	P2	AC	RC
Education									
Illiterate	0.193	0.053	0.364	0.065	0.014	0.366	0.019	0.006	0.374
	(0.009)	(0.004)	(0.008)	(0.005)	(0.002)	(0.010)	(0.003)	(0.001)	(0.013)
Primary Level	0.138	0.064	0.377	0.041	0.015	0.388	0.015	0.006	0.394
	(0.008)	(0.004)	(0.008)	(0.004)	(0.001)	(0.010)	(0.002)	(0.001)	(0.013)
Secondary Level	0.115	0.030	0.210	0.023	0.008	0.204	0.011	0.003	0.191
	(0.009)	(0.002)	(0.006)	(0.003)	(0.001)	(0.006)	(0.002)	(0.005)	(0.007)
Higher Level	0.089	0.046	0.008	0.013	0.001	0.041	0.006	0.0005	0.004
	(0.011)	(0.0007)	(0.001)	(0.003)	(0.0002)	(0.001)	(0.001)	(0.0001)	(0.001)
Employment									
Employee	0.149	0.069	0.476	0.041	0.019	0.479	0.016	0.007	0.484
	(0.007)	(0.004)	(0.008)	(0.004)	(0.002)	(0.010)	(0.002)	(0.001)	(0.019)
Self-Employment	0.123	0.019	0.132	0.032	0.004	0.134	0.014	0.002	0.130
	(0.005)	(0.001)	(0.009)	(0.010)	(0.003)	(0.007)	(0.003)	(0.001)	(0.011)
Inactive	0.111	0.031	0.218	0.029	0.008	0.212	0.012	0.003	0.208
	(0.009)	(0.003)	(0.007)	(0.004)	(0.001)	(0.009)	(0.002)	(0.0009)	(0.011)
Unemployed	0.299	0.024	0.171	0.069	0.007	0.176	0.019	0.003	0.176
	(0.029)	(0.001)	(0.003)	(0.020)	(0.001)	(0.004)	(0.015)	(0.0002)	(0.014)
Total	0.145	0.145	1	0.039	0.039	1	0.016	0.016	1

our computes based on INS data

This impact is even greater in the case where the head of household is unemployed female and live in rural areas. Those who managed to get a good public sector job had to wait longer after leaving school: suffering through more than 2 to 3 years of unemployment. The relationship between the position on the labor market and the economic situation of households is complex. Indeed, the link between unemployment and Poverty is not automatic. If the former refers to individual activity, poverty refers to the lack of household resources. In addition, Poor people are largely related to growth through the labor market (Bourguignon (2003), Bourguignon (2004), Arndt et al. (2010), Ravallion and Datt (2002)). In rural areas, the demand is very dependent on rainfall, which is lower in drought years. In light of these changes, agriculture has created very few jobs in the long term (Irz et al. (2001)), growing by only 5% in forty years. Moreover, the increase of Rural-urban migration may explain this near-stagnation of total employment in the agricultural sector during this long period which shows therefore that this sector has hardly created any jobs for poor.

Poverty measurement by region :

As many developing countries, poverty in Tunisia is rather concentrated in rural areas and in some regions of the country, particularly the west areas [13]. Households with higher level of poverty rate are more concentrated in the interior regions of the country than the inland ones. A strong variation in poverty rates between regions (table 4) may be the cause of social instability and population movement. Thus, measurement of poverty at the regional level allows bettering defining the priorities for regional development. The decomposition of the impact of global poverty by region presented in Tables 4 is considered as an important profile. Results show that poverty rate varies significantly between regions. Regions of Middle west and North west of the country remain the poorest, but west area has the highest poverty rates with an incidence of about 31% compared to other regions. It appears, from table 4, that poverty is unequally distributed by regions. When we consider the distribution of poverty among the three areas with reference to poverty line, we observe the preeminence of west area for the three indices. Not only its incidence is higher, but also it is in west areas that poverty is considered as the deepest and the most intense with comparison to other regions.

regional equity in Tunisia is one of the major and priority areas in the development program of the country. The government objectives are concentrated to inequality and poverty

13. INS report, 2012

reduction across regions, by upgrading basic infrastructure, developing human resources and a widening equity regional structures. Unfortunately, Despite all efforts to reduce it, poverty remains concentrated in the western parts of the country [14]. Poverty decreased from 2005 to 2010. This decrease faces to a higher consumption disparities with an economic inequalities, asserts that the GDP growth was biased towards the non-poor. Until now, the adopted economic and social development does not correspond to good regional governance objectives that Tunisia should achieve.

14. The entire data sets are available on http://www.ins.nat.tn/indexfr.php (last visit: August 1, 2015)

Table 2.4 – Poverty Measurement by Region - Tunisia 2010

	Headcount ratio			Poverty Gap Measure			Squared Gap Measure		
	P0	AC	RC	P1	AC	RC	P2	AC	RC
Greater Tunis	0.071	0.0113	0.050	0.007	0.009	0.064	0.002	0.0003	0.023
	(0.004)	(0.002)	(0.004)	(0.003)	(0.0006)	(0.004)	(0.001)	(0.0003)	(0.004)
North East	0.098	0.013	0.092	0.0209	0.014	0.095	0.007	0.0009	0.060
	(0.013)	(0.002)	(0.005)	(0.005)	(0.0008)	(0.005)	(0.003)	(0.004)	(0.006)
North West	0.254	0.036	0.242	0.0704	0.009	0.2473	0.028	0.004	0.249
	(0.013)	(0.002)	(0.006)	(0.007)	(0.001)	(0.008)	(0.005)	(0.008)	(0.010)
Middle East	0.064	0.012	0.082	0.0015	0.003	0.07180	0.0009	0.001	0.064
	(0.011)	(0.002)	(0.006)	(0.004)	(0.001)	(0.006)	(0.003)	(0.0006)	(0.007)
Middle West	0.312	0.047	0.327	0.098	0.015	0.377	0.042	0.006	0.417
	(0.012)	(0.003)	(0.007)	(0.007)	(0.001)	(0.009)	(0.006)	(0.001)	(0.012)
South East	0.135	0.013	0.095	0.034	0.006	0.096	0.0125	0.0013	0.084
	(0.016)	(0.002)	(0.006)	(0.008)	(0.001)	(0.008)	(0.006)	(0.0008)	(0.010)
South West	0.150	0.016	0.108	0.036	0.004	0.099	0.014	0.0015	0.098
	(0.015)	(0.002)	(0.006)	(0.008)	(0.001)	(0.007)	(0.005)	(0.0007)	(0.009)
Total	0.145	0.145	1	0.039	0.039	1	0.016	0.016	1

our computes based on INS data

The impact of poverty depending on age, sex and size of household head

Poverty rate varies according to several criteria, such us sex and households age. Results show that household heads belonging to the first and second group are more exposed to poverty than others. In Tunisia, as in other developing countries, women's participation in development process remains marginal. Yet the conceptual approaches in terms of research suggests that women can effectively contribute to a country's development process.

However, according to the INS report [15] poverty does not affect men and women equally. The relationship between gender and poverty may also indicate another targeting strategy for poverty reduction. In Tunisia about 15% of the population lives in households headed by women. Results show that, the poverty rate was slight lower among femaleheaded households (14%) than among male-headed households (15%). In this case, targeting interventions based on the gender of the head of household would not help to distinguish the poor from the non-poor.

The gap is also important for the age group 18-34 years. Before age 18, women are slightly less likely to be poor than men. The girls continue their studies longer than boys who thus enter younger and less skilled in working life. Poverty rate is close to that age for both sexes.

According to our results, poverty affects firstly adults. In fact, the notion of "poor adults" hides the heritage poverty of parents. There are poor because their parents have insufficient income.

This does not mean that their situation is less serious, some of these people, especially in rural areas, survive on very low incomes.

On other hand, there is a considerable consensus of the negative correlation between consumption (income) and household size (Lipton and Ravallion (1993), Visaria (1980), Nelson and Phelps (1966). Results highlight that households with a large size (more than 8 person) are more exposed to poverty than other. Results show also that couples without children are the less vulnerable to poverty, where their poverty rate reached only 8%. In fact, the more you can count asset in a family, the higher the probability of being poor is low. For some families, there is the lack of reasonably priced childcare makes it even more difficult access to employment.

15. statistics are available on http://www.ins.nat.tn/indexfr.php

Table 2.5 – Poverty Measurement according to some characteristics of household - Tunisia 2010

	Headcount ratio			Poverty Gap Measure			Squared Gap Measure		
	P0	AC	RC	P1	AC	RC	P2	AC	RC
Household Size									
[1 - 2 Person]	0.059	0.009	0.063	0.014	0.002	0.036	0.003	0.001	0.033
[3 - 4 Person]	0.093	0.034	0.240	0.022	0.008	0.212	0.008	0.003	0.198
[5 - 6 Person]	0.173	0.061	0.421	0.043	0.014	0.404	0.017	0.006	0.386
[7 - 8 Person]	0.303	0.028	0.198	0.092	0.008	0.2240	0.039	0.004	0.241
[> 8 Person]	0.403	0.011	0.077	0.142	0.004	0.101	0.066	0.002	0.119
AGE									
[18 - 35 Old[	0.178	0.010	0.072	0.065	0.004	0.086	0.024	0.002	0.098
[35 - 60 Old]	0.151	0.096	0.663	0.041	0.026	0.663	0.016	0.010	0.663
[> 60 Old]	0.121	0.038	0.264	0.030	0.009	0.248	0.011	0.004	0.239
Sex									
Woman	0.141	0.021	0.148	0.038	0.032	0.828	0.014	0.012	0.810
	(0.008)	(0.001)	(0.008)	(0.001)	(0.001)	(0.011)	(0.0006)	(0.003)	(0.016)
Man	0.146	0.124	0.852	0.044	0.007	0.171	0.019	0.003	0.189
	(0.0036)	(0.003)	(0.008)	(0.003)	(0.0004)	(0.011)	(0.002)	(0.0003)	(0.016)
Total	0.145	0.145	1	0.039	0.039	1	0.013	0.013	1

our computes based on INS data

2.3.2 Analysis of determinants of poverty using binary logistic regression

Reduce poverty is considered as the most important goals of development and is defined as "pronounced" deprivation in well-being. According to the world bank, the well-being can be measured by education, households possession of income, health, households size, etc. Following Achia et al. (2010), Alkire et al. (2015), Babu et al. (2014), we build a profile of poverty by socio-demographic characteristics of households (see previous paragraph) through a logit regression to identify variables that influence the household's well-being. By dichotomous model, we build a statistical model in which the dependent variable can take two modalities. Generally, we explain the achievement or not of an event or a choice Maddala and Lee (1976).
In this study we consider poor/non poor household's statut as categorical variable:

$$y_i = x_i\beta + \varepsilon_i \tag{2.6}$$

Where y_i is a binary variable, x_i the vector of household characteristics, β parameter of the model, i = 1, .., n represent the i^{th} houshoulds and ε is the residuals.
Dichotomic poor/non-poor variable is defined as follow:

$$y_i = \begin{cases} 1 & \text{if} \quad y_i^* \leq s, \\ 0 & \text{if} \quad y_i^* \geq s. \end{cases} \tag{2.7}$$

Equations 4 – logit model

As we work with a subjacent model, the rule probability decision becomes:

$$\begin{aligned} prob(y_i = 0) &= prob(x_i\beta + \varepsilon_i > s) = 1 - prob(\varepsilon_i > s - x_i\beta) \\ prob(y_i = 1) &= prob(x_i\beta + \varepsilon_i \leq s) = 1 - prob(\varepsilon_i > s - x_i\beta) \end{aligned} \tag{2.8}$$

In this study we use total expenditure per equivalent adult to give a classification scale which enable us to rank households between poor and non-poor.

$$\begin{aligned} prob(y_i = 0) &= prob(\varepsilon_i > x_i\beta) = 1 - F(-x_i\beta) \\ \text{and} \quad prob(_i = 1) &= prob(\varepsilon_i \leq -x_i\beta) = F(-x_i\beta) \end{aligned} \tag{2.9}$$

Model specification

Logit regression requires that the anticipated value of the endogenous variable must always be in the interval $]0,1[$, regardless the value of the exogenous variables.
We define the characteristics of this regression as follow:

$$\Phi(x_i\beta) = \frac{exp(x_i\beta)}{1 + exp(x_i\beta)} \tag{2.10}$$

In contrast with the normal law function, these equation can be easier computed:

$$1 - \Phi(x_i\beta) = \Phi(-x_i\beta) = \frac{exp(-x_i\beta)}{1 + exp(-x_i\beta)} = \frac{1}{1 + exp(x_i\beta)} \tag{2.11}$$

It is evidently clair that the probability associated to the logistical law can be reversed. Pose p_i the probability when $y_i = 1$, we have:

$$log(\frac{p_i}{1 - p_i}) = x_i\beta \tag{2.12}$$

The estimation of this function gives us the following expression:

$$L(y, x, \beta) = \prod_{i=1}^{N}([\frac{1}{1 + exp(x_i\beta)}]^{1-y_i}[\frac{exp(-x_i\beta)}{1 + exp(-x_i\beta)}]^{y_i} \tag{2.13}$$

Then we have,

$$logL = \sum_{i=1}^{N}[1 - y_i]log[(1 + exp(x_i\beta))^{-}1] + y_i(x_i\beta) - y_i log(1 + exp(x_i\beta) \tag{2.14}$$

For testing the model, we estimate $\chi^2 = 2[Log(L_0) - Log(L_1)]$ and maximize the likelihood function.
If ρ related to χ^2 is statistically significant, we conclude that the model is better adjust than the nul model and our parametres are significant.

Empirical evidences

For the explanatory variables we selected socio-economic variables (qualitative and quantitative) related to the head of household. Our choice is justified by the fact that the head of family is the principal source of income, and it is usually to him the role of managing the assets and resources of the household. In addition, other variables which are related to

the entire household are included to take into account the other members and the place of residence of the household. As a demographic variable [16], we use household size, age of head of household, age squared and gender of household head (1 for women). We also integrate education level and employment statut.

And finally, we have included the area as explanatory variable with two modalities:Urban and Rural areas.

The estimation of the model gives rise to some interpretations. First of all, the odds ratio enables to directly release the probability of poverty of the household [17]. Usually, an odds ratio value greater than 1 imply that the variable increases the probability. Results show that the probability of being poor for a household increases when household is headed by a woman, who are unemployed and lives in the west region in a free housing. In fact, women are generally less paid than men which can influence the household well-being. The study shows also, that education plays a very important role in explaining poverty. Ceteris paribus, a family which is guided by a higher educated person is less likely to be poor. In addition, we note that households who live in the West regions are more likely to be poor compared to other regions (odds ratio 2.695). In fact Great Tunis, which covers around 17% of the total population, is characterized by a very special social and economic properties. Tunisian East has shown, since the statehood, a remarkable economic and social prosperity. This coastal strip, that extends from north to south contains, with the Greater Tunis, the essential tourist and industrial activity in the Tunisian economy. However, despite some economic progress in the last decade, we underline a social and economic imbalance between West and east area of the country mainly due to marginalization policies of the government. As a results, west region highlight a quasi suspension of the labor market, explosion of unemployment and a higher poverty rates compared to other regions [18].

16. see previous section for more details
17. Table 2.6
18. The entire data sets are available on http://www.ins.nat.tn/indexfr.php (last visit: August 1, 2015)

Table 2.6 – Logit Model Results

Variables	*Std*	*Odds ratio*
Constant	0.399*	1.074
sex		
Women (reference)		
Men	0.082*	0.627
Age	0.013*	0.897
Age^2	0.001*	1.0007
Household size	0.023*	1.451
Region		
Greater Tunis (reference)		
East	0.075	0.869
West	0.163*	2.696
Education		
Illitirate (reference)		
Primary level	0.040*	0.543
Secondary level	0.022*	0.224
High level	0.008*	0.019
Employment		
Employee (reference)		
Inactive	0.169*	1.755
Independant	0.096	0.972
Unemployed	0.598*	3.611
Housing		
Owner (reference)		
Tenant	.154*∗	1.281
Free house	0.105	0.813
Marital status	0.242*	1.269
Number of observation	11281	
Pseudo R^2	0.1963	
Prob > chi2	0.00	
Goodness-of-fit test (Hosmer-Lemeshow)	Prob > chi2 = 0.6425	

*variables are statistically significant at 1%, ** variables are statistically significant at 5%

2.3.3 Fuzzy Approach to the measurement of poverty

Fuzzy logic based on membership values that can range (inclusively) between 0 and 1. In addition, the degree of truth of a statement can also range between 0 and 1 and is not restricted to the two values (false (0), true (1)) as in classic logic (Mehta and Shah (2001)). In contrast to fuzzy set theory, the crisp logic affirm that variables have only two possible value of membership (0 or 1). Instead, we need to capture and preserve the interpretive richness of this approach in our description of well-being. Therefore, fuzzy logic is considered as a consequence of the development of fuzzy sets theory proposed by Zadeh**?**.

Following, Hauser-Davis et al. (2012), Pourahmad et al. (2011), Honzík et al. (2010), Kaur and Pulugurta (2008), this study aims to illustrate that, in contrast to fuzzy approach, ordinary logistic regression can not provide ideal assumptions

Logic of Sub-Fuzzy Sets

A portion$A$ of a set E is usually associated with its characteristic function. This shall apply to the elements x of E. It takes the value 0 if x does not belongs to$A$ and 1 if x belongs to A. we want to define a fuzzy subset A of E by attributing to elements x of E a particularly high degree of membership, it is higher if we desired to express certaintly the fact that x is part of A. This value is set to 0 if we desired to express that x is not certainty part of A, it will be equal to 1 if we want to express that x belongs to A for sure. And finally, it will take a value between 0 and 1 depending on whether we estimates more or less certain the membership of x in A. It is therefore necessary to define a fuzzy part as follows: A fuzzy part (or fuzzy set) of a set E is an application of E in $[0, 1]$. Generally, if L is a complete lattice, distributive and complemented, we define an $L - fuzzy$ part as an application from E to L. If $L = [0, 1]$, we find the previous definition of fuzzy part, and $L = \{0, 1\}$, there is the usual notion of party E. A fuzzy part A of E is characterized by an application of E in $[0, 1]$. This application, called membership function and denoted φ_A represents the degree of validity of the statement "x belongs to A" for each element of E. If $\varphi_A(x) = 1$, the object x belongs completely to A. And if $\varphi_A(x) = 0$, it is not belongs to him. For a x given element, the value of the membership function $\varphi_A(x)$ is called the degree of membership of the element x to subset A (Zadeh, 1975 Gupta and Kaufmann, 1991). The set E is given by the membership function identically equal to 1. The empty set is given by the membership function identically null.

Observing how the usual operations behave facing to the functions characteristics of parts, we extend these operations to the membership functions of fuzzy parts.
Let φ_i, $i \in N$ a family of subsets of a fuzzy set E, given by their membership function. We define the union of these parties through the following membership function:

$$\varphi(x) = sup\{\varphi_i(x), i \in N\} \tag{2.15}$$

With the same logic, we define the intersection as follow:

$$\varphi(x) = inf\{\varphi_i(x), i \in N\} \tag{2.16}$$

The complement of a fuzzy set given by his membership function $\bar{\varphi}$ is the fuzzy part of which the membership function is $1 - \varphi$.
The complement of an intersection remains equal to the union of complements, and the complement of an union is the intersection of complements. The complement of complement gives again the initial part. However, the union of a fuzzy part and its complement does not always give the set E, and the intersection of a fuzzy part and its complement does not give the empty set.
Let us consider, for example, the fuzzy part F of E given by the following membership function: $\forall\ x \in E$, $\varphi(x) = 1/2$.
This fuzzy part is equal to its complement because its membership function satisfies $\varphi = 1 - \varphi$.
We then deduce that $F = \bar{F}$ and $F \cup \bar{F} = F \cap \bar{F} = F$.

Fuzzy rules

The methodology is based on two essential steps: construction of the rule base and the proposal of the membership function which is our originality compared to other works. First of all, we present the following fuzzy rules:

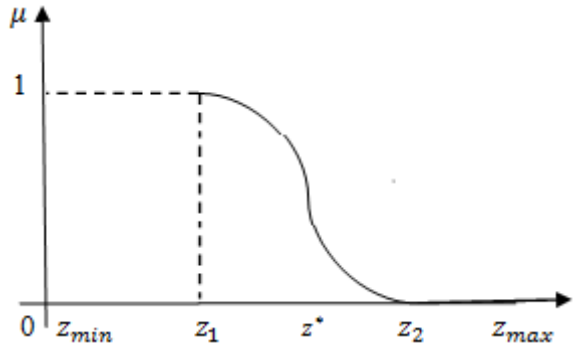


Figure 2.1 – Sinusoid membership function

i) R_1 : if x_i belongs to $[z_1, z^*[$ then poverty decline with expenditures;

ii) R_2 : if x_i belongs to $[z^*, z_2[$ then poverty continues to decline but with an important rhythm.

Poverty line computing

The study of poverty and its possible measures must inevitably begin with the definition of poverty, which can be absolute, relative or subjective (Hagenaars et al. (1995)). Whatever the definition of poverty that we accept, a partition of the population is carried out between poor and non-poor based on a poverty line below which a person is considered as poor (Foster et al. (1984)).

A crucial question concerning poverty analysis is the identification of the upper and the lower bounds of individual well-being measure (ie. expenditure or income). Absolute poverty line fixed according to the nutrition-based methods (Greer and Thorbecke (1986b), Greer and Thorbecke (1986a), Ravallion and Bidani (1994)), and relative poverty thresholds have been strongly criticized of being ad-hoc judgement dependant. Zedini and Belhadj (2015) have proposed a fuzzy parametric approach based on the identification of three privation states for the measurement of poverty. According to this purpose it is the data which suggest the appropriate thresholds rather than fixing it in advance.

The framework enable to compute boostrap percentile confidence intervals to estimate fuzzy non parametric measures to each privation state, at level α, $\alpha \in [0, 1]$. Then the proposed confidence intervals for the strong, medium and weak privation are, respectively,

as follows:

$$\begin{aligned} I_s &= [L_{s\frac{\alpha}{2}}, U_{s(1-\frac{\alpha}{2})}], \\ I_m &= [L_{m\frac{\alpha}{2}}, U_{m(1-\frac{\alpha}{2})}], \\ I_w &= [L_{w\frac{\alpha}{2}}, U_{w(1-\frac{\alpha}{2})}]. \end{aligned} \tag{2.17}$$

The fuzzy boostrap percentile confidence interval is defined by applying the min-max operators on the lower and upper bounds. The lower bound of the interval, at a level α, for three state of privation, is defined as follow,

$$L_{p\frac{\alpha}{2}} = \vee(L_{s\frac{\alpha}{2}} \wedge L_{m\frac{\alpha}{2}} \wedge L_{w\frac{\alpha}{2}}) \tag{2.18}$$

The upper bound of the interval, at a level α, for three state of privation, is defined as follow,

$$U_{p(1-\frac{\alpha}{2})} = \vee(U_{s(1-\frac{\alpha}{2})} \wedge U_{m(1-\frac{\alpha}{2})} \wedge U_{w(1-\frac{\alpha}{2})}) \tag{2.19}$$

where $(\vee, \wedge)$ the fuzzy max-min convolution.
Finally, we propose arithmetic mean as a measurement of z^*:

$$z^* = \frac{L_{p(\frac{\alpha}{2})} + U_{p(1-\frac{\alpha}{2})}}{2} \tag{2.20}$$

Membership functions

We then propose to define the membership function as follows:

$$\varphi_z(i) = \begin{cases} 1 & \text{si} \quad z_{imin} \leq x_i \leq z_1, \\ 1 - \frac{1}{2}(\frac{z_1 - x_i}{z_1 - z^*})^2 & \text{si} \quad z_1 \leq x_i \leq z^*, \\ \frac{1}{2}(\frac{z_2 - x_i}{z_2 - z^*})^2 & \text{si} \quad z^* \leq x_i \leq z_2, \\ 0 & \text{si} \quad z_2 \leq x_i \leq z_{imax}. \end{cases} \tag{2.21}$$

Equations 5 – membership function

Individual Measurement of Fuzzy Poverty

Following Betti et al. (2006), intersection and union operators are used to determine fuzzy individual measures of poverty. Thus, according to fuzzy logic, we define the union of fuzzy

groups by the following membership function:

$$\varphi(x) = sup\{\varphi_i(x), i \in N\} \, équivaut \, \text{à} \; \varphi = \bigvee_{i \in N} \varphi_i \tag{2.22}$$

and the intersection of fuzzy groups is defined as follows:

$$\varphi(x) = inf\{\varphi_i(x), i \in N\} \, équivaut \, \text{à} \; \varphi = \bigwedge_{i \in N} \varphi_i \tag{2.23}$$

Various individual measures of poverty are expressed by the membership function φ are expressed as a function of expenditure variable (income) and must belong to the interval [0,1].

Overall Measurement of Fuzzy Poverty

The overall measure of fuzzy poverty required the use of a set of elementary indicators. we propose a total fuzzy index equal to the arithmetic mean of individual measures. Obviously,

$$\varphi_G = \frac{1}{N} \sum_{i}^{N} \varphi_i(x) \tag{2.24}$$

Equations 6 – fuzzy index

$\varphi_G = 0$ if and only if $\varphi_i(x) = 0$, in this case there is complete absence of poverty, and $\varphi_G = 1$ if and only if $\varphi_i(x) = 0$, $\forall \; i$, this is the case of extreme deprivation for the entire population. However, these two situations represent two particular cases, we usually will be in an intermediate case; $0 \leq \varphi_G \leq 1$.

The overall poverty rate φ_G is increasing relative to poverty level of each household and decreasing relative to income $\frac{d\varphi_G}{d(x)} = \underbrace{\frac{d\varphi_G}{d\varphi_i}}_{\geq 0} * \underbrace{\frac{d\varphi_i}{d(x)}}_{\leq 0}$. As a consequence a deterioration of living conditions of a household belonging to the fuzzy set of poor causes an increase in in this index.

Empirical evidences

We seek to illustrate that the ideal assumptions of ordinary logistic model may not hold in practice. Compared to the logit model, the interpretation of estimated variables by fuzzy approach don't requires a reference category. Indeed, each variable has its degree

of belonging to the poor/non-poor set. Results (expressed in dinars) of this proposal are exposed as follows:

Table 2.7 – Average Fuzzy poverty by educational level (2010)

	z^*	$[z_1, z_2]$	φ_G
Illiterate	1340	[906 – 1774]	0.102
Primary	1168	[820 – 1516]	0.101
Secondary	1732	[1223 – 2241]	0.093
Higher level	2938	[2144 – 3732]	0.089
Fuzzy Poverty			0.096

We select as attributes Economic Region (Greater Tunis, urban East, Rural East, Urban West, and Rural West); activities of household head (Inactive, Independent, Employee, unemployed); and the level of education of household head (Illiterate, Primary, Secondary and Higher level).

Table 2.8 – Average fuzzy poverty by activity of household head (2010)

	z^*	$[z_1, z_2]$	φ_G
Employee	1280	[905 – 1654]	0.094
Independent	1241	[882 – 1600]	0.079
unemployed	942	[650 – 1233]	0.096
Inactive	1938	[1326 – 2550]	0.099
Fuzzy Poverty			0.092

Table 2.8 shows that unemployed and inactive are the most affected by poverty with a degree of membership respectively 9.6% and 10%. Moreover, individuals under the age of 35 and over 66 (retirees) are more vulnerable compared to others. Results show also that retirees have the highest degree of belonging to the class of poor compared to other categories (table 2.9).

Table 2.9 – Average Fuzzy Poverty by age of household head (2010)

	z^*	$[z_1, z_2]$	φ_G
[18 à 35]	1573	[1076 – 2069]	0.086
[36 à 65]	1360	[951 – 1769]	0.083
Plus de 66	1938	[1262 – 2482]	0.091
Pauvreté floue			0.087

We note that, in 2010, for Great Tunis, household with annual expenditure less than 1420 DT is considered as poor with a higher membership degree. On the other hand, a household whose total annual expenditures exceeds 2842 DT is considered as non-poor. It appears, from table 2.10, that poverty is unequally distributed by regions. When we consider the distribution of poverty among the three areas with reference to poverty line, we observe the preeminence of the West region with a level of 21.1 % for rural-west and 19.7 % for the urban-west.

Table 2.10 – Average fuzzy poverty by region (2010)

	z^*	$[z_1, z_2]$	φ_G
Great Tunis	1573	[1420 – 2842]	0.201
Rural East	1263	[902 – 1624]	0.184
Urbain East	1340	[956 – 1724]	0.181
Rural West	1141	[763 – 1519]	0.211
Urban West	1660	[1172 – 2148]	0.197
Fuzzy Poverty			0.194

While Logit analysis provides general picture of poverty and hold up to view the importance of one dimension; such as the acuteness of poverty in west areas, and other interesting paradoxical conditions (education, type of job ... etc), the fuzzy sets analysis offers more robust results than other approaches. Indeed using the fuzzy set approach gives a higher percentage of poor and a gradual assessment of poverty which gives a more credence to the fuzzy set analysis.

Based on the empirical results, one can highlight that policy recommendations should be based on a structurally sound socio-economic policy to reduce poverty which take into consideration labour market reforms and improvements of housing conditions. In addition, reduce regional imbalances though pro-rural development policies, and increase the stock

of social capital through empowerment of civil society and networking.

These results are very important, but how robust is the poverty profil of Tunisia relative to the different measurement assumptions ?

To answer on this question, several methods are available.

2.4 Robustness study: Incidence of Poverty, Test of Sensitivity and Dominance

2.4.1 Test of Sensitivity

To verify the robustness of the founded results we consider a sensitivity test enable to perform a sensitivity analysis Ravallion and Bidani (1994). Therefore, we compute a new measurements of poverty for alternative poverty lines. For example by increasing or decreasing successively the poverty line by 10%. This test enable to understand successively increasing and decreasing in poverty and to examine his consequences for considered socio-economic groups.

In the present case, this test can be conducted on two definitions of poverty namely the half median f expenditures per equivalent adult fixed at 1016349 milims and the half mean of expenditures per equivalent adult fixed to 1328530.75 millims. Results are presented in Table 2.11 and 2.12.

Table 2.11 – Poverty Incidence by region and Sensitivity Test

Parameters	T_1= 1016349			T_2 = 1328530.75		
	T_1-10%	T_1	T_1+10%	T_2-10%	T_2	T_2+10%
Great Tunis	0.015	0.071	0.089	0.045	0.102	0.175
North East	0.044	0.098	0.168	0.114	0.219	0.342
North West	0.150	0.254	0.367	0.283	0.0421	0.531
Middle East	0.033	0.064	0.099	0.072	0.128	0.205
Middle West	0.202	0.312	0.416	0.337	0.469	0.565
South East	0.082	0.135	0.191	0.139	0.240	0.337
South West	0.077	0.150	0.248	0.163	0.308	0.420
Total	0.083	0.145	0.215	0.159	0.260	0.355

A variation by 10% of the poverty line leads to a slight variation in the incidence of poverty, but this variation don't affect our results. Rural area and Middle West remains te most vulnerable region.

These results conduct us to the robustness of the the poverty poverty line.

Table 2.12 – Sensitivity Test for areas

Parameters		T1 =	1016349	T2 =	1328530.75	
	T_1 - 10%	T_1	T_1 + 10%	T_2 - 10%	T_2	T_2 + 10%
Urban	0.055	0.106	0.165	0.118	0.203	0.296
Rural	0.133	0.215	0.305	0.232	0.360	0.460
Total	0.083	0.145	0.215	0.159	0.260	0.355

In fact, the sensitivity analysis, which is useful for verifying that poverty is relatively independent of small changes in the level of the poverty line, can be extended to take into account a wider variation in the poverty line and also include about changes in the measurement of poverty (Lachaud (1995)). This involves an analysis of dominance and requires to carry on the distribution curves inherent to areas or socio-economic groups.

2.4.2 Stochastic Dominance

Stochastic dominance makes possible obtaining robust results in a change in poverty index or poverty line (Duclos et al. (2003), Jenkins and Lambert (1997), Whitmore (1970), Davidson and Duclos (2000)). One of the properties of stochastic dominance is to detect situations where a change in poverty index could reverse the order established between two groups. For example, poverty headcount between two groups, with a determined poverty line, group A may have a higher index than group B. However, if we suppose that the ranking between the two groups is reversed when we move to the average difference of poverty, the significance of the results from the poverty headcount would be limited. This case necessarily reflect the intersection of dominance curves of group A and group B.

Therefore, we can affirm that a ranking is robust, to a change in poverty index, only when dominance curves of studied groups do not intersect. Another important advantage of the stochastic dominance is that it allows you to organize distributions of income without having to set a poverty line. This is an advantage, because we have there is an uncertainty about the values of poverty line.
Moreover, the ranking in terms of poverty between two distributions can be reversed when the threshold is changed. However, it is possible that in some cases the method of stochastic dominance will fail to decide between two income distributions: For this reason this method gives us a “partial” orders.

Stochastic Dominance: First- Order

Stochastic dominance for different orders predicts for classes of index, if poverty, welfare and inequality are higher or lower in a distribution than another. To affirm without risk of error that households living in specific areas experiencing more poverty and inequality, so less welfare than others. Then we use the test of stochastic dominance. Otherwise, the robustness of poverty comparisons, as inequality and welfare requires judgments based on rankings unambiguous. Analysis of poverty, can be extended to take into account a wider change in the poverty line and also to include changes in the extent of poverty. According to Ravallion and Jalan (1996), this implies an analysis of the stochastic dominance of the first order. An analysis of first-order dominance, is to test if changes in the poverty line preserve the same ranking of subgroups in the incidence of poverty. Stochastic dominance of first order, involves comparing the cumulative distribution functions of the indicator of well-being (income or expense) for each year of the survey or for different groups of households. In addition, Davidson and Duclos (2013) describe the principal logical reasons and the benefits of stochastic dominance test on a limited area. They also emphasize the fact that this approach would avoid comparisons on areas where we do not have enough information.

Let us consider two distributions A and B of a given indicator of well-being x (In our case annual expenditure). Let F_A and F_B be their cumulative functions. We say that B stochastically dominates A at order 1 if:

$$F_A(x) \geq F_B(x) \ \forall \ x \in [0, z_{max}]$$

where z_{max} is a threshold determined poverty. This means that for a given x below the poverty line z_{max}, there are more households with annual consumption per unit of consumption is below this level in the$A$ distribution as the distribution B. In order to perform this test comparability, we simply draw the cumulative distribution curves A and B in $[0, z_{max}]$. If they do not intersect and the distribution curve A is always above the distribution B, then B stochastically dominates A.
For this method, we draw - using the appropriate procedure developped by Araar et al. (2009) - the distributions functions corresponding to each group.

First order dominance curve according to Urban-Rural decomposition We can observe clearly that the prevalence of poverty in urban area dominates rural area at every

point of the distribution. Otherwise, we register in urban environment the low poverty compared to rural areas.

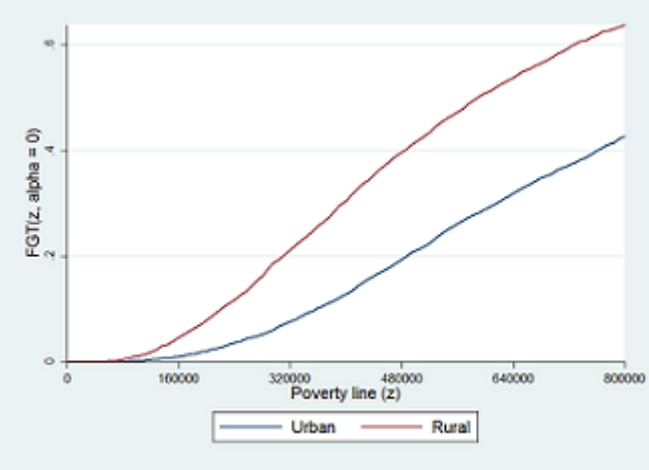


Figure 2.2 – First order dominance curve according to urban-rural decomposition

First order dominance curve according to Region In addition, Middle West dominates all other region folLowing by the North West. Moreover the west and east south and the west and east north intersect each other and gives some ambiguity in our analysis. In total, dominance stochastic of first order reveals that the extent of monetary poverty is on average higher in the interior cities than in other and especially in rural and west area.

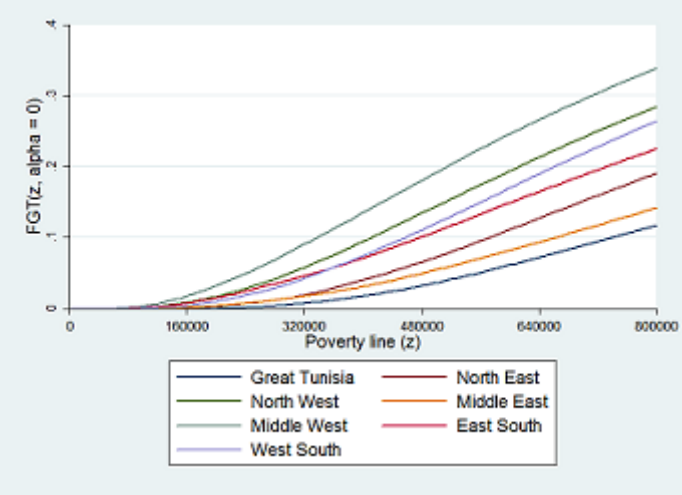


Figure 2.3 – First order dominance curve according to Region

First order stochastic dominance by educational level: Figure 2.4 shows the inverse relationship between the level of education and the prevalence of poverty. The

higher level of education is associated with a curve with a low prevalence of poverty, whatever the considered threshold levels, followed by secondary and primary education. We observe that illetrate group is still dominated at all levels.

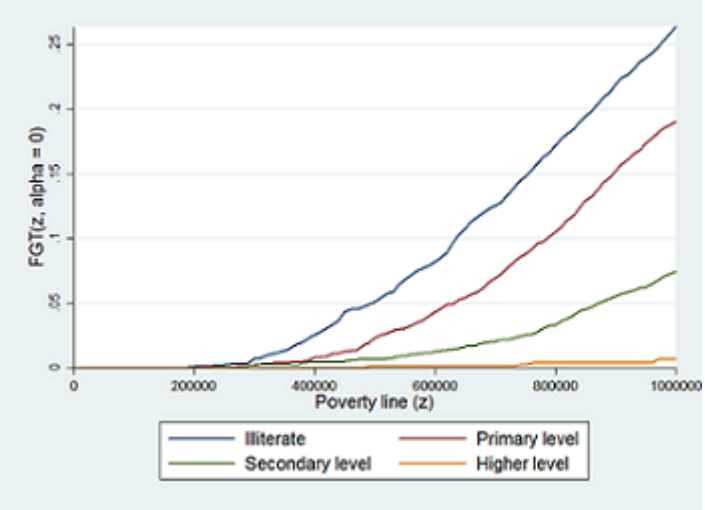


Figure 2.4 – First order dominance curve according to the education of household heads

First order dominance curve according to the sex of household heads FGT indices calculated previously confirms the dominance of the curve of household head compared to women, in every point of the distribution.

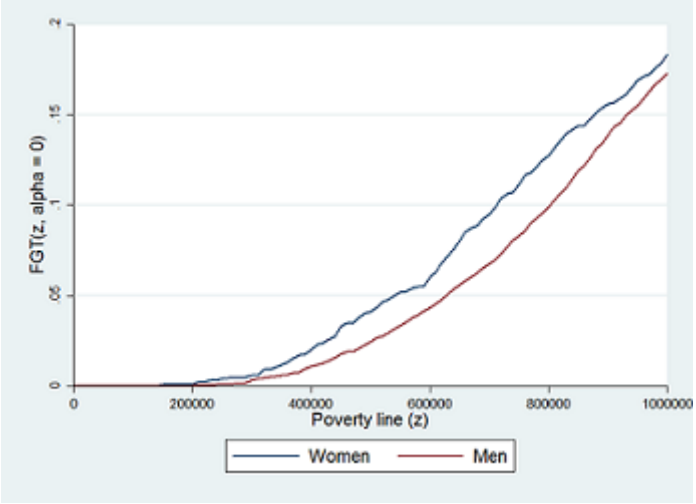


Figure 2.5 – First order dominance curve according to the sex of household heads

Second-order stochastic dominance and TIP curve

The test of second-order dominance uses Jenkins and Lambert approach (Jenkins and Lambert (1997), Davidson and Duclos (2000)), based on the "Three 'I' Poverty (TIP)" [19]. TIP curves can be used to summarize the three dimensions of poverty (Headcount, Poverty Gap and Scared Gap) using a graph, having as abscissa the cumulative proportions of households or individuals, and having as ordinate, aggregate poverty gap per capita.

Figure 2.6 shows the relative distribution of equivalent adult expenditure adjusted by

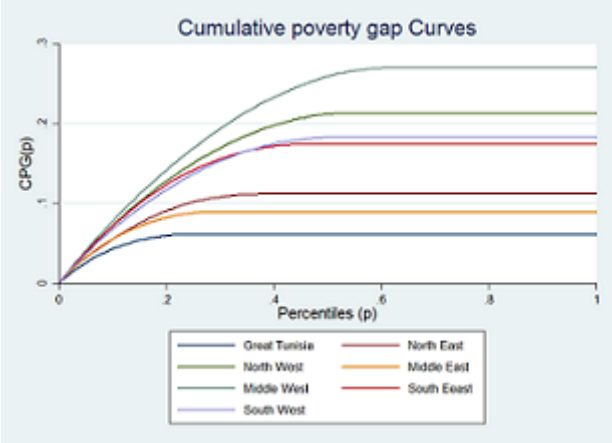


Figure 2.6 – TIP dominance curves according to the location of households

geographic area. We observe that the curve relative to Middle West areas is in every way above the other groups. Therefore, whatever the line or poverty measure, the proportion of poor households is higher in this group than in the remaining regions. We can observe a clear ambiguity between the South East and the South West areas, as the cumulative curves intersect. This means that changes in poverty can lead to alternative rankings for these areas.

Conclusion

Poverty measurement can improve public policy and the targeting of interventions. In developing poverty alleviation programs and allocating grants, resources will be allocated more effectively if the most-vulnerable class can be better targeted. In addition collecting information about individuals and their economic status, one can distinguish who gains from

19. The three 'I' are the three poverty indexes (Headcount, Poverty Gap and Scared Gap). The TIP is also called " generalized inverse Lorenz curve". It is also called "cumulative poverty gap", Davidson and Duclos (2000)

public grants. In this chapter we examine the profile of poverty in Tunisia, our empirical analysis relies on the Tunisian Living Standards Surveys of 2010. Thus we measure poverty according to several socio-economic variables related to household's welfare by combining both monetary and non-monetary approaches. For this purpose we applied the composite index FGT (Foster-Greeck-Thorbecke) then, we estimate a logit model using the same variables selected by the first method. Moreover, to take into consideration different composition of household we use equivalence scale approach. Finally, we introduce a new approach based on fuzzy set resoning. This approach aims to build a membership function based on the logistic function that enable a comparison between conventional logit model and fuzzy approach. The study requires the selection of a well-being indicator's; income or consumption. In this study we use real consumption expenditures per equivalent adult. Our choice is based on several criteria. Firstly, because the income is difficult to observe. In addition, consumption expenditures are characterized by their stability over time.

Computing the three methods exposed previously, this chapter shows a higher disparities between regions. Indeed, Greater Tunis have the lowest poverty rate, while the west regions are the most affected by poverty. In addition to these results, we find that some characteristics, such as employment and educational level, may improve the well-being of household. In addition, stochastic dominance and sensitivity test reveal the robustness of these results.

Regarding to the poverty level, Tunisia still succeeded in reducing poverty, but inequality keep up to be a challenge and poverty remains dominant in rural areas. In the light of these finding, it is further recommended that policymaker's efforts should be addressed to reduce inequality in living stabdards between areas. The next chapter expose these issues.

Chapter 3

Urban-Rural poverty gap in Tunisia: A counterfactual Decomposition using semi-parametric regression

3.1 Background

Despite all policies for social development in Tunisia, poverty and inequality are still dominant phenomena. A strong variation in poverty rates between regions may cause a sense of injustice and social instability. Moreover, the level of welfare in a country can not be only analyzed through average consumption level or poverty rate. In fact, quality of life in a country also depends on how consumption is distributed throughout its population. The analysis of the distribution of consumption allows us to better assess the relevance of social policies.

Measuring welfare was the objective of several studies and theoretical foundations. We emphasize the development of several approaches that aim to analyze welfare, which can be classified according to Money Metric or Non-Money Metric approaches. In fact, most analyzes in social welfare typically use Money Metric measures such as income or consumption expenditures. Non-Money Metric depends on the different assets that a household has available. These measures often apply a multivariate analysis.

There are several indexes to measure the inequality of the distribution. The two leading indexes of well-being are Gini index and polarization index. They are important, but not sufficient for the analysis of the inequality of the consumption expenditure distribution. In this context, economists have tried to apply econometrics models in order to analyze the degree of inequality between regions and, especially between urban and rural areas. Hence several studies have been published, addressing this subject. Nguyen et al. (2007) discuss the welfare inequality between urban and rural areas from 1993 to 1998 in Vietnam. In this study, they conclude that inequality differences between the two regions were due to education, ethnicity, and age. In the same context, Albrecht et al. (2009) uses quantile regressions, based on Machado Mata decompositions, for the analysis of the wage gap between genders in the Netherlands. They found that the wage gap is due essentially, to differences between the returns due to the labor market rather than differences in characteristics.

Many economists focus on the role of education in the fight against poverty and inequality especially in poor countries Barouni and Broecke (2014). Skills are the key way in which education reduces poverty. Education makes it more likely for men and women not just to

be employed, but to hold jobs that are more secure, provide good working conditions, and pay a decent wage (Schultz (1961)). In so doing, education does not just help lift households out of poverty, but also guards against them falling into, – or falling back into, poverty. In this context, several studies were developed, Hossain (1996) reports that the poorest quintile of households in China spend 14.2 percent of their annual income on education, while the wealthiest quintile spend only 5.5 percent. Filmer and Pritchett (1999) argues that poverty is related to a low level of education and a larger gender gap. On the other hand, Chu Ng and Li (2000) study the efficiency of educational reform in China. They test the research performance of institutions and discuss the impact of regional differences in the effectiveness of institutions. Gupta et al. (2002) propose that the size and efficiency of education expenditures are crucial for the improvement of socioeconomic performance. Stevens et al. (2008), Breen and R (2010) and Jensen (2011) finds that education is less redistributive than other social policies. As it is well known, access to higher levels of education is easier for the upper class. Pfeffer (2008), finds that the extent of educational inequality is associated with the institutional structure of the national education system (see alsoVan de Werfhorst and Mijs (2010) for a literature review). The hypothesis of an urban-biased system has been advocated by Lipton (1977), government policies tend to direct resources from the rural to urban areas. Fesselmeyer and Le (2010) provide some examples for developing contries.

In Tunisia in particular, it is commonly accepted that poverty is mainly a rural phenomenon and particularly affects farmers. The poverty rate in rural areas is 23% compared to 15% in the urban environment (INS). We point out that households spend 3.45% of their expenditures, on average, on education ((with 2.35 % for urban areas and only 1.1 % fir rural ones). Thus, the impact of educational policies on rural households is particularly important.

As many developing countries, poverty in Tunisia is concentrated in rural areas and in some regions of the country, particularly the West (INS report). Thus, the analysis of poverty and inequality at the regional level is very important in order to better understand and define the priorities for regional development. In addition, it is widely accepted that the increase in inequality between regions indicates that the alienation and the feeling of injustice increases, as the average living standards become more unequal. This feeling of

injustice is stronger between urban and rural regions. In fact, the slower growth in the average living standards of the poorest regions compared to the most affluent aggravating regional disparities. This chapter focuses on the determinants of household welfare in Tunisia. Welfare is measured by real per capita household expenditure (income). We examine the inequality gap in consumption and education then we compare rural and urban areas. Our empirical analysis relies on the Tunisian Living Standards Surveys from 2010. In order to analyze the gap between the two regions we applied both quantile regressions and Machado-Mata decompositions. We also use censored and uncensored quantiles regressions for disaggregate consumption expenditures. This study offers an another analysis of the sensitivity of some indicators such as health, food and especially education, with regional disparity in developing countries. It also examines the relationship between education and development disparities across the two areas. The objective is to identify the extent of inequality in Tunisia and to look on how we can improve the fight against social exclusion. In this study we use the quantile regression model (Koenker and Bassett Jr (1978)) and a new decomposition technique developed by Chernozhukov et al. (2013) to examine inequality in expenditure across both urban and rural areas. Following Nguyen et al. (2007), we use socio-demographic variables such as: employment and educational level of the head of the household. Other variables, which may influence household conditions, such as foreign transfer, are also included in our model. This chapter makes two original empirical contributions to the literature compared to previous studies on the same topic: in comparison to Hassine (2015), Fang and Sakellariou (2013), Fesselmeyer and Le (2010), Chang (2012), Chamarbagwala (2010), Skoufias and Katayama (2011) and Pieters (2011). First we use censored and uncensored quantile regression (Chernozhukov and Hong (2002), Chernozhukov et al. (2015)) on disaggregate expenditures data taking into account the existence of a high number of zeros (especially for education and leisure expenditures). Finally, we use the new decomposition technique developed by Chernozhukov et al. (2013), which encompass Mata-Machado decomposition as a special case and enables to test the hypothesis of omitted variables, to specify whether expenditure differences between rural and urban areas are related to difference in characteristics effects or whether this is due to the returns effects.

The remainder of the chapter is organized as follows. Section 3.2 deals with descriptive statistics and provides a measure of welfare. Section 3.3 focuses on the determinants of well-being in both urban and rural areas. In section 3.4, we discuss the extent of inequality

in the two groups urban and rural areas with a decomposition method. And finally, the fifth section 3.5 concludes.

3.2 Welfare measures and data source

3.2.1 Welfare and poverty in Tunisia

In this chapter, we favor the Money-Metric measure, as this approach takes into consideration all the members of the household even those who do not participate in labor market, (Leibbrandt and Levinsohn (2011)). Most previous studies use income to measure welfare. Here we will deal with consumption expenditure because in developing countries the income is not observable. In fact, difficulties to introducein obtaining information about savings and, large under-estimations of declared income in some cases leads to a large deficits in balances when comparing income to consummation. Thereforen, total expenditure is taken as a standard of living indicator. Indeed, household expenditures are further characterized by their stability over time compared to income fluctuations. They provide information about the degree of satisfaction that comes from the consumption of goods and services. This appoach has been advocated in recent studies by Fang and Sakellariou (2013), Chamarbagwala (2010) or Pieters (2011).

After the revolution, Tunisian is boldly emerging from the recession, the longest period of economic downturn ever, since the establishment of statehood. More than 800.,000 people were unemployed in 2014 and the poverty rate reached 15% of the population according to data released by the national institute of statistics (INS). Naturally poverty rate is correlated with unemployment rate, illiteracy, access to health services and especially education (African Development Bank, 2013). Therefore, poverty in Tunisia is concentrated in rural areas and in some regions of the country, particularly the Center West, the region where the revolution was triggered. In addition, the weakness of infrastructure in these areas, such as roads and communication, may limit poor people to have access to information or to labor markets. The deterioration of living conditions of the rural population, the increase in the unemployment rate and the inflation of consumer prices of basic goods associated to climate change and water scarcity problems, which threaten the sustainability of growth in this areas, has provoked the uprising of the people in the interior regions which was the main cause of the Tunisian revolution (Ayeb (2011), Breuer et al. (2015)).

We use the 2010 national survey “Tunisian Living Standards Survey” as a data resource.

This survey takes a representative sample of the Tunisian population of 11281 households with 50371 individuals. The data collected includes information concerning the head of the household, composition, location, of the household and total household expenditures. Inequality has decreased to some extent at a national level with a Gini index 1 from 37.5 in 2000 to 35.8 in 2010. However, this trend is based only on the reduction in inequality within regions (which rose from 21.1 in 2000 to 17.6 in 2010), inequalities between regions rose over the same period (up from 16.4 in 2000 to 18.2 in 2010). Moreover, the INS noted that households' whose head is unemployed and / or does not have a high level of education are more likely to be poor. In fact, poverty rates are higher in rural and medium towns than in large cities 2. It seems to us that there are glaring differences between the two areas. The standard index can not explain and decompose the gap of consumption expenditure between urban and rural regions. For this purpose, we deal with quantile regression and Machado Mata decomposition to elucidate the origin of this difference.

3.2.2 The sample characteristics

We use data from the 2010 National Survey on Households' Budget, Consumption and Living Standard. This survey is conducted by the INS every five years and provides socio-demographic and economic characteristics of households and individuals. Indeed, for 2010, it takes a representative sample of 11281 households with 50371 individuals. The data collected includes information concerning the head of the household, composition, area of household's location and total household's consumption expenditures. For explanatory variables we use household size, the proportion of children under 15 years old in each household, the age of the head of household as well as the age squared and the gender of household head. For, the household education and employment characteristics we use include the schooling of household head. For this variable, we take four levels: illiterate (as reference), primary, secondary and higher level. For employment variable [1] we select four sectors: governmental sector (as reference), private sector, self-employed and agricultural sector. Because transfers from foreign countries are frequent, we use a dummy variable indicating if a household received transfers from abroad. We also include the west regions as an explanatory variable since these regions has the highest poverty rate [2] (INS). Finally,

1. We did not detail the Sector of activities for the simple reason that our unit of observation is the household rather than the individual, and using a wide sector is not within the scope of our study

2. This variable was inserted as we are interested in the study of well-being; this region is the most vulnerable, since it has the highest poverty rate 79.5% according to INS. We wanted to add interaction variables (age*women, for example, to show the expenditure of old women), but according to both AIC

we use log of real per capita expenditure as our dependent variable [3].

Table 3.1 – Quantitative variables for both Urban and Rural Areas

	Total		Rural		Urban	
	Means	Std.dev	Means	Std.dev	Means	Std.dev
Consumption expenditure (Tunisian millims)	1457248	1714634	1743354	1976768	940476.5	881890.7
Log Consumption expenditure	13.843	0.805	14.053	0.758	13.464	0.746
Age	54.321	14.289	54.153	13.652	54.625	15.369
Household size	4.465	1.885	4.353	1.757	4.667	2.081
Percentage of children	0.209	0.231	0.203	0.226	0.219	0.240
Number of observation	11281		7261		4020	

A look into descriptive statistics gives us more details about our variables. First of all, we underlined that 85.22% of urban households are led by a man against 84% in rural areas. However, in rural zones the numbers of households headed by a woman exceed the urban ones. With regards to table 3.2, we underline that household head's in rural areas are less educated than their counterparts in urban zones. In fact about 47.68% of rural household head's are illiterate against 24.07% in urban area. But the most important statistic is the higher level of education which was recorded: 10% for heads in urban zones against only 1.29% in rural zones. This finding can be explaining by the fact that individuals how live in rural areas do not have the ability to continue their educational path due to their financial situation and by the fact that the schools are not close to their home.
A look at the employment variable enabled to make some interpretations. The share of rural regions from the governmental sector is only 8% in reference to the urban areas. For the private sector, we emphasize 11.45% in urban zone. However, in the rural zone, the share of this sector is only 5.32% (the half of the urban one). In fact, it is hard to invest in this region because they do not have good infrastructures. As expected, rural areas have the largest part of the agricultural sector which is 77%. This statistics can partially explain the increase of poverty and the unemployment rate in these areas.

To better understand the difference between urban and rural characteristics, we plotted

and BIC criteria the most appropriate model is the one that we have chosen

3. It corresponds to the per capita expenditure during the 12 months preceding the start of the investigation, measured in January 2010. We use per capita household expenditure and we consider that all members of the households have the same weight in the denominator. Then we divided total household expenditure by the square root of number of members (in this case, square root was used as scaling factor). For more details see Buhmann et al (1988). We used a log transformation to get a normal distribution of the consumption expenditure

Table 3.2 – Qualitative variable for both Rural and Urban Areas

variables	Rural %	Urban %
Gender		
Men	85.23	84.08
Women	14.77	15.92
Education		
Illiterate	24.07	47.68
Primary level	36.33	38.59
Secondary level	29.67	12.96
Higher level	9.91	1.29
Area		
East	71.10	28.9
West	28.89	71.11
Sector Governmental Sector	19.93	8
Private Sector	11.45	5.32
Self employed	21.29	10.49
Agricultural Sector	4.8	29.85
Housing		
Homeowner	84.39	95.17
Tenant	11.51	1.02
Free housing	4.09	3.8
Foreign transfer	1.58	1.21

kernel densities for the two areas (Figure 3.1). We found that there are more individuals from urban areas (respectively from rural areas) in the highest level (in the lowest level) of expenditure than from rural areas (fro m urban areas). If we divide population into poor and rich we find that rich urban are better off than rich rural and poor rural are more vulnerable than poor urban.

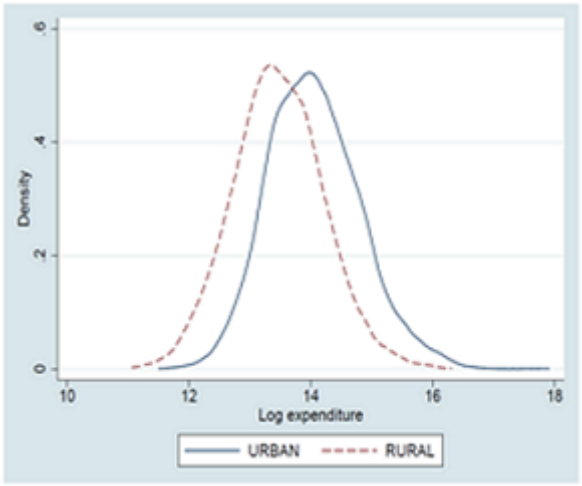


Figure 3.1 – Kernel density of rural-urban expenditure

Figure 3.2 illustrates that the effects of log consumption range from 12 to approximately 18. Whereas these effects are present across all quantiles, it does more adjudge for the highest quantile. We can conclude that more we consume, more we are victim of urban-rural disparities.

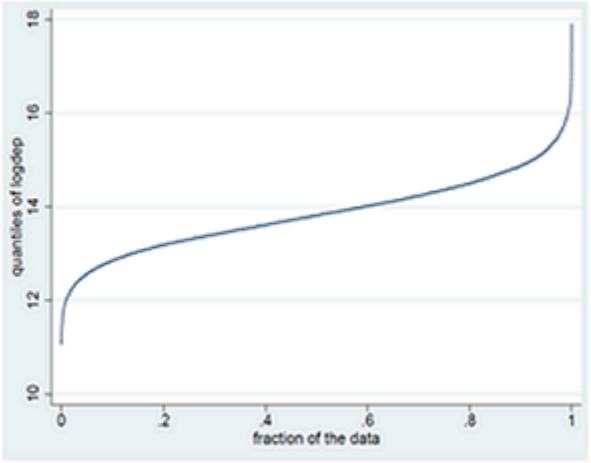


Figure 3.2 – Decomposition of log expenditure per capita by quantiles

3.3 The Determinants of Well-Being in both Urban and Rural areas

3.3.1 Mean Differences versus Quantile regression

A majority of empirical economic studies focus on the average modeling. This approach makes an essential information but still limited. For exemple, the average income does not inform on the varying unequal distribution of income in the population. In this regard, quantile regression is a useful tool available to the econometrician to respond to these inherent limitations. It allows for a more clear description of the distribution of a conditionnal variable to its determinants than a simple linear regression, which focuses on the conditional mean. If Its principle is old, it has recently rebounded. Charnoz et al. (2013), examine the determinants of wage inequality. And recently, Cornec (2014) to predict economic conditions.

The goal of this section is to assess the role of various household characteristics to explain inequality through consummation expenditures, between urban and rural areas. Most empirical studies focus on means modeling, which gives essential but limited information. Average consumption expenditures can not analyze inequality in the expenditure distribution . This is why we choose, in this chapter, to deal with quantile regression, which is a semi-parametric model. Generally quantile regression has the following advantages. First of all, it is simple to implement. secondly, since the technique is non-parametric we are not constrained by the nature of our data. Finally, It allows to test the robustness of our poverty line.

Quantile analysis allows us to estimate the effect of independent variables across the distribution. Furthermore, quantiles represent an approximation of poverty lines. Lower quantiles can represent the proportion of poor in the distribution while higher quantiles representing the richest proportion. With this approach, the percentage of people who have less than 10% of the consumption expenditure (income) are regarded as the poorest proportion. Like the model proposed by Bassett and Koenker [4], we present our model as follows: Where Y is log expenditure, $Q_q[Y \backslash X]$ is the $q^(th)$ conditional quantile of y,α_q is the regression intercept. This condition is similar to that performed in the standard linear

4. for more details see Koenker and Bassett Jr (1982)

$$Q_q[Y\backslash X] = \alpha_q + X\beta_q \tag{3.1}$$

Equations 7 – Quantile regression model

regression $E[Y\backslash X] = \alpha + X\beta$. An important difference, here, is that the coefficients are allowed to differ from quantile to another. This provides additional information that is not apparent from a simple linear regression.

The goal of the estimation is to solve the following minimization program :

$$\hat{Q_q} = arg\min_{\beta} \frac{1}{n}\sum_{i}^{n} \rho_q(Y_i - X_i\beta) \tag{3.2}$$

There is no explicit solution to equation (2) , so the minimization program must be solved numerically. One problem is that the objective function is not differentiable (ρ_q the function is not derivable in 0) neither strictly convex. Standard algorithms such as the Newton Raphson can not be used here. The solution is to reformulate (2) as a linear program:

$$\min_{(\beta,u,v)\in\mathbb{R}^p * \mathbb{R}_+^{2n}} q\mathbf{1}'u + (1-q)\mathbf{1}'v \iff X\beta + u - v - Y = 0$$

where $X = (X_1...,X_n)'$, $Y = (Y_1...,Y_n)'$ and $\mathbf{1}$ is a vector composite with 1 and with size n. Such linear problems can be solved efficiently by the simplex (for small samples) or interior point methods [5] (for large samples).

This estimation can be used for all quantiles q where $0 \leq q \leq 1$ and $\rho_q(x) = (q\text{-}1(x \leq 0))x$ (Koenker et al, 1987). Then there are an infinite number of possible quantile regressions.Standard in comparable studies, we choose to deal with seven quantile (5^{th}, 10^{th}, 25^{th}, 50^{th}, 75^{th}, 90^{th} and 99'$^{\text{th}}$ percentiles).

The Kennedy Transformation

We note that the consumption functions are estimated with log-linear models thus dummy variables (X_i^D) cannot be estimated like the constant explanatory variables (which are interpreted as the elasticity of Y relative to x). Usually, the interpretation of the coefficient,

5. The simplex method allows to solve linear programs with this form: $\min_{(x)\in\mathbb{R}^n} C'x \iff x \in S = \{u/Au \geq, Bu = c\}$ (a), where $C \in \mathbb{R}^n$, A and B are two matrix (note that we must take "$\geq$" component by component). Then, we can show that S is a convex polyhedron and if solutions exist, then they are summits of S. The simplex method is then to go from summit to another by choosing each time the edge corresponding to the steepest slope.
Otherwise, the interior point methods are based on the idea of a litter changing in (a) into a standard program easily to solve.

β can be done with respect to the partial derivative of $ln(Y)$ relative to X. Then, Ceteris paribus, 100*β is the percentage change in Y for a small change in X (increase or decrease).

With the dummy variable this is not the case. The problem is, of course that these variables are not continuous, thus we cannot differentiate ln(Y) taking into consideration X_i^D. All we have to do is take the exponential of both sides of equation (1), then evaluate Y when $X_i^D = 0$ and when $X_i^D = 1$. The difference between these two values, divided by the expression for Y based on the starting value of X_i^D gives you the correct interpretation immediately:

i. If X_i^D passes from 0 to 1, the percentage effect of X_i^D on Y is 100[exp(β) - 1]

ii. If X_i^D passes from 1 to 0, the percentage effect of X_i^D on Y is 100[exp($-\beta$) - 1]

However, the resulting estimator of the percentage impact is then biased, In our study, for the interpretation of our dummy variables, we used the modification proposed by Kennedy (1981) (a formula that gives us an almost-unbiased estimator of the percentage impact of the dummy variable on Y) to calculate the quantile effect:
we just have to modify the formula in (1) by $\hat{q}$=100[exp($\hat{\beta}$-$\frac{1}{2}v(\hat{\beta})$)$-$1], Where β is the parameter of dummy variable, and $v(\hat{\beta})$ is the variance of β. This transformation assume the normality of errors.

Results and interpretation

We start by running an OLS regression to make a comparison with quantiles regression.

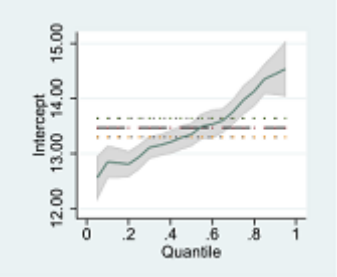


Figure 3.3 – OLS versus quantile regression

Figure 3.3 [6] allows us to make a comparison between the OLS and quantile regression. We chose to represent the coefficient estimates for the different deciles, with the confidence interval of 95% (shaded area), and for comparison, as the value of the coefficient ordinary least squares (dotted line). The coefficient of our constant can be regarded as the quantile of households with modality of reference (to be an illiterate women, inactive and living in urban east). It is not surprising that it is increasing with the quantiles (figure3.3). Thus, we pass from 12.5 for the first quantile to 14.5 for ninth quantile. While, the estimated ols coefficient is around 13.5. The ordinary least square regression gave us only one value which represents an average value for the whole distribution without taking into account the specificity of each point in the distribution.

In the pooled model, the rural variable was added (as a dummy variable), statistically significant at a level of 1% with a negative sign. This finding supports the fact that rural areas are more vulnerable and exposed to poverty than urban areas since it has the lowest part of consumption expenditure.

6. we have just put the graph of constant to make the comparison as we integrated the tables of the results of our estimates we do not need to put the graphics of the output as they give the same interpretation. For more details about other variables see Appendix

Table 3: OLS and Quantile Regression of Total Consumption Expenditure Per Capita

Variables	Means	Quantile regression						
		5th percentile	*10th percentile*	*25th percentile*	*50th percentile*	*75th Percentile*	*90th Percentile*	*99th percentile*
Intercept	15.109*	14.24*	14.37*	14.61*	14.95*	15.61*	16.15*	16.25*
	(0.085)	(0.166)	(0.197)	(0.085)	(0.129)	(0.148)	(0.204)	(0.524)
Gender	-0.106*	-0.025	-0.033	-0.046**	-0.098*	-0.164*	-0.204*	-0.134
	(0.015)	(0.030)	(0.026)	(0.020)	(0.014)	(0.020)	(0.032)	(0.094)
household size	-0.212*	-0.224*	-0.229*	-0.221*	-0.219*	-0.209*	-0.202*	-0.176*
	(0.003)	(0.0059)	(0.006)	(0.0036)	(0.004)	(0.005)	(0.007)	(0.018)
% children	-0.674*	-0.522*	-0.525*	-0.609*	-0.664*	-0.761*	-0.809*	-0.843*
(under 15 old)	(0.029)	(0.056)	(0.059)	(0.025)	(0.024)	(0.039)	(0.050)	(0.178)
Age	0.0144*	0.016*	0.017*	0.018*	0.020*	0.007**	0.001	0.004
	(0.0027)	(0.005)	(0.006)	(0.0031)	(0.004)	(0.004)	(0.006)	(0.016)
Age2*100	-0.009*	-0.011*	-0.012**	-0.01*	-0.01*	-0.002	0.003	0.005
	(0.002)	(0.004)	(0.005)	(0.002)	(0.003)	(0.003)	(0.006)	(0.014)
Tenant of house	-0.059*	-0.084**	-0.092*	-0.075*	-0.084*	-0.046**	-0.013	0.082
	(0.019)	(0.037)	(0.028)	(0.023)	(0.023)	(0.021)	(0.030)	(0.117)
Free housing	-0.131*	-0.133*	-0.114**	-0.116*	-0.140*	-0.106*	-0.180*	0.007
	(0.025)	(0.049)	(0.056)	(0.027)	(0.029)	(0.024)	(0.039)	(0.157)
Primary	0.180*	0.196*	0.187*	0.178*	0.184*	0.187*	0.166*	0.124
	(0.014)	(0.027)	(0.019)	(0.018)	(0.018)	(0.023)	(0.025)	(0.086)
Secondary level	0.455*	0.444*	0.442*	0.424*	0.458*	0.476*	0.474*	0.529*
	(0.016)	(0.032)	(0.024)	(0.021)	(0.019)	(0.023)	(0.042)	(0.101)
Higher level	0.876*	0.846*	0.868*	0.866*	0.868*	0.890*	0.884*	1.039*
	(0.024)	(0.048)	(0.044)	(0.019)	(0.026)	(0.047)	(0.051)	(0.152)
sector_Gov	0.104*	0.145*	0.138*	0.128*	0.103*	0.099*	0.085**	0.107
	(0.017)	(0.034)	(0.028)	(0.025)	(0.027)	(0.022)	(0.036)	(0.107)
sector_Priv	0.116*	0.162*	0.146*	0.139*	0.111*	0.103*	0.103**	0.112
	(0.020)	(0.039)	(0.023)	(0.021)	(0.019)	(0.025)	(0.045)	(0.122)
sector_Agri	0.014	0.050	0.036	0.030	0.005	0.017	-0.029	-0.051
	(0.016)	(0.032)	(0.023)	(0.020)	(0.020)	(0.021)	(0.030)	(0.101)
self	0.072*	0.076**	0.082*	0.085*	0.065*	0.097*	0.069**	0.126
	(0.015)	(0.030)	(0.025)	(0.016)	(0.016)	(0.024)	(0.029)	(0.094)
West	-0.274*	-0.305*	-0.308*	-0.299*	-0.276*	-0.254*	-0.242*	-0.109**
	(0.0108)	(0.021)	(0.018)	(0.014)	(0.015)	(0.012)	(0.023)	(0.066)
Rural	-0.266*	-0.331*	-0.293*	-0.270*	-0.261*	-0.231*	-0.218*	-0.246*
	(0.012)	(0.049)	(0.019)	(0.012)	(0.018)	(0.016)	(0.028)	(0.073)
Foreign Transfer	0.188*	0.134**	0.259*	0.179*	0.160**	0.183**	0.265*	0.237
	(0.041)	(0.080)	(0.082)	(0.035)	(0.071)	(0.088)	(0.082)	(0.254)
Number of observation	11281	11281	11281	11281	11281	11281	11281	11281
Pseudo R^2	0.572	0.358	0.356	0.359	0.359	0.352	0.336	0.288

Quantile regression and OLS estimates of total observation, with standard deviation in parentheses. Significance levels are respectively 1% (*) and 5% (**)

Table 3.3 shows that size is a determinant of household's welfare since it is significant. As for Lipton and Ravallion (1995) study, the coefficient of this variable has a negative sign. They explain this result by the fact that the welfare received per person is reduced in the case of an extended household.
But, to explain the sign of this coefficient, it will be better to decompose the total expenditure to see what type of expenditure negatively affects household size (in the second paragraph of this section). This finding may also reflect the fact that household members are unemployed or they have a low income. In table 3.3, the west variable [7] is found to be statistically significant. With a negative sign, it shows that the consumption expenditures of individuals who live in western areas are lower than those of eastern areas at all quantiles. The findings show that consumption expenditures of peoples, with higher education levels are higher than illiterate people and people who , have acquired just primary education and secondary education. *Ceteris paribus*, the effect of this variable is much higher with quantiles.

From table 3.3, we reveal that men's expenditures are consistently lower than those of women, but these differences are much greater in the upper quantiles. We note that this variable is not significant in the 10th percentile. We may explain this result by the fact that women spend much more than men. We note also that the dummy for the agricultural sector is not significant for both means and quantile regression. In addition, the effects of the public and private sectors are higher in the lower quantile, which means that as this variable increases, ameliorate the welfare of poor households improves. When the models are estimated separately for rural and urban areas, it is possible to see the differences in the factors affecting consumption expenditures. Most variables of both rural and urban models are significant.

7. This variable was inserted as we are interested in the study of well-being; this region is the most vulnerable, since it has the highest poverty rate 79.5% according to INS

Table4 - Quantile Regression of the Urban Consumption Expenditure Per Capita

	Urban						
Variables	*5th Percentile*	*10th Percentile*	*25th Percentile*	*50th Percentile*	*75th Percentile*	*90th Percentile*	*99th Percentile*
Intercept	13.97*	14.13*	14.34*	14.81*	15.41*	15.69*	16.31*
	(0.201)	(0.247)	(0.125)	(0.131)	(0.140)	(0.215)	(0.819)
Men	-0.036	-0.047**	-0.060*	-0.111*	-0.171*	-0.149*	-0.043
	(0.036)	(0.021)	(0.022)	(0.031)	(0.022)	(0.041)	(0.149)
Household Size	-0.244*	-0.241*	-0.235*	-0.240*	-0.235*	-0.228*	-0.175*
	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.008)	(0.030)
% Of Children	-0.425*	-0.406*	-0.505*	-0.557*	-0.613*	-0.674*	-0.782*
(Under 15 Years)	(0.068)	(0.073)	(0.063)	(0.051)	(0.046)	(0.073)	(0.276)
Age	0.015**	0.016**	0.019*	0.017*	0.009**	0.0002	-0.012
	(0.006)	(0.007)	(0.004)	(0.0041)	(0.005)	(0.007)	(0.026)
Age2*100	-0.008	-0.01	-0.01*	-0.01*	-0.002	0.002	0.021
	(0.005	(0.006)	(0.003)	(0.003)	(0.004)	(0.006)	(0.022)
Homeowner (Ref)							
Tenant	-0.101*	-0.098*	-0.092**	-0.094*	-0.053**	0.004	0.087
	(0.037)	(0.021)	(0.027)	(0.021)	(0.025)	(0.038)	(0.150)
Free Housing	-0.126**	-0.137*	-0.136*	-0.151**	-0.103*	-0.05	-0.105
	(0.058)	(0.039)	(0.033)	(0.061)	(0.038)	(0.057)	(0.238)
Illiterate (Ref)							
Primary Level	0.233*	0.205*	0.230*	0.209*	0.218*	0.17*	0.037
	(0.035)	(0.031)	(0.022)	(0.024)	(0.023)	(0.039)	(0.143)
Secondary Level	0.486*	0.465*	0.479*	0.510*	0.524*	0.432*	0.484*
	(0.038)	(0.032)	(0.025)	(0.022)	(0.028)	(0.04)	(0.154)
Higher Level	0.913*	0.877*	0.907*	0.863*	0.913*	0.835*	0.989*
	(0.051)	(0.046)	(0.039)	(0.031)	(0.030)	(0.053)	(0.209)
Sector_Gov	0.142*	0.115*	0.102*	0.089*	0.072*	0.307*	-0.088
	(0.038)	(0.025)	(0.025)	(0.019)	(0.019)	(0.04)	(0.155)
Sector_Priv	0.184*	0.126*	0.115*	0.088*	0.084*	0.313*	0.017
	(0.043)	(0.035)	(0.024)	(0.023)	(0.029)	(0.046)	(0.178)
Sector Agri	0.013	-0.049	-0.056	-0.036	-0.042	-0.028	-0.299
	(0.057)	(0.049)	(0.048)	(0.043)	(0.038)	(0.073)	(0.231)
Self	0.070**	0.031	0.030	0.0208	0.036**	0.011	0.049
	(0.034)	(0.025)	(0.024)	(0.023)	(0.019)	(0.033)	(0.138)
Center-West	-0.334*	-0.299*	-0.303*	-0.287*	-0.265*	-0.246*	-0.114
	(0.025)	(0.014)	(0.019)	(0.014)	(0.020)	(0.039)	(0.105)
Foreign Transfer	0.114	0.246**	0.183*	0.123**	0.081	0.061	-0.278
	(0.092)	(0.123)	(0.056)	(0.071)	(0.059)	(0.096)	(0.376)
Number Of	7261	7261	7261	7261	7261	7261	7261
Observation	0.315	0.316	0.330	0.343	0.340	0.330	0.254
Pseudo R^2							

Quantile Regression Estimates Of Urban Observation, With Standard Deviation In Parenthesis. Significance Levels Are Respectively 1% (*) And 5% (**).

The quantile regression results for both rural and urban areas are given in the table 3.3 and table 3.4. Several variables show interesting results. First of all, the education level increases across all quantiles and it is much higher in urban areas. This finding proves, as expected, that the higher the educational level, the more we consume and the greater the well being is improved. We also record the lowest percentage in rural samples in particular in the higher quantile. Results also show, that the variable "size of the household" is found to be significantly. *Ceteris paribus*, with a unit change in the household size, the level of expenditure of household's declines by approximately 23.2% for urban areas against 18.4% for rural areas.

Results show also that, for urban area estimates, age is statistically significant and it positively influences consumption expenditures. But it decreases with quantile and became insignificant in 90^{th} percentile, while in the rural regression, the effect of this variable is not significant except for the 25^{th} and 50^{th} percentile. The finding also shows that the housing variable has a significant effect on welfare for urban regression. In fact, consumption for the homeowner is higher than for tenants or those who have a free house across all quantiles. In the rural sample, these variables are not significant except in the 50^{th} and 75^{th} percentiles for just free housing with a negative sign. Results suggest that gender variable is statistically significant in the urban model for the means regression as well as for the quantile estimates. Although, for the rural model this variable is not significant in the mean and quantile regression, except in the 25^{th} and 50^{th} percentiles. For rural set, we underline a difference between the higher and the lower quantiles (the richer and the poorest) especially for variable sex. In fact, women who live in these areas are not educated and do not have any resource (except for work in agriculture) they are totally dependent on the man (husband) is for this reason that the coefficients of the sex variable are not significant for the first quantiles.

In the estimation, for the whole population (combining rural and urban areas), women's welfare is rather close to the values obtained for the same variables in the urban estimates. This result shows that rural areas do not have much influence on the estimation of these variables. Results also show that the agricultural sector has a positively significant coefficient in rural areas at all quantiles excluding the 25^{th} and the 90^{th} percentile. Unlike for the urban model, like in the pooled regression, this variable is not significant. For both urban and rural areas, welfare is determined by governmental and private sectors, since

they are statistically significant with a positive sign. In the urban regression, the effect of these variables is higher in the upper quantile. While, in the rural regression, they are much higher at the bottom of the distribution.

Table5 - Quantile Regression of the Rural Consumption Expenditure Per Capita

	Rural						
Variables	*5th*	*10th*	*25th*	*50th*	*75th*	*90th*	*99th*
	Percentile	*Percentile*	*Percentile*	*Percentile*	*Percentile*	*Percentile*	*Percentile*
Intercept	13.40*	13.92*	14.24*	14.46*	15.19*	15.52*	15.58*
	(0.331)	(0.308)	(0.203)	(0.190)	(0.180)	(0.228)	(0.577)
Men	-0.026	-0.053	-0.037	-0.106**	-0.115*	-0.187**	-0.251**
	(0.064)	(0.055)	(0.036)	(0.043)	(0.033)	(0.074)	(0.112)
Household Size	-0.203*	-0.205*	-0.197*	-0.193*	-0.176*	-0.175*	-0.163*
	(0.011)	(0.013)	(0.007)	(0.006)	(0.006)	(0.007)	(0.020)
% Of Children	-0.684*	-0.724*	-0.804*	-0.824*	-0.962*	-0.903*	-0.910*
(Under 15 Years)	(0.122)	(0.092)	(0.053)	(0.059)	(0.054)	(0.074)	(0.213)
Age	0.024**	0.011	0.017**	0.015*	0.001	0.004	0.012
	(0.010)	(0.010)	(0.006)	(0.005)	(0.005)	(0.005)	(0.019)
Age2*100	-0.022**	-0.009	-0.01**	-0.01**	-0.0624	-0.003	-0.003
	(0.009)	(0.009)	(0.005)	(0.004)	(0.005)	(0.005)	(0.016)
Homeowner (Ref)							
Tenant	0.058	-0.082	-0.018	0.065	0.057	-0.144	0.304
	(0.212)	(0.137)	(0.166)	(0.125)	(0.072)	(0.109)	(0.371)
Free Housing	-0.058	-0.054	-0.070	-0.119*	-0.121**	-0.234*	0.027
	(0.112)	(0.059)	(0.044)	(0.040)	(0.064)	(0.054)	(0.195)
Illiterate (Ref)							
Primary Level	0.122**	0.144*	0.162*	0.166*	0.132*	0.088**	0.214**
	(0.055)	(0.040)	(0.028)	(0.021)	(0.030)	(0.034)	(0.096)
Secondary Level	0.334*	0.331*	0.315*	0.362*	0.355*	0.389*	0.525*
	(0.077)	(0.061)	(0.048)	(0.042)	(0.048)	(0.062)	(0.135)
Higher Level	0.350**	0.749*	0.794*	0.805*	0.725*	0.762*	0.856**
	(0.203)	(0.127)	(0.099)	(0.070)	(0.074)	(0.113)	(0.355)
Sector_Gov	0.270*	0.296*	0.205*	0.149*	0.122**	0.098	0.505*
	(0.090)	(0.057)	(0.044)	(0.039)	(0.048)	(0.080)	(0.157)
Sector_Priv	0.174**	0.147**	0.179**	0.182*	0.094**	0.092**	0.335**
	(0.102)	(0.081)	(0.069)	(0.050)	(0.059)	(0.042)	(0.178)
Sector Agri	0.097**	0.131*	0.084*	0.035	0.037**	-0.027	-0.021
	(0.052)	(0.032)	(0.022)	(0.024)	(0.017)	(0.022)	(0.091)
Self	0.203*	0.250*	0.252*	0.220*	0.192*	0.166*	0.193
	(0.077)	(0.061)	(0.040)	(0.040)	(0.031)	(0.035)	(0.134)
West	-0.280*	-0.270*	-0.275*	-0.239*	-0.233*	-0.192*	-0.069
	(0.044)	(0.021)	(0.021)	(0.022)	(0.027)	(0.028)	(0.076)
Foreign Transfer	0.061	0.089	0.153**	0.221*	0.572*	0.568*	0.309
	(0.193)	(0.202)	(0.072)	(0.082)	(0.203)	(0.139)	(0.338)
Number Of	4020	4020	4020	4020	4020	4020	4020
Observation	0.270	0.279	0.294	0.288	0.276	0.265	0.242
Pseudo R^2							

Quantile Regression Estimates Of Rural Observation, With Standard Deviation In Parenthesis. Significance Levels Are Respectively 1% (*) And 5% (**).

In sum, the number of the significant factors affecting the consumption expenditures for rural areas is rather low. The pooled model for the total consumption expenditures and the subsamples for rural and urban models give us a preliminary observation about regional differences in welfare. The following paragraph deals with quantile estimation of disaggregate expenditure to give us more detailed interpretations.

3.3.2 Censored quantile regression with disaggregate expenditures

Theoretical presentation

The "tobit" regression (Tobin (1958)) has taken a large attention in the econometric literature since its initial introduction, which may explain the emergence of a variety of semi-parametric and parametric methods of estimation. Morever, the tobit model estimation in the presence of quantile regression was motivated by the increasing interest in quantile model, in which the problem of censoring point is introduced frequently [8]. The censored quantile regression is an extension form of "tobit" model (Tobin (1958)). Many papers in the literature deal with this approach. Powell (1986b) and Newey et al. (1990) have put forward the conditional quantile in the the presence of symmetry restrictions. Honoré and Powell (1994), Moon (1989) and Horowitz (1988) proposed a framwork to explore the expected independence between the regressors and the error term and then suggest a consistent estimators.

The works of Powell (1984) and Powell (1986a) have made an important contribution to the model proposed by Tobin. In fact, censored regression is firstly known as the "Tobit" model then we can describe the latent variable as follow:

$$Y_i^* = X_i'\beta_\theta + \epsilon_{\theta i} \tag{3.3}$$

where Y_i^* is our latent variable and it can be observed only it is higher than some point Y_i^0 which represent the threshold point, for all $i = 1, ..., n$, and $\epsilon_{\theta i}$ is iid with a distribution function F. Then, we can write the observed dependent variable as $Y_i = max\{Y_i^0, X_i'\beta_\theta + \epsilon_{\theta i}\}$. Following Koenker and Bassett Jr (1978), we can assume that $Q_\theta(\epsilon_{\theta i}\ X_i) = 0$.

8. a set of papers that involve quantile regression estimation which we cite: Powell (1984) Koenker and Bassett Jr (1982)...

The conditional quantile functions are given by:

$$Q_{Y_i\ X_i}(\theta\ X_i) = F^{-}1(\theta) + X_i'\beta \tag{3.4}$$

This function can be estimated, setting $\rho_\theta(\epsilon) = \epsilon(\theta - I(\epsilon < 0)$, as follow: where

$$\hat{\beta} = argmin_{b\in\mathbb{R}^p} \sum_{i=1}^{n} (Y_i - max\{Y_i^0, X_i'\beta\}) \tag{3.5}$$

Equations 8 – Censored quantile regression

$\rho_\theta(\lambda) = [\theta - I(\lambda < 0)]\lambda$ is the control function and $I(.)$ represent the characteristic function. This estimation is true as long as the matrix of values of explanatory variables (ie. $X = x_i$)contains a constant able to absorb the θ dependent contribution $F^{-1}(\theta)$.

As we know, the Household budget surveys represent an important source of information about consummer expenditures, and not for the individual level but also for aggregate level. However, some categories of expenditure present a large number of zero.

In his paper, Deaton and Irish (1984) used the Tobit specification to avoid the understatement problem in the case of total tobacco or alcohol expenditures since the britsh survey exclude many individual amongs whom the expenditures of this items was higher.

We propose to model zero expenditure, according to the three-step framwork proposed byChernozhukov and Hong (2002). In fact, Chernozhukov and Hong (2002) present a *censored Quantile Regression* in the case of a known censoring point. This estimator also enables the estimation of many traditional mosels, namely the famous Amemiya-Tobin model.

The estimation of this estimator Requires a three essential stages :

- **Step1**:we estimate a probability of the model as follow:

$$\sigma_i = p(\dot{X}_i'\gamma) + \epsilon_i$$

  where σ_i is the "not-censoring" indicator and $\dot{X}_i'$ takes into account the transformation of the couple (X_i, Y_i^0). Know, we select the sample $J_0 = \{i : p(\dot{X}_i'\gamma) > 1 - \theta + c\}$,

we consider that c is not too small and $0 < c < \theta$. For choosing the value of c, the authors suggest a comparison between the size of $J(c)$ when $c = 0$ and when it takes other values (for exemple, $c = qth$ quantile).

- **step2**: obtain the inefficient initial estimator $\hat{\beta_0}(\theta)$ by the minimization of the standard quantile regression program,

$$\min_{\beta} \sum_{i \in J_0} \rho_\theta(Y_i - \dot{X}_i')$$

then we select $J_1 = \{i : p(X_i')\hat{\beta}_0(\theta) > C_i + \sigma_n\}$

- **step3**: we run the minimization program with J_1 instead of J_0 to get the three-step estimator denoted by $\hat{\beta}_1(\theta)$

- **step4**:(This step is facultative), we repeat previous step one (or more) time, but we use the sample $J_I = \{i : p(X_i')\hat{\beta_{I-1}}(\theta) > C_i + \sigma_n\}$, in the place of J_1, with $I = [1, 2, ..., K]$.
  Finally, we get the K-step estimator denoted by $\hat{\beta}_I(\theta)$

Data Application and Results

In this section, we choose to deal with disaggregate expenditures to explain inequality in education and development between urban and rural areas. Here we use uncensored and censored quantile regression (CQR), this choice is justified as the estimator CQR enabled us to manipulate the censure at zero. [9]

we assume the CQR model form as follow (with $Y_i^0 = 0$):

$$Q_{YX}(\theta) = (\alpha(\theta) + X^{'}\gamma(\theta)) \vee 0 \tag{3.6}$$

Here, the conditional quantile function of the desagregate expenditure is either 0 either have a linear form.

9. For more details see Chernozhukov and Hong (2002)

Table 6 – Censored quantiles Regressions of the disaggregate expenditures

Education and leisure expenditure														
Quantiles	0.05		0.10		0.25		0.5		0.75		0.9		0.95	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Intercept	0	-32.916*	-18.307*	-8.748*	-11.42*	-15.723*	-11.36*	-2.647*	1.526*	6.202*	6.762*	9.638*	10.596*	12.133*
Men	0	-0.080	-0.230*	-0.224*	-0.536*	0.183	-0.762*	-0.040	-0.547*	-0.287*	-0.387*	-0.359*	-0.251*	-0.236*
Household Size	0	0.202*	0.596*	0.265*	0.597*	0.766*	0.520*	0.301*	0.223*	0.088*	0.082*	0.011	0.033	0.010
% Children (Under 15 Years)	0	15.793*	13.615*	15.382*	12.021*	5.199*	3.400*	1.428*	0.939*	0.140	-0.378*	-0.502*	-1.081*	-0.795*
Age	0	1.137*	0.535*	0.452*	0.367*	0.639*	0.726*	0.424*	0.329*	0.191*	0.186*	0.117*	0.066*	0.038*
Age2 *100	0	-1.005*	-0.391*	-0.189*	-0.303*	-0.609*	-0.712*	-0.409*	-0.312*	-0.175*	-0.174*	-0.105*	-0.061*	-0.033*
Tenant	0	-0.378	-0.109	-0.217	0.760	0.212	0.009	0.129	-0.055	0.101	0.090	-0.002	0.346	0.002
Free Housing	0	0.075	-0.408	-0.203	-0.288	-0.183	-0.009	0.077	-0.238	0.009	-0.303*	0.038	-0.561*	-0.078
Primary Level	0	0.124	0.291*	0.277*	0.923*	2.392*	0.728*	0.890*	0.347*	0.666*	0.190*	0.486*	0.100	0.385*
Secondary Level	0	0.614*	0.231*	0.614*	0.825*	3.509*	1.075*	1.672*	0.577*	1.315*	0.441*	1.113*	0.612*	1.030*
High Level	0	2.446*	2.575*	2.112*	2.200*	4.603*	1.747*	2.663*	1.074*	2.085*	0.891*	1.714*	0.960*	1.592*
Gov_sector	0	0.259	0.621*	0.895*	1.389*	0.604*	0.409*	0.214*	0.451*	0.144*	0.273*	0.274*	0.178	0.093*
Priv_sector	0	-0.387	1.218*	0.397*	1.002*	0.556*	0.546*	0.214*	0.517*	0.208*	0.359*	0.242*	0.141	0.137*
Agri_Sector	0	-0.143	0.067	-0.011	0.339*	-0.165	0.339*	-0.130	0.247*	-0.229	0.078	-0.246	0.078	-0.203
Self	0	0.077	0.398*	0.298*	1.003*	0.586*	0.240*	0.189*	0.372*	0.082	0.495*	0.161*	0.374*	0.074
West Region	0	-0.086	-0.067	-0.054	-0.118	-0.501*	-0.188	-0.310*	-0.059	-0.280*	0.039	-0.330*	-0.016	0.300*
Foreign transfer	0	0.310	0.179	0.345*	0.358	0.612	0.906	0.262	0.463	-0.255	0.785	-0.143	-0.003	-0.148

Education expenditures

The estimated of disaggregate expenditures [10]gave us interesting results regarding the disparity between urban and rural areas in consumption. In particular, it emphasizes the importance of education as an explanatory variable factor of inequality between the two regions. It therefore seems important to understand the composition of the educational expenditure of households and examine the variability depending on the socioeconomic status of households and educational levels according to which these expenditures are devoted.

In his study, Deaton (1974), showed that the proportion of income allocated to housing, clothing (...) remains constant with income, but the proportion spent on food decreases as income increases and vice versa, the proportion allocated to other expenses (health, education, leisure, luxury products) increases as income increases.

All results prouves that education, and especially basic (primary) education, have a central role in fight against inequalities. With regard to the situation of education and training in Tunisia and the level of development of the country, the priorities of the education sector are the universalization of primary education, improving quality at all levels and and finally improving the management and governance.

Food Expenditures

Differences in the distribution of food expenditures between urban and rural environments, is the first note to emphasize in our study. In contrast to rural areas, in urban areas food expenditures increase with household size. That is logical. Moreover, for most quantiles we note that there 'is a positive and significant relationship between food expenditures and education in rural areas. That is to say, education improves the standard of living in rural areas. Table 6 shows that rural areas in the western region have less food consumption compared to the Eastern areas. For both urban and rural zones, a higher level of education increases food expenditure except for the 5^{th} percentile (for urban area). For both the urban and rural samples, the coefficients of education are statistically and positively significant.

10. we used seven type of expenditure: food expenditures, housing expenditures, clothing expenditures, health expenditures, telecommunication and transport expenditures, education and leisure expenditures, other expenditures

Table 6– *(Continued)*

Food expenditure														
Quantiles	0.05		0.10		0.25		0.5		0.75		0.9		0.95	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Intercept	12.746*	13.937*	12.481*	14.062*	13.167*	14.249*	13.678*	14.378*	14.252*	14.442*	14.838*	14.655*	14.801*	14.677*
Men	0.135	0.005*	0.157*	-0.003	0.102*	-0.002	0.018	-0.024*	-0.046	-0.016	-0.074*	-0.003	-0.091*	0.002
Household size	-0.095*	0.002*	-0.104*	0.003*	-0.102*	0.015*	-0.106*	0.021*	-0.106*	0.009*	-0.098*	0.004*	-0.088*	0.003*
% children (Under 15 years)	-0.586*	0.001	-0.489*	0.022	-0.520*	0.022	-0.533*	0.044*	-0.586*	0.020*	-0.580*	0.006	-0.568*	0.002
Age	0.015	-0.001*	0.022**	-0.003*	0.014*	-0.009*	0.011*	-0.012*	0.005	-0.004*	-0.006	-0.003*	-0.002	-0.002*
Age2 *100	-0.015	0.001	-0.019*	0.002*	-0.010	0.007*	-0.007	0.011*	-0.002	0.004*	0.006	0.002*	0.003	0.0016*
Tenant	0.121	-0.013*	-0.0207	0.022*	-0.002	-0.024*	-0.063	-0.053*	-0.058	-0.019*	-0.166*	-0.026*	0.237*	0.022*
Free housing	-0.149	-0.002	-0.124	-0.012*	-0.017	-0.035*	-0.040	-0.047*	-0.119*	-0.021*	-0.233*	-0.011*	0.164*	-0.014
Primary Level	0.102*	-0.002	0.103**	-0.001	0.105*	0.007	0.129*	0.049*	0.129*	0.032*	0.092*	0.005*	0.131*	-0.0001
Secondary Level	0.289*	-0.007*	0.223*	-0.010*	0.256*	-0.018*	0.281*	0.015	0.264*	0.033*	0.241*	0.005	0.332*	-0.003
High level	0.602*	-0.011*	0.570*	-0.008	0.640*	0.018*	0.657*	0.019	0.627*	0.026*	0.514*	-0.001	0.565*	-0.0008
Gov_sector	0.308*	-0.004	0.334*	-0.002	0.203*	-0.003	0.111*	-0.010	0.073*	-0.003	-0.036	-0.001	-0.031	-0.007
Priv_sector	-0.021	0.007*	0.134	0.010*	0.197*	0.008	0.162*	-0.005	0.092*	-0.019*	-0.012	-0.015*	-0.143	-0.011*
Agri_sector	0.143*	0.015*	0.272*	0.025*	0.109*	0.072*	0.117*	0.038*	0.111*	0.022*	0.062*	0.009*	0.036	0.004
Self	0.232*	-0.006*	0.143*	-0.011*	0.239*	-0.025*	0.156*	-0.034*	0.116*	-0.008	0.113*	-0.006*	0.081	-0.003
West region	-0.335*	0.254*	-0.272*	0.241*	-0.212*	0.221*	-0.206*	0.270*	-0.177*	0.210*	-0.118*	0.112*	-0.076*	0.096*
Foreign transfer	-0.109	-0.006	0.061	0.001	0.132	0.019	0.186*	0.105*	0.315*	0.119*	0.621*	0.026*	0.489*	0.016*

Table 6– *(Continued)*

Housing expenditure														
Quantiles	0.05		0.10		0.25		0.5		0.75		0.90		0.95	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Intercept	12.787*	13.246*	12.712*	13.521*	13.312*	13.754*	13.793*	14.181*	13.988*	14.461*	13.975*	15.102*	14.328*	15.248*
Men	-0.057	-0.002	-0.066*	-0.001	-0.072*	-0.069*	-0.118*	-0.105*	-0.161*	-0.149*	-0.166*	-0.229*	-0.148*	-0.200*
Household Size	-0.188*	-0.221*	-0.181*	-0.218*	-0.179*	-0.212*	-0.159*	-0.207*	-0.142*	-0.200*	-0.133*	-0.191*	-0.140*	-0.183*
% Children (Under 15 Years)	-0.212*	-0.165*	-0.242*	-0.227*	-0.309*	-0.208*	-0.475*	-0.226*	-0.608*	-0.240*	-0.600*	-0.299*	-0.478*	-0.265*
Age	0.021*	0.024*	0.014*	0.021*	0.013*	0.021*	0.008*	0.018*	0.015*	0.017*	0.024*	0.006	0.026	0.005
Age2 *100	-0.018*	-0.018*	-0.011*	-0.015*	-0.009*	-0.014*	-0.005	-0.011*	-0.012*	-0.009*	-0.018*	0.002	-0.019	0.004
Tenant	-0.016	-0.171*	-0.055	-0.116*	0.163*	-0.090*	0.133	-0.111*	-0.002	-0.116*	0.048	-0.091*	0.161	-0.117*
Free Housing	-0.118	-0.144*	-0.044	-0.123*	-0.066*	-0.140*	-0.144*	-0.152*	-0.169*	-0.198*	-0.169*	-0.216*	-0.341*	-0.292*
Primary Level	0.054*	0.199*	0.0805*	0.152*	0.106*	0.175*	0.134*	0.176*	0.128*	0.200*	0.161*	0.295*	0.035	0.258*
Secondary Level	0.206*	0.374*	0.240*	0.363*	0.294*	0.425*	0.364*	0.444*	0.462*	0.493*	0.588*	0.567*	0.529*	0.532*
High Level	0.198*	0.631*	0.338**	0.642*	0.601*	0.737*	0.725*	0.787*	0.866*	0.867*	0.998*	0.956*	1.016*	0.963*
Gov_sector	0.104	0.078*	0.107*	0.063*	0.124*	0.082*	0.153*	0.087*	0.197*	0.120*	0.219*	0.194*	0.303*	0.177*
Priv_sector	0.106*	0.144*	0.111*	0.107*	0.087*	0.065*	0.165*	0.048*	0.132*	0.110*	0.149*	0.195*	0.172	0.210*
Agri_Sector	-0.004	-0.085*	0.027	-0.123*	0.010	-0.041*	0.018	-0.072*	0.011	-0.094	0.094	-0.037	0.101	-0.017
Self	0.068	0.062	0.178*	0.056*	0.159*	0.054*	0.211*	0.054*	0.239*	0.054*	0.339*	0.033	0.403*	-0.008
West Region	-0.238*	-0.402*	-0.255*	-0.149*	-0.291	-0.407*	-0.326*	-0.411*	-0.314*	-0.372*	-0.303*	-0.355*	-0.339*	0.278*
Foreign transfer	-0.009	0.027	0.052	0.021	0.235	0.100*	0.230*	0.036	0.666*	0.071	1.025*	0.092	1.265*	-0.025

Housing Expenditures

We underline that housing expenditures increase with the level of education. The effect of this variable is higher in urban areas than rural areas. Results show that, *Ceteris paribus*, a higher level of education increases housing expenditure for rural and urban areas. It was also noted that housing expenditure decrease with household size or the number of children . For the west region, compared to other regions, households spend less for their housing (accessories, furniture ..). It makes sense, as these areas have the highest national rate of poverty . So the priority is mainly to purchase goods needed for survival. Results also show that, clothing expenditures increase with the level of education. Compared to non-educated the most educated spend more on their clothing, which is applicable for both areas, but especially urban areas.

Health Expenditures

We underline that there is a statistically significant and positive relationship between the level of education and health expenditures. This is true for both urban and rural areas for all quantiles except for the richest of the distribution. This is not surprising; this class (i.e. Rich households) does not need a high level of education or other criteria for spending and improving their living standards.

In addition, our result shows that expenditure devoted to education and leisure, increase with the public and private sector, the more we are educated more we are likely to have a good job and a decent standard of living. This relationship is stronger in urban areas. The distribution of employed between urban and rural areas explains the difference between the first and higher quantile. In fact, the most paid salaried rather located in urban areas. The estimation results also show that, compared to the eastern zone, households in the urban area of the west spend less on education and leisure. For rural areas of this region there are no significant results. In fact, this part represents the most vulnerable and poorest area compared to other regions of the country. Generally, individuals keep leaving education at the primary level because they do not have the resources to finance their education. For these people leisure activities are null.

Table 6– *(Continued)*

Health expenditure														
Quantiles	0.05		0.10		0.25		0.5		0.75		0.9		0.95	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Intercept	-6.279	10.823*	5.377*	12.099*	11.482*	12.646*	13.257*	13.337*	13.632*	14.399*	14.885*	15.482*	14.823*	15.640*
Men	5.956*	0.434*	2.491	0.110	0.099	0.040	0.008	-0.019	0.038	0.011	0.023	-0.169	0.074	-0.161
Household Size	0.261*	0.056*	0.113*	0.002	0.033	-0.040*	-0.036*	-0.083*	-0.080*	-0.112*	-0.121*	-0.116*	-0.137*	-0.115*
% Children (Under 15 Years)	-2.578*	-1.262*	-1.809*	-1.031*	-1.406*	-0.801*	-1.228*	-0.670*	-0.936*	-0.675*	-1.104*	-0.616*	-1.017*	-0.569*
Age	0.149*	-0.049*	0.047	-0.054*	-0.031*	-0.037*	-0.045*	-0.035*	-0.028*	-0.039*	-0.042*	-0.049*	-0.027	-0.045*
Age2 *100	-0.177*	0.037*	-0.044	0.044*	0.028*	0.033*	0.037*	0.038*	0.025*	0.040*	0.038*	0.051*	0.025	0.049*
Tenant	0.737	0.042	0.488*	-0.002	0.108	0.029	-0.004	-0.019	0.0006	-0.049	0.124	-0.050	0.036	-0.178*
Free Housing	-0.471	0.042	-0.171	-0.163	-0.276	-0.101	-0.201	-0.025	-0.128*	-0.124	-0.253	-0.033	0.018	-0.109
Primary Level	1.004*	0.184	0.555*	0.212*	0.310*	0.165*	0.156*	0.285*	0.048	0.086*	0.103	0.144*	-0.013	0.188*
Secondary Level	1.402*	0.485*	0.929*	0.506*	0.630*	0.502*	0.417*	0.591*	0.339*	0.427*	0.386*	0.390*	0.226*	0.435*
High Level	2.201*	1.146*	1.845*	1.143*	0.948*	0.999*	0.982*	1.079*	0.369*	0.831*	0.548	0.754*	0.244	0.719*
Gov_sector	-0.497	0.025	-0.109	-0.040	0.148	-0.051	-0.056	-0.070	-0.073	-0.089	-0.025	-0.058	-0.111	-0.137
Priv_sector	0.597	0.190	0.428*	0.121	0.289	0.061	0.134	0.042	0.084	0.028	-0.047	0.016	0.091	-0.056
Agri_Sector	-0.186	-0.008	0.180	-0.189	0.014	-0.239*	-0.113*	-0.201*	-0.101*	-0.212*	-0.155*	-0.225*	-0.225*	-0.162
Self	0.235	-0.226*	0.390*	-0.135	0.225*	-0.092*	0.071	-0.065	0.144	-0.098*	-0.021	-0.141*	-0.146	-0.158*
West Region	-0.946*	-0.368*	-0.605*	-0.264*	-0.394*	-0.302*	-0.268*	-0.320*	-0.209*	-0.350*	-0.201*	-0.343*	-0.111	-0.307*
Foreign transfer	0.678	0.177	0.420	-0.030	0.749*	0.064	0.432*	0.013	0.272*	0.208	0.160	0.323	0.181	0.138

Table 6– *(Continued)*

Telecommunication and transport expenditures														
Quantiles	0.05		0.10		0.25		0.5		0.75		0.9		0.95	
	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
Intercept	-8.490*	-1.153	-13.644*	-0.326	4.804*	9.855*	10.451*	11.299*	12.085*	12.371*	12.488*	12.847*	12.540*	13.757*
Men	-0.580	0.088	2.676**	0.264*	0.627*	0.118	-0.002	-0.009	0.008	-0.009	0.011	0.034	0.107	0.091
Household Size	1.071*	0.342*	0.638*	0.209*	0.135*	0.056*	0.061*	0.0042	0.033*	-0.023*	-0.004	-0.037*	0.030*	-0.068*
% Children (Under 15 Years)	-5.248*	-3.145*	-2.707*	-2.628*	-2.021*	-1.932*	-1.725*	-1.539*	-1.576*	-1.271*	-1.323*	-1.018*	-1.046*	-0.804*
Age	0.287*	0.042	0.550*	0.048*	0.201*	0.065*	0.068*	0.049*	0.036*	0.037*	0.043*	0.030*	0.048*	0.008
Age2 *100	-0.245*	-0.040*	-0.514**	-0.054*	-0.196*	-0.062*	-0.066*	-0.044*	-0.035*	-0.032*	-0.037*	-0.022*	-0.040*	-0.002
Tenant	-1.839	0.170	0.176	-0.014	0.622	-0.051	0.258	-0.098*	0.070	-0.081	0.057	-0.036	0.354	-0.022
Free Housing	-0.849	-0.268	-1.698	-0.218	-0.394	-0.213*	-0.253	-0.285*	-0.203	-0.297*	-0.128	-0.232*	-0.116	-0.240*
Primary Level	1.646*	8.018*	2.357*	9.257*	0.160	0.492*	0.172*	0.346*	0.127*	0.290*	0.152*	0.162*	0.052	0.136*
Secondary Level	4.128*	9.388*	3.245*	9.962*	0.580*	1.010*	0.482*	0.836*	0.462*	0.748*	0.409*	0.714*	0.287*	0.689*
High Level	6.417*	10.757*	4.421*	11.088*	1.134*	1.899*	1.159*	1.628*	1.084*	1.477*	0.934*	1.430*	0.730*	1.382*
Gov_sector	0.720	0.730*	1.230	0.330*	0.348*	0.176*	0.265*	0.107*	0.104	0.107*	0.166	0.105*	0.184	0.086
Priv_sector	2.031	1.233*	1.936	0.571*	0.420*	0.298*	0.326*	0.238*	0.238*	0.101*	0.149*	0.134*	0.168	0.036
Agri _Sector	0.843*	0.408	1.410	-0.045	0.150*	-0.098	-0.006	-0.070	-0.117*	-0.137*	-0.110	0.062	-0.074	0.101
Self	0.915	0.699*	1.630	0.333*	0.271*	0.042	0.205*	0.069	0.067	0.018	0.180*	0.061	0.191*	0.007
West Region	-0.598	-0.583*	-0.878	-0.549*	-0.310*	-0.546*	-0.281*	-0.428*	-0.294*	-0.409*	-0.346*	-0.316*	-0.377*	-0.304*
Foreign transfer	1.211	0.146	0.617	0.718*	0.644	0.271*	0.305	0.233*	0.275	0.183*	-0.089	0.175	-0.209	0.237

u: Quantile estimates are calculed using the uncensored option in the CQIV Stata command (Chernozhukov et al. 2012

*: coefficient is different from 0 at 95%

Telecommunication and Transport Expenditures

Results also show a positive relationship between education and telecommunication and transport expenditures. This finding is not a surprise as transportation and medical services have influences on education.

Desagregated censored quantile data, presented in this section, poses a challenge relative to other applications. This approach, not only, enable us to surround the problem of censored data in 0, but also to present the effects of different expenditures on the urban-rural households well-being. This modelling is important but not enough to asses the gap between urban and rural araes. In fact, welfare disparities between urban and rural areas of Tunisia continue to remain large, in spite of many government programs established to alleviating such disparities. In the recent literature, one meeting two opposing views exposing alternative explanations for these spatial disparities. The first view is that poor zones arise from the persistent concentration in these zones of individuals with personal characteristics that inhibit growth in their well-being. According to this opinion, otherwise individuals with the same attributes will have the same potential growth independent of where they live. consequently, geography would not play a causal role in explaining the level of living standards. However, the second view suggests that geography itself is the cause of the weak growth of households living standards. In zones better endowed with public resources, such as better infrastructure and basic services (water and sanitation, electricity), there may be geographic externalities that facilitate higher returns. Therefore, we classify the factors associated with spatial welfare disparities into two set: a group of 'covariates' that summarize the non-geographic attributes of the household, such as, level of education, age etc. and a group of 'coefficients' that summarize the marginal living standards gains associated with these characteristics.

In the next section, we address the question of whether spatial welfare disparities are better explained by the sorting of individuals with low portable attributes in some areas (e.g. less-educated individuals being concentrated in rural areas) or by persistent spatial differences associated with portable attributes such as human capital.

3.4 Sources of welfare disparities between rural and urban areas: Counterfactual decomposition methods

3.4.1 Econometric Theory

In this part, we try to explain and describe the main counterfactual decomposition technique presented in the literature. These approachs have been generalized to analyze inequalities and poverty gaps observed between interest groups Bourguignon et al. (2008); Yun (2004); Yun (2009)).

The Oaxaca-Blinder wage Gap decomposition:

Blinder (1973) and Oaxaca (1973) suggest estimating wage discrimination between men and women as follows. The wage equations are estimated separately on the subpopulation of men (h) and the subpopulation of women (f).

$$\begin{cases} W_{ij}^{f} = X_{ij}^{f}\beta^{f} + \epsilon_{ij}^{f}, \\ W_{ij}^{h} = X_{ij}^{h}\beta^{h} + \epsilon_{ij}^{h}, \end{cases} \tag{3.7}$$

Here, the dependent variable is the logarithm of wage (W_{ij}) of individual i working in the company j. The wage logarithm is explained by a vector of explanatory variables (X_{ij}) and is ϵ_{ij} a perturbation. With this model, we can calculate the wages that would benefit women if paid like men, and that men would earn if they were paid like women.

Based on the estimate of returns observable characteristics ($\hat{\beta}$) the gap between the average wages of men and women ($\overline{W^h} - \overline{W^f}$) can be decomposed into a component explained by the difference in average observable characteristics ($(\overline{X^h} - \overline{X^f})\beta^h$) and unexplained component linked to a different returns of observable characteristics for men and women ($\overline{X^f}(\hat{\beta^h} - \hat{\beta^f})$), then the equation of the wage gap can be presented as follow:

$$(\overline{W^h} - \overline{W^f}) = \underbrace{((\overline{X^h} - \overline{X^f})\beta^h)}_{\textit{Difference in characteristics}} - \underbrace{(\overline{X^f}(\hat{\beta^h} - \hat{\beta^f}))}_{\textit{Difference in returns of characteristics}} \tag{3.8}$$

Equations 9 – The Oaxaca-Blinder (OB) Decomposition

Oaxaca-Blinder is the first decomposition (or we can simply note Oaxaca decomposition) method used to explain the differences between two groups. Initially this method was

developed to decompose the wage differential between men and women on the labor market in two parts. The first one can be explained by observable variables (i.e. the level of education, level of experience) and a portion that can not be explained by observable variables. The method was developed simultaneously by Blinder (1973) and Oaxaca (1973) on two separate articles. In fact, this statistical method is a simple decomposition technique of the wage gap in the explained component (i.e. differences in characteristics), and unexplained component (i.e. differences in returns to those characteristics).

After this two publication, we underline the emergence of much research. This technique of decomposition has become a fundamental tool for studying inequalities differentials and discrimination, and was admitted to a judicial dispute about discrimination (Ashenfelter and Oaxaca (1987)). Miller (1987) introduces a modified version of the OB decomposition with ordered probit model estimation. Dolton et al. (1989), and Neuman and Oaxaca (2004) focus on the selection bias correction. In the same context Bourguignon et al. (2007) use a multinomial logit model to deal with the selection bias. But all these studies focus on the estimation of the difference in wage at the mean [11].

Machado-Mata Counterfactual Decomposition:

Machado-Mata decomposition method (Machado and Mata (2005)) allows the decomposition of the gap at each quantile of the distribution on two component: 1) a component due to differences in the distributions of returns (coefficients), and 2) a component due to differences in returns of these characteristics .

If we take the example of the urban-rural gap, we denote the counterfactual distribution by $V(Y_c\ z_u, b^r)$ where Y_c is log expenditure for generated values, z is the distribution of covariates, and b is the vectors of quantile regression coefficients. We denote that u and r designate urban and rural values. With reference to the machado-mata algorithm, the counterfactual function $V(Y_c\ z_u, b^r)$ is constructed following many stapes . The main objective of the decomposition is the counterfactual distribution with the reel urban and rural distribution. We present the difference between the two distributions as follows:

Machado-Mata algorithm decomposes the gap into two parts. The first one, refer to difference in characteristics (endowments) between urban and rural households. And the second refer to the differences in returns to these characteristics (coefficients effects) for

11. There are many other techniques (Lemieux (2006) , and Paarsch et al. (2006) ...)

$$Y_u(\theta) - Y_r(\theta) = \underbrace{\{Y_u(\theta) - Y_c(\theta)\}}_{\textit{Difference in characteristics}} + \underbrace{\{Y_c(\theta) - Y_r(\theta)\}}_{\textit{Difference in returns of these characteristics}} \tag{3.9}$$

Equations 10 – Machado-Mata Decomposition

the whole distribution. Then our counterfactual distribution gives us the log expenditure distribution that rural households would satisfy if they had urban characteristics. After the publication of Machado and Mata (2005), many studies focus on a more general counterfactual distribution. Machado-mata method is a special case of the general framework of Chernozhukov et al. (2013).

Recentered Influence Function (RIF):

RIF-regression is a convenient tool to conduct an OB type decomposition for other method besides the mean, such as quantiles regression. Therefore, when we perform quantile model, RIF-regression will be considered as rescaled linear model. According to this definition, rescaling factor relies to the estimate of the interest quantile density:

$$RIF(y, Q_q) = Q_q + \frac{q - \mathbf{1}\{y- \leq Q_q\}}{f_Y(Q_q)} \tag{3.10}$$

The interest distributional statistic can be written based on the conditional expectations of its recentered influence function: We can, then, performed an OB decomposition using

$$v(F_g) = \mathbb{E}_X[\mathbb{E}[RIF(y_g, v)/X = x]] = \mathbb{E}[X/G = g].\gamma^{v_g} \tag{3.11}$$

Equations 11 – Recentered Influence Function (RIF)

the RIF as response variable (dependent variable).

The General Chernozhukov-Decomposition:

At the beginning of this chapter, we discuss the fact that the yields of some characteristics are not the same through the conditional quantiles of the distribution of log expenditure. The most important point is that there is a clear difference between both urban and rural areas and the distributions of covariates differ between the two areas. Many types of decomposition were developed to analyze the gap between two groups [12], we have: With $F_{Y(u\backslash \mathtt{u})}$ and $F_{Y(r\backslash \mathtt{r})}$ the observed distribution functions for the urban and the rural areas. $F_{Y(r\backslash \mathtt{u})}$ is the counterfactual distribution functions of expenditures that would have

12. see Firpo et al. (2011) or Chernozhukov et al. (2013)

$$F_{Y(u\backslash \mathtt{u})} - F_{Y(r\backslash \mathtt{r})} = \underbrace{[F_{Y(u\backslash \mathtt{u})} - F_{Y(u\backslash \mathtt{r})}]}_{\textit{Difference in characteristics}} - \underbrace{[F_{Y(r\backslash \mathtt{u})} - F_{Y(r\backslash \mathtt{r})}]}_{\textit{Difference in coefficients}} \tag{3.12}$$

Equations 12 – The General Chernozhukov-Decomposition

prevailed for urban area had they faced the expenditure program $F_{Y_r\backslash \mathtt{X_r}}$:

$$F_{Y(r\backslash \mathtt{u})}(Y) = \int_{\chi u} F_{Y_r\backslash \mathtt{x_r})}(y\backslash \mathtt{x}) \mathtt{dF_{Xr}(x)} \tag{3.13}$$

With Y is the log expenditure and χu the support of urban characteristics.

We strat by considering two groups, I and J, that have characteristics given by a stochastic vector X_I for group I and X_J for group J. The realizations of these vectors is denoted by x_I and x_J. We also consider that X_I and X_J have distribution functions G_{X_I} and G_{X_J} and have dimension K. Assume that endogenous variable for group I is Y_I and Y_J for group J, associated to the unconditional distribution function F_{Y_I} and F_{Y_J}, respectively.

Many types of decomposition were developed to analyze the gap between two groups (see Fortin et al. (2011) or Chernozhukov et al. (2013)), although Chernozhukov et al. (2013) show that they rely on the same asymptotical properties. We choose the second one because of its implantation in Stata by Chernozhukov et al. (2012). Furthermore Chernozhukov et al. (2013) propose a variety of counterfactual distribution for the equation(4). In our case we use counterfactual distribution based on conditional quantile modems (Chernozhukov et al. (2013)).

We should not that we were not able to correct for the potential selectivity bias due to rural-urban migration. Indeed contrefactual decomposition makes the assumption that the localization is fully explained by our observables variables. But localization may depend on unobservable variables. But we are lacking instrumental variables in our data. This question could be the object of later research.

In the next section, we present the details of our decomposition method adapted to the context of poverty and inequality analysis between rural and urban areas in Tunisia.

Based on our results we try to explain the differences in poverty between the two areas. Finally, we conclude and present some recommendations.

3.4.2 Empirical Result

General Chernozhukov-Decomposition method

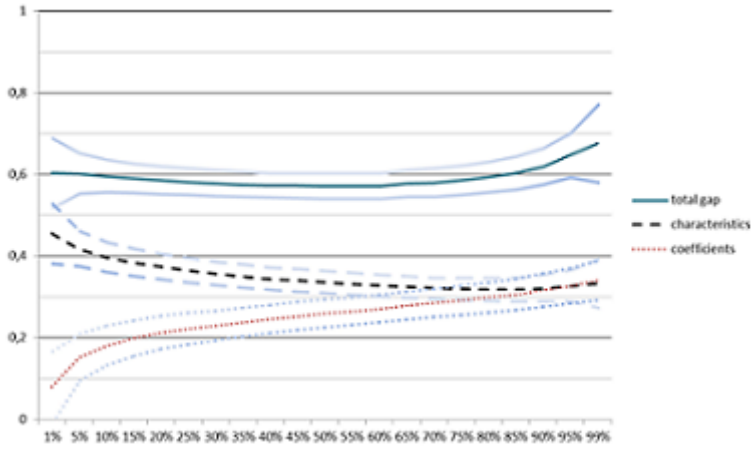


Figure 3.4 – Counterfactual decomposition of the rural-urban gap (*Lecture*: 95% confidence interval)

The gap in equation (3.11) is decomposed into two parts. The first one refers to a difference in characteristics (endowments) between the areas. And the second refers to the differences in returns to the characteristics (coefficients effects) for the whole distribution. Then, our counterfactual distribution gives us the log expenditure distribution that rural households would satisfy if they had urban characteristics. Figure3, shows returns and characteristics effect across all the distribution. We note that the total gap is increasing in the higher level of welfare distribution.

Following Melly (2005), Chernozhukov et al. (2012) we propose to test the effects of residuals using a Kolmogov-Smirnoff test of the equality of distribution. We can not reject the hypothesis of an effect of residuals equal to 0 (p-value>0.11). Therefore no important variable explaining the gap between rural and urban areas seem to have been missed. This may explain the difference between our results and a previous study (Hassine (2015)). In order to establish systematic comparison across different countries, Hassine (2015) did not include some explanatory variables that are not available in some national survey. Therefore important and significant variables such as housing or foreign transfer have been

omitted in her paper. We provide a more reliable decomposition [13]. We observe that the gap is higher in the tails of the distribution (the richest and poorest households) (see table 7). For characteristics effect (endowments), it is much higher in the 5^{th} Percentile (42%) and it decreases with the distribution (33% in the 95^{th} Percentile). In contrast, returns (proportion due to coefficients) increases gradually (from 15% to 33%). That is logical, since the poorest people in rural areas suffer from poor infrastructure and lack of resources (labor market, schools, leisure means, etc.) compared to the urban area. We note also that the gap is great in higher quantile with the same level of both coefficient and characteristics effects. This finfing can be explain by the fact that this part of the distribution represent the rich population. They represent great employees or wealthy people who have a very high level of education and well-being.

These results also show that the gap is explained by only coefficient effects and returns effects, since the residuals effect is not significant effect for most quantile.

Table 3.7 - urban-rural gap estimate

	Raw Gap	Coefficients Effects	Characteristics Effects	Residuals Effects
5th Percentile	0,601823*	0,151049*	0,417113*	0,033661
10th Percentile	0,595731*	0,181029*	0,396819*	0,017884
25th Percentile	0,581305*	0,221906*	0,364286*	-0,004888*
50th Percentile	0,571688*	0,259256*	0,336543*	-0,024111*
75th Percentile	0,585155*	0,291642*	0,319868*	-0,026355
90th Percentile	0,619629*	0,326897 *	0,320544*	-0,006632

*: coefficient is different from 0 at 95%

In sum, this result proves that coefficients effects are greater in higher quantiles. This finding conducts us to bring some explanations. In fact, investing a lot more in education (that is the characteristics effect) able us to create economic growth and then decrease poverty and have a more equitable society. But, in reality, it 'is not the case for the whole population. The cycle of poverty (and inequalities) in rural zones continuous because too fewer profits go to poor rural areas relative to urban one. Recognizing the important role of education in the development of human resources in general and therefore in the fight against poverty and inequalities, states should place the education at the center of their objective for the fight against these scourges. If we allocate more resources (more qualified teachers, computers, internet etc., that is an endowment effect) to the poorest

13. Difference can also attributed to a definition of the expenditures (more restrictive in Hassine (2015) and the use of RIF regression that may lead to local approximation issues (Firpo et al. (2011)).

areas, the most marginalized people will have a chance to benefit from education, whatever the quality of the educational system. Otherwise this results prove that the problem is not only about equality but also it is an equity issue. Such equity, implies that policy of fighting against poverty and inequality should be based on positive discrimination in favour of marginalized areas.

RIF-regression method

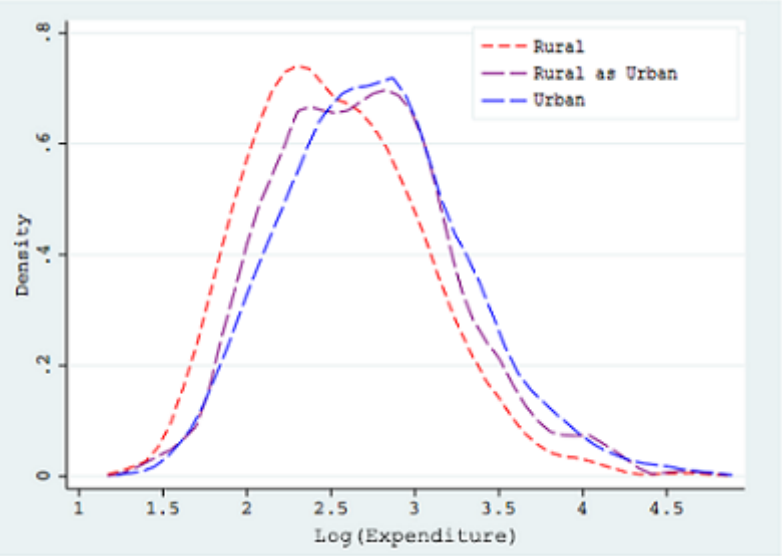


Figure 3.5 – Densities of urban and rural expenditures

When we perform rural density with urban characteristics, we found a graph very close to the urban one. This means that the gap will be reduced when we attribute the same characteristics in both urban and rural zones.

Results show, that poverty gap between poor rural and poor urban households may be explained by the constant term of the coefficient effect (14.8%) [14]. This is mean that, even with urban characteristics, poor rural households will suffer from a poverty gap of arround 9.36% from urban households.

Our results show that differences in the type of employment and education explain, respectively 4.58% and 18.32% of the poverty gap between rural and urban areas for the

14. coefficient effect is significant only in the 10^{th} percentile which represent the poorest parts of the distribution

poorest households. Similarly, if the conditions of the labor market in rural areas were similar to those of urban workers, the poverty gap could be reduced by 3 percentage points. The main reason which may explain why rural households are poorer than urban households in Tunisia come from the education variable which .

Finally, poverty gap decomposition between rural and urban areas enables us to conclude that the actions to be taken in Tunisia should be focused on the "reduction" of existing differences in the characteristics of household heads as education level or type of employment. However, coeficient effects prove that difference in households characerisics are not enough to reduce the gap between rural and urban poverty.

Table 3.8 - Urban-Rural welfare gap (RIF-regression)

	10^{th} percentile		50^{th} percentile		90^{th} percentile	
	estimated	std	estimated	std	estimated	std
Reference Group: Urban Coef.						
Estimated log expenditure gap: E[RIF_q (ln(Exp^u))]-E[RIF_q(ln(Exp^r))]	-0.633***	(0.023)	-0.564***	(0.018)	-0.614***	(0.025)
Composition effects attributable to						
Age, gender, household size, foreign transfer and logement	-0.069***	(0.021)	-0.071***	(0.015)	-0.075***	(0.021)
West region	-0.070***	(0.011)	-0.077***	(0.007)	-0.056***	(0.011)
Education	-0.116***	(0.020)	-0.117***	(0.013)	-0.156***	(0.020)
Employment	-0.029**	(0.013)	-0.034**	(0.009)	-0.035**	(0.014)
Agregated characteristics effects	-0.297***	(0.030)	-0.314***	(0.021)	-.614***	(0.025)
Regional structure effects attributable to						
Age, gender, household size, foreign transfer and logement	0.494	(0.319)	-0.079	(0.224)	-0.036	(0.353)
West region	0.031**	(0.013)	0.003	(0.009)	0.017	(0.014)
Education	-0.116***	(0.020)	-0.084**	(0.033)	-0.148***	(0.051)
Employment	0.075**	(0.031)	0.041*	(0.021)	0.040	(0.033)
Constant	-0.0936***	(0.330)	-0.073	(0.232)	-0.117	(0.366)
Agregated coefficient effect	-0.335***	(0.036)	-0.249***	(0.024)	-0.277***	(0.037)

our computing usind households well-being data 2010

standard errors are in parentheses and(*** significant at 1% ,** significant at 5%,*significant at 10%)

3.5 Conclusion and recommendations

We examine the disparities in living standards in rural and urban areas. Our empirical analysis relies on the Tunisian Living Standards Surveys of 2010. In order to analyze the gap between the two regions, we applied counterfactual decompositions based on quantile regressions in order to treat the potential endogeneity of localisation choices. We also use censored and uncensored quantiles regressions for disaggregate consumption expenditures. This study offers another analysis of the influence of some indicators such as health, food expenditures and especially education on regional disparities in developing countries. It also examines the relationship between education and development disparities across the two areas. We found that welfare (consumption) disparities can be explained by differences in characteristics (gender of household head, size of household...), and in particular education. Our methodology also suggests that the characteristic effect (that is objective characteristics, mainly the structure of the education system) is increasing and dominant for households at lower welfare distribution, while the returns effect (efficiency of educational system for identical characteristics) is higher for wealthier households.

We performed a mean and quantile regression for the whole sample. Our goal is to see if rural areas have, on average, a lower consumption compared to urban areas, and we went on to compare results for all quantiles. Then we separated the overall sample into two subsamples for urban and rural data. Thus we estimate two models with OLS and quantile regression in order to separate the effect of each variable on both urban and rural areas.

This chapter makes a new contribution to existing literature. Using the last available detailed data, we estimate disaggregated expenditure using a censored and uncensored quantile estimator. This estimation gave us a more detailed picture of welfare inequality between rural and urban areas. Indicators can show reliably differences in people's well-being between urban and rural areas. As a result, we assert that education has a much deeper impact on people's lives than had been previously suggested. We conclude that development is based not only on economic growth, but also on achieving social objectives such as promoting equality in education.

Finally, we used counterfactual decomposition to discover if differences in ob served consumption expenditure between urban and rural regions are due to differences in characteristics or if they are due to coefficients effects (returns effects). We show that the return to education is higher in urban region than in rural region with the highest difference for

the lowest quantiles. The issue of equitable access to education, especially the higher level, is probably a real issue that must be addressed as part of an overall review. The fight against social and regional inequalities is not just a matter of equity, but also is a question of economic development. As advocated by previous studies (see for exemple Fesselmeyer and Le (2010)). The rule for development is found in the country's human resources . This is true across all countries and regions of the same country. Deprived areas will not know real development without the development of its human capital. It will not serve to implement projects and invest if these areas do not have a human capital capable of leading the development. We should know that the development of social groups and deprived regions inevitably involves a strategy to reduce regional education inequality.

By decomposing the gap between urban and rural area, this study shows that the problem is not only about equality but also it is an equity issue. Such equity, implies that resources should be allocated equally between areas with regard to the quality. Therefore, the counterfactual decomposition used in this study may be an appropriate tool that can help policymaker to assess regional inequality. But it remains incomplete as for a social phenomenon, such as inequality, a dynamic analysis is required. So a dynamic model used to measure and evaluate the gap between the two areas over time, can provide effective solutions in terms of social welfare, an issue left for the next chapter.

Chapter 4

Poverty dynamics analysis using potential outcomes approach and multiple imputation: A new proposal

4.1 Introduction

For its socio-economic challenges, poverty is considered as a serious concern of public authorities. In fact, it is one of the biggest issues faced by various society in the current world. It's consequences vary depending on the region of the world, starting from social exclusion to malnutrition and death. Several essays have been made in terms of studies and researches to understand the phenomenon. The fight against poverty using individual living environement improvement programs constitutes nowadays a remarkable leitmotif. The reason for choosing such a subject is justified by the scale and urgency of the problems related to individual poverty conditions. However, despite the considerable improvements in poverty reduction policies over the world, some elements of individuals (households) deprivation are not sufficiently explored in developing countries, which may handicap effective policy against poverty.

The concept of poverty persistence is an important issue to understand poverty dynamics. According to this approach individuals who have experienced poverty in the past have a higher probability to be poor in the future. According to Heckman (1978) the persistence of some economic phenomena is caused by individual heterogeneity or the past experience of these phenomena. In the same reasoning, Cappellari and Jenkins (2002) and Biewen (2009) introduce this approach in poverty persistence. Mainly this heterogeneity comes from the difference in individual's characteristics which increases the chance of living the experience of poverty repeatedly. Evidently, some characteristics are observable and able us to perform empirical analysis. The difficulties come from the unobservable characteristics which necessarily influences the status of poverty. Among these characteristics, we mention the culture of poverty, risk attitude, etc. Moreover, Dutta (2015) examines the welfare household dynamics by identifying the nature of poverty trap, even single or multiple.

Furthermore, although the reducing of poverty in the world remain major challenges in developing countries due to the absence or scarcity of data. Some authors have tried to overcome this difficulty through a cross-sectional analysis. Gibson (2001) measure chronic poverty in Papua New Guinea without a panel data using a decomposed cross-sectional poverty method. Mehta and Shah (2001), Okidi et al. (2002) and many other authors determine chronic poverty on the basis of household surveys. They have used information about household living standard to distinguish between chronic and transient poverty. Several economists, such as Bourguignon et al.(2004), Gibson (2001) and Suryahadi and

Sumarto (2003), used different methods to estimate the dynamic aspect of poverty without recourse to panel data. However, Bourguignon's study analyzed vulnerability to ex-ante poverty, it was not intended ex-post analysis of the determinants of mobility entering-exiting of poverty. In fact, this is the difference between vulnerability and poverty study's. But when having two or more cross-sectional surveys, we can compare the values of poverty index calculated on the basis of each survey. In this case, we can only analyze the variation of poverty aggregate characteristics over time. Therefore, we are not able to follow poor individuals over time. The solution proposed by Deaton (1985), Browning et al. (1985), Gardes et al. (1996), Alessie et al. (1997), Gardes and Loisy (1998) and Beaudry and Green (2002), is to create panels data from averages information and taken cohorts (classified according to criteria that ensuring some homogeneity) as units. In fact, this technique allows finding some advantages of panel model. As the ability to model the dynamic effects, while avoiding the problem of "attrition", cited by Baltagi and Li (1995), Ermisch and Jenkins (1999) and Deaton (1997), which corresponds to the loss of individuals over time. However, the disadvantage of this method is that it can not able us to analyze poverty dynamics within groups, so we can not distinguish chronic poverty from transient poverty within each cohort. Perhaps because of this point pseudo-panel models have not been broadly applied to analyze poverty dynamics.

In particularly, in Tunisia, the analysis of poverty with pseudo-panel data was applied by Ben Rejeb (2008). The author has concluded that in addition to the arbitrary nature of poverty, the scope of application of pseudo-panels with Tunisian data has various significant limitations. Indeed, he said that, as indicates by Serge (2000), the poor have not the same conditions that is why we should apply a finer stratification. But he has not used this proposition due to the nature of the data. In addition, he believes that poverty has a multidimensional character. The last years have been marked by significant efforts to analyze and fight against poverty. In fact, the evolution of poverty in Tunisia shows a decline in urban poverty, but in rural areas, poverty remains relatively stable over the same period (report, 2010). Rural populations are the most remarkably affected by poverty. The implementation of effective socio-economic policies therefore depends on better understanding explanatory mechanisms of poverty in these areas.

In addition, poverty studies in Tunisia have demonstrate that some groups of the population are more exposed to poverty than other such as: households that live in west region,

illiterate individuals, etc.(INS [1], report). In addition, according to the INS's statistics, the poverty rate decreased from 23% in 2005 to 15% in 2010. This remarkable reduction in poverty seems to us unjustifiable and it may be biased, since there are no reasons that can explain this reduction. In our case where information is incomplete through time and surveys are not in form of panel data, we consider an alternative "potential outcomes" or "counterfactual" approach [Splawa-Neyman et al. (1990), Rubin (1974), Rubin (1987)] combined with multiple imputation to get around this problem. In fact, our proposition is to impute potential variables able to run a longitudinal analysis. The method allows multiple imputation of an entire blocs of interest variables. This study presents a contribution to the extant literature about poverty dynamic studies in the case of independant surveys. Moreover, our study examines the trajectories of poverty based on the distinction between chronic and transient poverty on a rural-urban disparities context: These distinct forms of poverty, do they have specific determinants that would justify the implementation of different policies ?

The rest of the chapter is organized as follows. We will begin by providing some background knowledge (section two). We present the proposed framework in section three. The data source and the econometric modeling is described in section four. In the fifth section, we will discuss the extent of poverty and regional disparity over time. And finally, the sixth section concludes.

4.2 Background and related literature

Literature about poverty dynamics presents several approaches aim to analyze this phenomenon in order to find the best effective policy. Later, in this section, we will try to present the principal approaches about poverty dynamics.

4.2.1 Longitudinal studies: A chronic - transient poverty approach

These studies suggest that the analysis of poverty dynamics can be performed using the whole sequence information about the living standards of individuals to define and distinguish transitory poverty from chronic poverty. The majority of these studies, involving a chronic-transitory distinction, uses panel data and focuses on the living level indicators

1. All information are vailable on www.ins.nat.tn/indexfr.php

such as the level of consumption or within household income. However, it is important to remember that this distinction between chronic and transient poverty is also relevant to study the non-monetary dimensions of poverty using panel data. In this point, we may remember the importance of this distinction in nutrition levels or children's schooling, especially in studies focusing on developing countries (McKay and Lawson (2002)).

A conventional method in these studies, to identify the permanent component of the living standards of a household, is based on the estimation of intertemporal average level of income or consumption (Jalan and Ravallion (1998); McCulloch and Baulch (1999); Carr-Hill et al. (1998)). So, let be $(y_i1, y_i2, ...Y_id)$ different levels of income (or consumption) of a household at d dates in time [2]. An intertemporal measurement of poverty for household i is then given by $P(y_i1, y_i2, ...Y_id)$ where P(.) represent a measure of poverty. According to Ravallion (1988)), the transitory component $T(.)$ Of $P(.)$ can be defined as a part of P caused by transient variations in the level of income: $T_i = P(y_i1, y_i2, ...Y_id) - P(E_{y_i}, ..., E_{y_i})$, where E_{y_i} is the the expected value of the intertemporal level of the income of household i, and then we define the chronic component of observed poverty as: $P(E_{y_i}, ..., E_{y_i})$. Housholds (individuals) are defined as chronically poor if the level of average income, throughout the period of analysis, is below the fixed threshold [3]. And they may be classified as transiently poor if their average income is above the poverty threshold. Recently Duclos et al. (2006) developed a variant of this method to distinguish the permanent and transitory components of poverty through a measurement known by the Equally-Distributed Equivalent (EDE) poverty gap. In other words, we measure the poverty gap as might have, distributed equally among individuals and periods, it would produce the same level of poverty as the one given by the distribution of observed poverty gaps.

4.2.2 The variance decomposition studies

This approach enables a decomposition of income dynamics between permanent and transitory components using the full distribution (not just the tail of the distribution which defined the poor). Lillard and Willis (1978) are the first to use these models in order to analyze the dynamics of poverty. These authors used only wage income data and focused

2. y_{it} corresponds to any measurement of household living standards, normalized to reflect different demographic compositions within households (this refers to the equivalence scales) and if necessary taking into account the differences in price levels (purchasing power parity)

3. The use of non-dichotomic measures of poverty is also possible, such as chronic poverty gap by measuring the distance from this longitudinal average to poverty line

on the dynamics of low wages. Since this study, a large literature has developed. A review of the early work on the analysis of labor mobility can be found in Atkinson and Bilger (1992). The first applications of these models to the question of poverty dynamics, using household income data as the dependent variable, were due to Duncan (1983) and more recently, Duncan and Rodgers (1991), Stevens (1999), De vincenti (2001) and Biewen (2005), etc.

In fact, The basic model of variance decomposition considers the income of an individual i in time t as a $log - normal$ function of the determinants, which may be either invariants over time (Z) or it changes over time (X):

$$log(Y_{it}) = Z_i\alpha + X_{it}\beta + \epsilon_{it} \tag{4.1}$$

with $\epsilon_{it} = \sigma_i + V_{it}$ and $V_{it} = \gamma V_{it-1} + n_{it}$

In addition to observable explanatory factors, ϵ_{it} can be also decomposed on a permanant component σ_i and a transitory component V_{it}. The objective of this decomposition is to appear an unobservable heterogeneity term specific to household, and a residual term. This residual term takes into account the fluctuations unexplained by the other variables and the measurement error in the standard of living. In this model, γ allow us to capture, on the one hand, the random effects of shocks and on the other hand, the non-observable characteristics of individuals, knowing that the two effects may be correlated. But several alternative hypotheses can be established from the structure of V_{it}. Indeed, if we have an enough number of observation some flexibility in modeling unobservable heterogeneity V_{it} is then possible (we may introduce a terms in trend, quadratic, a structure of autocorrelation of errors with a superior order than the Simple AR(1) described here). The choice and the degree of complexity of the model are thus limited by the number of waves available in the used panel.

Variance decomposition models have some advantages. First of all, it able us to analyze income variable without requiring to use a dichotomic poverty measure, determined from a poverty threshold, that must necessarily be fixed arbitrarily, which wasted some information. On other side, the continuous nature of the dependent variable also allows us to use econometric methods of estimation that exhibits less technical difficulties. But these models also have some disadvantages. In particular, the studies of Stevens (1999) on the United States and De vincenti (2001) on the Great Britain show that these models

are less efficient than the time models (Bane and Ellwood (1986)), in terms of predictive power of poverty profiles, when they are estimated on the entire population. Instead of using the same process to characterize individuals initially heterogeneous, it would be possible to improve the fit of the variance decomposition models by focusing on specific sub-populations, such as young workers (Jenkins et al. (2001)).

4.2.3 Studies of transition probabilities with time models

One of the most used methods to analyze poverty episodes, is the time or survival models. This approach have a dual purpose: first, it aims to analyze the duration of these episodes, and secondly, to study the transitions from one situation to another (ie. the events of movements into and out of poverty). Since, its rarely that panel data allow us to reconstruct economic situation of households throughout their life cycle, several methodological problems arise in the analysis of duration.
In multivariate survival models, the probabilities of exit/entry (or return) in poverty are estimated using a set of standard variables that capture the general characteristics of the household. Thus, according to Jenkins et al. (2001) the exit probability is defined as:

prob(individual "i" is not poor in date t \ individual "i" is poor in date t-1, $X_i t$, Z_i, γ)

and the entry (or return) probability is defined as:

prob(individual "i" is poor in date t \ individual "i" is not poor in date t-1, $X_i t$, Z_i, γ),

where Z_i is the unchanged characteristic over time, $X_i t$ represent the characterustic which changes over time (here we can include the duration) and γ is a vecteur of parameters. To explain why comparable households in terms of socioeconomic and demographic characteristics have different poverty paths, a set of event variables is sometimes included ($\delta X_i t$).
The first application of duration models for dynamic analysis of poverty was proposed by Bane and Ellwood (1986) for the United States. The use of this models allowed them to distinguish a list of economic and demographic events correlated with poverty transitions. Indeed, and following the work of Bane and Ellwood (1986), Jalan and Ravallion (1998) proposed a hierarchy of events linked to poverty transitions. He suggests to examine as a

first step, following a change in household head, what type of demographic change may be associated with the transition in poverty. For households that did not changed the head, the idea is to compare the evolution of needs relative to monetary income with specifying the most contributed source. Among the factors related to changes in income, we may cite the variations of the head of household incomes, those of the spouse, those related to labor income or other types of income (transfers, capital income, etc.). Demographic changes result in the arrival of new members either by birth, marriage, arrival of other related-family and unrelated or by decreasing the size of the household due to the death of a member, to rupture of the couple or other members who have left home (Herrera and Roubaud (2003)).

Subsequent studies have addressed some of the limitations of Bane and Ellwood (1986) work, especially the fundamental need to include multiple episodes of poverty in the modeling of poverty transitions. we can cite, among others, Stevens (1999), Cantó (2003), Schluter (1998), Jenkins et al. (2001) and De vincenti (2001).

However, the time models (or duration models) are not without disadvantages. As the explanations of Aassve et al. (2005), these models are not able to model demographic or labor market interactions. For example, although the approach of these models is essentially dynamic, some invariance assumptions of the explanatory variables are needed. Thus, the characteristics of X_{it} that may vary over time, are only considered unchanged between different episodes (transitions) [4]. Another problem of these models is their inability to distinguish and identify the different events that are simultaneous.

4.2.4 The Markovian chains models

Cappellari and Jenkins (2004) proposed a method that serves to complete the time models and variance decomposition models. They provide an estimation of the determinants of low incomes transitions through a first order Markov chain model which takes into account the problem of "initial conditions" (individuals which were considered poor in the initial period are not necessarily drawn with a randomly manner), this model also evokes the problem of attrition (ie. the permanence in the longitudinal data of the panel may also be non-random). The model considers transitions out of and into poverty between two consecutive periods "t" and "t-1", using a trivariate probit. In fact, it characterizes the determinants of persistent

4. this is not the case when the individual is in non-poor episode

poverty and the probability of entry into poverty as a combination of four components: 1) determining poverty status in period t-1 (to take into account the initial conditions problem), 2) permanence in the panel (for attrition), 3)determining the poverty status in period t and 4) correlations with the unobservable characteristics. This method also has some disadvantages, especially, the dynamics of poverty is modeled only through a first order dynamics (from "t-1" to "t") and thus the method underestimates the duration and the persistence of poverty.

4.2.5 Structural models

The last method, that we will present here, which serves to explain the dynamics of poverty is structural models [5]. As its name suggests, their purpose is to model the training process of the level of household income, through the inclusion, in the model, of the existing various structural relations with its determinants. Instead of just linking transitions out and into poverty with the various events that determine the level of household income (marriage, divorce, fertility, participation in the labor market), it is now time to model them. When these events can not be considered as exogenous to individuals, it is insufficient to treat them as simple factors explaining transitions in poverty. In addition, a similar approach to that of Bane and Ellwood (1986) identifies in each case an associated factor with transitions in poverty, but it does not model the relationship between different events which sometimes are simultaneous. When this is the case, the choice of the event that will be considered responsible is totally arbitrary. The hierarchy of events Bane and Ellwood is to consider any change of household head as the primary cause. But these behaviors could also reflect reactions or expectations of individuals to other shocks (for example, to employment shocks, etc.).

In the decomposition methods of the variance in Lillard and Willis (1978), there is a modeling effort wage equations (referring to the theories of human capital).

5. The difference between structural and non structural model resides in the fact that, in the first case, the explicatives variables is explained by other variables (endogenous variables) and, in the second case we consider that the variables are exogenous (ie. don't dependent to other variables).

4.3 Multiple imputation of missing data: The causal inference problem

"For over three decades, I have believed that all problems of causal inference should be viewed as problems of missing data: the potential outcomes under the not-received treatment are the missing data. A straightforward and valid way to think about missing data is to think about missing data is to think about how to multiply impute them."

D.R. Rubin,
Direct and Indirect Causal Effects
via Potential Outcomes

Missing data is an unavoidable problem in the practice of statistics. In fact, most statistical methods can not be directly applied on an incomplete set. However, simple imputation, remains a limited method in the sense that it does not take into account the uncertainty of imputed data. Thus, if a statistical method is applied to an imputed set the variability of the estimators will be underestimated. To solve this problem, we can perform multiple imputation (Rubin (1987), Little and Rubin (2014)). In this case more values are predicted for each missing data, which leads us to consider several imputed table. Thus, inter-imputation variability reflects the prediction variance for each missing data. When the tables are imputed, we apply the statistical method on each of them and then aggregates the results according to the rules Rubin (Rubin (1987)) to obtain an unique estimates for the parameters of the method as well as an estimate of the variability associated. The model is based on an assumption of normality $I \sim \mathcal{N}_k(\mu, \sum)$ and therefore requires some preliminary transformations of data.

Rubin counterfactual model is based on two basic concepts: the causal statements and potential responses. Causal statements are also called treatment in the tradition of the counterfactual causal analysis. Each unit of analysis of a study should potentially be found in any of the examined causative states. This approach is close to the matching method in which researchers apply a treatment to a group in order to compare it with another group that did not receive the treatment. Random assignment of an experiment ensures that each unit of analysis will be potentially found in a causal statements Little and Rubin (2014). Conceptually, fifty percent of the information is not observable. This is a missing data problem.

4.3.1 Potential Outcomes approach (Rubin Causal Model) and Missing data

With reference to the notion proposed by Gelman et al. (2014), we can note that an observation is considered to be MAR (Missing At Random) if and only if conditional to the observed value the probability of missingness is unrelated to the unobserved value.

$$P_r(I\backslash y, \Phi) = P_r(I\backslash y_o, y_m, \Phi) = P_r(I\backslash y_o, \Phi) \tag{4.2}$$

here y is the total of y_o and y_m respectively defined as the observed and the missing part of y, I an indicator variable wih $I = 1$ if y is observed and $I = 0$ if y is missed, and Φ the parametes ruling the mechanism of missing data.
Knowing that θ represent the parameters of the proposed data model, we have: Following

$$P_r(y_o, I\backslash\Phi, \theta) = P_r(I\backslash y_o, \Phi)P_r(y_o\backslash\theta) \tag{4.3}$$

Equations 13 – Missingness problem

this notation, we assume that $y_o = (y_{o,1}, y_{o,0}), y_m = (y_{m,1}, y_{m,0})$ and finally I can be seen as the indicator choice of the treatment.
As a result to our presentation, we can assume that potential outcome framework makes it possible that causal inference can be regarded as a particulary case of missing data problem, as presented below (Gelman (2011)).

Table 4.1 – Illustration of missing data among potential outcomes

Treatment Status	Y(2005)	Y(2010)
T = 2005	Observed	Not observed
T = 2010	Not observed	Observed

4.3.2 Amelia technique: bootstrap-based EMB algorithm

Potential outcome framework demonstrates that we can treated causal inference as a particular case of missing data problem (Piesse et al. (2010)).
Following Gelman et al. (2014) we suppose M to be the indicator matrix of missing data and $\gamma = (\mu, \sum)$ the parameters of the model. We assume that the data are in MAR [6](Missing

6. In the case of missing at random (MAR) data, the probability of absence is related to one or more other observed variables (Rubin (1987))

at random), and we use the amelia II algorithm to impute the missing variable. This algorithm combines the classic algorithm (EM) [7] with the bootstrap approach (figure 4.1). Let M be the indicator matrix of missing data and $\gamma = (\mu, \sum)$ the parameters of the model.

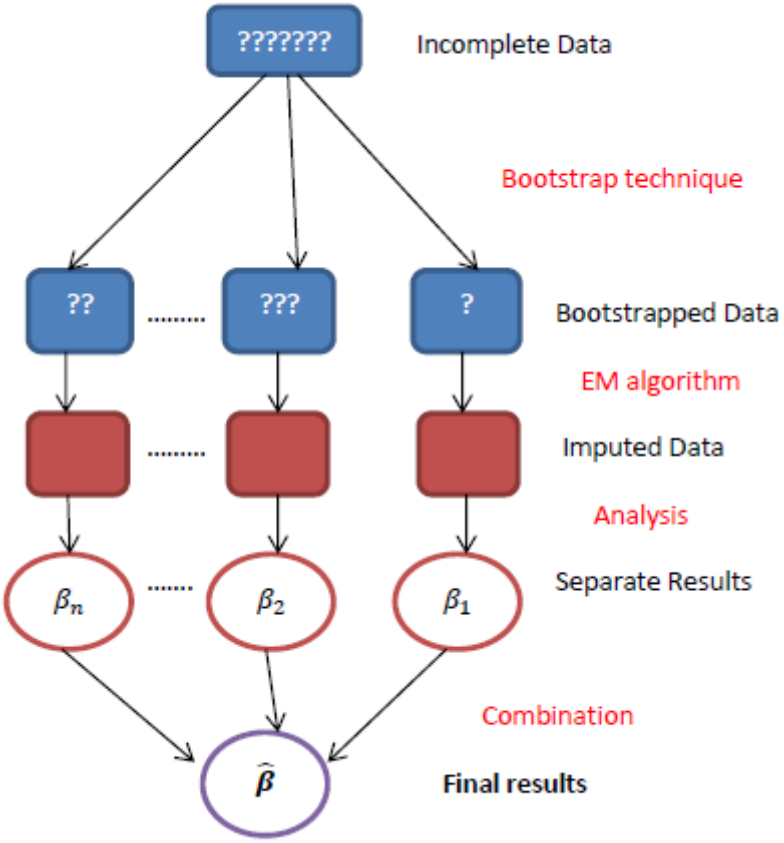


Figure 4.1 – Schematic of the multiple imputation approach with the EM-Bootstrap algorithm

We assume that the data are in MAR [8] (Missing at random), we have therefore

This programm combines the classic algorithm (EM) with the bootstrap approach, we assume that:

$$p(I^{ob}, M \backslash \gamma) = p(M \backslash I^{ob}) p(I^{ob} \backslash \gamma) \tag{4.4}$$

we write the likelihood as follow:

$$L(\gamma \backslash I^{ob}) \propto p(I^{ob} \backslash \gamma), \tag{4.5}$$

7. The classic algorithm of maximum of likelihood (Dempster et al. (1977))
8. In the case of missing at random (MAR) data, the probability of absence is related to one or more other observed variables (Rubin (1987))

and

$$p(I^{ob}\backslash\gamma) = \int p(I\backslash\gamma)dI^{mis} \tag{4.6}$$

the posteriori law is then defined

$$p(\gamma\backslash I^{ob}) \propto p(I^{ob}\backslash\gamma) = \int (I\backslash\gamma)dI^{mis} \tag{4.7}$$

The EMB [9] algorithm of Amelia II combines the classic EM algorithm with a bootstrap approach. For each draw, the data are estimated by bootstrap in order to simulate the uncertainty, and then the EM algorithm is executed to find the posterior estimate $\hat{\gamma}_{MAP}$ for bootstrapping data (figure 4.1).

Diagnostics and Tests

Choice of the number of imputation :

How many imputation to use, is the question we are asking before execute the algoriyhm. First of all, we must choose the number of imputation (m). This choice is not arbitrary, it has been a subject of several controversies. The classic choice is to work with a low number of imputation choosen in the basis of the missing information. This low number able to enlarge the estimate between-imputation variance "v" through the factor $\frac{1}{m}$ before computing our total variance: $T = \hat{U} + (1 + m^{-1})V$ (Van Buuren (2012), p. 49). In this context, (Schafer (1997), p. 107), argue that the intended additional resources to generate and reserve more imputations number would not be adequately spent. However, several authors looked in the influence of "m" on the final results. According to Royston (2004), the number of imputation must be "at least" 20. The author justifies this choice by the fact that the confidence interval also depends on the degree of freedom and evidently on "m". Besides that, Graham et al. (2007) proposes to use some sort of scale based on the proportion of missing data: when we have $P = (0.1, 0.3, 0.5, 0.7, 0.9)$ we must set $m = (20, 20, 40, 100, > 100)$, respectively ($P$ is the proportion of missing data).

Missingness Maps :

This procedure is among the most useful tools for identifying missing data in a database. It is a kind of map that explores missingness by visualizing the dataset in colors and grid. The column of the grid represent the variables and the rows the observations. Tis map

9. The classic algorithm of maximum of likelihood (Dempster et al. (1977))

allows a quick summary of the missing data (see appendix C).

Comparing densities test :

This test make possible the check of the feasibility of the imputation by checking the imputed values distribution to the observed values distribution. Evidently we can not assert, *a priori*, that the two distribution

Overimpute test :

This technique aims to assess the adjustment of our imputation. Overimputation diagnostic consists of sequentially treating each observed values as if they had effectively been missing. In fact, for each observed value we then generate an unlimited imputed values, as though it had been missing. Using Amelia program we can plot a 90% confidence intervals that able us to inspect the behavior of our imputation model (see a recent paper of Honaker et al. (2014) for more argumentation).

Overdispersed Starting Value :

If the used data in Amelia program has a weak behaved likelihood, the Expectation–maximization (EM) algorithm

4.4 Poverty Decomposition Approach's

It is generally recognized that poverty dynamics studies are required to deepen knowledge about poverty persistent, since static assessment have restricted explanatory power and can hide the root causes of persistent poverty. As described in the first section, there are a set of methodological choices to analyze poverty dynamics and it's trajectories, in this section we choose to deal with a poverty decomposition method. Our choice is based on the fact that there is a significant movement in and out of poverty as well as poverty itself, the analysis of the transitory and chronic component of poverty enables to around this issue.

4.4.1 The Jalan - Ravallion approach

Jalan and Ravallion (1998) proposed a methodology enables to decompose poverty into two components: chronic poverty, which reflecting the persistence of the phenomenon, and

transient poverty, identifying conjectural aspects. The implementation of this decomposition in the case of Tunisia, will help us to clarify our understanding of the phenomenon and to guide socio-economic policies.

The main categories of poor according to the Jalan-Ravallion (JR) approach were twofold: The first category represent the chronically poor, this is mean that individuals are poor at each date of the observed period (ie. the observed individual (household) has an income below a level z1 from the poverty line, throughout the observed period). The second one, is transient poverty, this is mean that individual have an average consumption above the poverty line but are sometimes poor. In fact, The average inter-temporal would be the permanent welfare and serve to assess the chronic nature of poverty while the residue would serve as a transitional welfare. Component method mentioned above needs to develop an indicator of individual economic well-being [10]. Consider y_i the level of welfare of household i, n total sample population and t represents the period.

Based on the P_α class of Foster, Greer and Thorbecke (FGT) [11] indices (Foster et al. (1984)), total poverty is measured [12] by:

$$P_\alpha(y_i) = \frac{1}{nt}\sum_{i=1}^{n}\sum_{j=1}^{t}(\frac{z-y_i}{z})^\alpha \tag{4.8}$$

For simplicity, we use the concept of *poverty gap* [13]. Then we have $g_{ij} = max\,[(1 - y_{ij}), 0]$. Total poverty function became then:

$$P_\alpha(g_i) = \frac{1}{nt}\sum_{i=1}^{n}\sum_{j=1}^{t}(g_{ij})^\alpha \tag{4.9}$$

Following the definition presented by Foster et al. (1984) where $\alpha = 0$ the proportion of the poor (n) in the total population in the period t. In the case where $\alpha = 1$, we obtain the average poverty gap and finally for $\alpha > 1$ is the poverty severity index [14]. Using FGT poverty indices, JR suggest a methodology enable to measure chronic and transient poverty. Firstly, they consider that $\widehat{\overline{y_i}} = \frac{1}{t}\sum_{j=1}^{t} y_{ij}$ reflects an estimate of the permanent income

10. following the previous chapters we choose to deal with consumer spending rather than income, for more details see section1 of chapter1

11. This class of indices have interesting properties of decomposability, for more details see the second chapter

12. To simplify the modeling, we assume that each income y_{ij} was normalized initially by the poverty line in period j

13. Using poverty gap is not necessary but it enable to simplify the modeling

14. Several economists have introduced the concept of Poverty aversion or a measure of inequality aversion when $\alpha \geq 0$

during the t periods (Jalan and Ravallion (1998)). They show that an estimate of the component chronic poverty of an individual i may be obtained by replacing his income, of the considered period, by the estimated Permanent income.

Chronic Poverty

Chronic poverty is define as extreme poverty, which extends over a long period of time, several years or even a lifetime. A person living in chronic poverty can not satisfy its minimum needs of food, clothing or housing. Such levels of poverty can be passed from generation to generation: this is called the Intergenerational Poverty. Poverty researchers have demonstrated that, people who live in transient poverty situation succeed to leave from the state of long-term poverty while others remain prisoners of the "poverty traps". In literature there are many factors that causes chronic poverty, such as regional disparities, environment degradation, poverty culture (figure 4.2), etc.

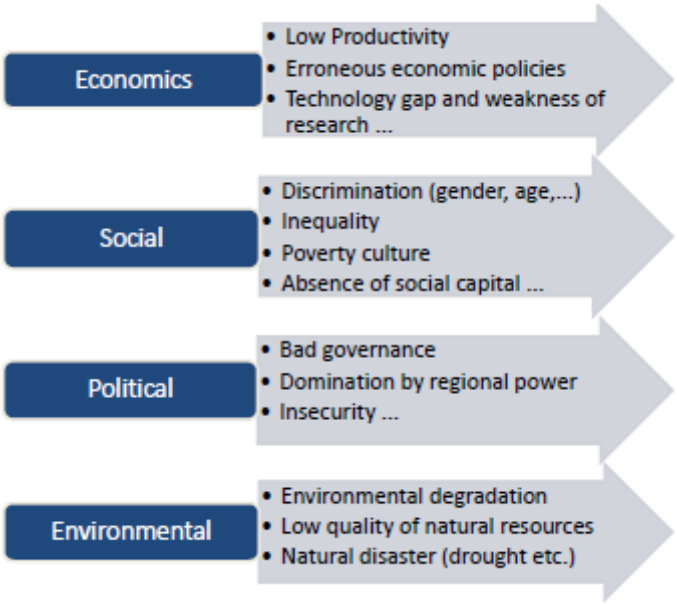


Figure 4.2 – Principal Causes of Chronic Poverty

According to the JR approach, we defined chronic poverty of the i^{th} individual as follows:

Thus we can deduced the overall function of chronic poverty:

$$p_{\alpha}^{c}(y_i) = max\,(\frac{1}{t}\sum_{j=1}^{t}(1-\widehat{\overline{y_i}})^{\alpha}, 0) \tag{4.10}$$

Equations 14 – Individual Chronic Poverty Function

$$P_{\alpha}^{C}(Y) = max\,(\frac{1}{n}\sum_{j=1}^{n}(1-\widehat{\overline{y_i}})^{\alpha}, 0) \tag{4.11}$$

Equations 15 – Agregate Chronic Poverty Function

Transient Poverty

Transient poverty defines a situation where individual has experienced at least one sequence of poverty and non-poverty in some periods of his life. The causes of transient poverty are primarily conjunctural and closely related to the situation on the labor market.
Transient poverty represents the difference between total and chronic poverty. We can now determine the transient component of poverty.

Moreover, using inequality rather than the incidence of poverty provides more robust

$$P_{\alpha}^{T}(Y) = P_{\alpha}(g) - P_{\alpha}^{C}(Y) \tag{4.12}$$

Equations 16 – transient poverty

results taking into account axiomatic properties of this index [15].
Based in data from the INS, we used these definitions, households are called chronically poor if their average consumption over the period is below the poverty line. However, the transitional poor households are those whose average consumption over the period is above the poverty line but for at least one period (year), the expenditure is below the poverty line.

4.4.2 Equally-Distributed Equivalent Poverty Gaps

An easy transformation of the FGT index gives us a useful and important measure of poverty. Following the development of Kolm et al. (2007) and Atkinson (1970), for a measure of social welfare and inequality, we denote by $\varphi_{\alpha}(g)$ EDE poverty gap, then we have:

15. The axiomatic appraoch which able us to define the quality of a poverty index was developed by Sen (1976b)

$$\varphi_\alpha(g)^\alpha \equiv P_\alpha(g) \tag{4.13}$$

Then we have:

$$\varphi_\alpha(g) = P_\alpha(g)^{\frac{1}{\alpha}} \tag{4.14}$$

Equations 17 – Equally-Distributed Equivalent Poverty Gap

If α =1, $\phi_1(g) = P_1(g)^{\frac{1}{1}} = P_1(g)$, we find the average poverty gap.

When we use poverty gap as indicator we do not take into account inequality in poverty.

Table 4.2 – EDE- FGT Index for region and sex variables

Group	$\alpha = 1$	$\alpha = 2$
Region		
Greater Tunis	0.0182	0.0754
	(0.0024)	(0.0083)
North East	0.0445	0.1265
	(0.0036)	(0.0072)
North West	0.1261	0.2344
	(0.0058)	(0.0072)
Middle East	0.0316	0.1116
	(0.0030)	(0.0073)
Middle West	0.1606	0.2774
	(0.0062)	(0.0072)
South East	0.0722	0.1779
	(0.0057)	(0.0090)
South West	0.0725	0.1684
	(0.0052)	(0.0081)
Sex		
Women	0.0846	0.2001
	(0.0055)	(0.0083)
Men	0.0717	0.1746
	(0.0018)	(0.0030)
population	0.0731	0.1776
	(0.0017)	(0.0028)

These considerations suggest a measure of poverty corrected from inequality, which should not be less than φ_1 in order to obtain a poverty measurement sensitive to the presence of inequality among poor.

$$C_\alpha(g) = \varphi_\alpha(g) - \varphi_1(g) \tag{4.15}$$

Where $C_\alpha(g)$ is the cost of the average poverty gap that a social decision maker would pay to eliminate all inequalities in the distribution of poverty gaps, without any change in total poverty and should be non-negative (Atkinson (1970)).
Then we can whrite total poverty as follow:

$$\varphi_\alpha(g) = \varphi_1(g) + C_\alpha(g) \tag{4.16}$$

Equations 18 – total poverty

The cost of inequality is then defined as the distance between $\varphi_\alpha(g)$ and $\varphi_1(g)$. Total cost of inequality can be divided into two components: *between*-inequality cost and *within*-inequality cost.

$$\underbrace{\ln\left(C_\alpha(g)\right)}_{Total\ Inequality} = \underbrace{\ln\left(C_\alpha(\tau_\alpha)\right)}_{Between\ Individuals} + \underbrace{\ln\left(\varphi_\alpha^T(g)\right)}_{Within\ Individuals} \tag{4.17}$$

Equations 19 – cost inequality

Transient and chronic poverty with the EDE poverty gap approach

Following Araar (2012), Araar and Duclos (2007), Jalan and Ravallion (1998), we consider:

$$\gamma_\alpha(g_i) = (t^{-1}\sum_{j=1} g_{ij}^\alpha)^{\frac{1}{\alpha}} \tag{4.18}$$

Taking into consideration the cost-inequality approach, we deduce a measure for the cost inequality of the transient component as follow:

$$\mu(g_i) = \gamma_\alpha(g_i) - \gamma_1(g_i) \tag{4.19}$$

we consider that, for each $\alpha \geq 1$, $\mu(g_i)$ is non-negative. According to this approach, we can interpret the EDE gap (γ_α) .
It is also widely recognized that these methods are very sensitive to the presence of measurement error (Rendtel et al. (1998)). A similar concern arises when only a relatively small number of observations of time is available for each individual over time and when the estimators of interest are non-linear over periods of time. In the next paragraph we

will present some statistical procedures enable to correct bias measurements.

4.4.3 Statistical procedures: Bias Correction

In the previous sections we presented the decomposition method using two approaches that aim to define the dynamic concept of poverty. The JR's approach defined on the basis of the FGT indices. As for the approach of Araar et al. (2013) is based on the concept EDE poverty gap.

These approaches can be easily implemented using the panel data. However, in the case of the developing countries, the panel data include, usually a relatively small number of periods. As we shall see, it can create significant systematic differences between the sample estimates and the value of true (unobserved) poverty indices. With the approach of JR, these biases directly affect the estimate of chronic poverty. For the EDE approach these bias will have a direct impact on the estimation of transient poverty. Transient poverty (JR) and chronic poverty (for the EDE approach) will also be biased because they are obtained as the differences between biased estimators. In the next paragraph, we present procedures to correct these bias (Duclos et al. (2006)).

Analytical bias corrections

JR Approach

In this section, we suppose that $\overline{y_i}$ is the permanent income expressed as $\overline{y_i} = \int y dF_i(y)$. Thus, an individual i is said to be, really, chronically poor (as opposed to estimated values) if: Using the panel data method, a given estimator of y may be presented as $\hat{\overline{y_i}} = \frac{1}{t}\sum_{j=1}^{t} y_{ij}$,

$$\overline{P^*}_{i,\alpha} = max((1-\overline{y_i})^{\alpha}, 0) \tag{4.20}$$

Equations 20 – chronic poverty function with bias correction

where y_{ij} represent the observed income of the individuali at time j. Thus we can deduce an estimator for the chronic poverty (it is simply $max[(1-\hat{\overline{y_i}})^{\alpha}, 0]$.

? prove that this estimator is baised when we are in the case of a small period. Than they propose to correct this bias as follow:

$$E[max[(1-\hat{\overline{y_i}})^{\alpha}, 0]] = \overline{P^*}_{i,\alpha} + \frac{\alpha(\alpha-1)}{2t} \tag{4.21}$$

EDE Approach

Following Duclos et al. (2006), this part propose an analytical bias corrections for the EDE estimator.

Bootstrap bias corrections

Another procedure to correct the founded bias is to estimate the bias resulting in numerical simulations of the longitudinal distributions of income. An adequate way to do this is bootstrapping (Efron (1992)) the empirical distribution of each periods and each groups of income. This can be done as follows:

A) In a first step we try to provide, for individaul i, an estimator η_i to chronic poverty $P_\alpha^C(Y)$ or to transient poverty $\phi_\alpha(g_i)$;

B) In a second step, we try to determine a "plug-in" estimator using the original subsample of income,$\{y_{i1}...y_{it}\}$, for individual i in period t.

C) In this step, we generate a sample of t income at random with replacement from the original subsample $\{y_{i1}...y_{it}\}$. And we calculate a new estimateurη_i^k for each simulated sample. Although Obviously k must be numerically large enough.

D) Now, we determine η_i^B which is defined as the mean of the K estimators (η_i^k). Then we would get, $\eta_i^B = \frac{1}{K}\sum_{k=1}^{K}(\eta_i^k)$. Our bootstrapping estimates bias is then computed as the difference between η_i^B and the "plug-in" estimator.

Monte Carlo simulation

In this section we use Monte Carlo simulation to examine the performance of bias correction procedures, discussed above. For this purpose we go through the following steps:

A) We assume a log-normal longitudinal distribution of incomes with mean and standard deviation both set to 1 (recall that incomes are normalized by the poverty line). We compute the statistics of interest for that distribution.

B) We choose a number t of longitudinal income observations to be drawn randomly and independently from that population. (Note again that step 2 above can be done with or without bias corrections.)

C) For each of h = 1; :::;H, we draw a sample of t such observations and estimate the statistics of interest, with or without bias corrections.

D) We compute the average of the H statistics estimated in the previous step, and compare that average to the true population statistics calculated in step 1.

Recall that biases arise because of the finite number of periods, not because of a finite number of households.

4.4.4 Empirical Illustration

In this chapter, consumption expenditures [16] are taken as indicators of welfare. A brief summary of this variables is given in Table 4.3.

Table 4.3 – Descriptive Statistics of the variable Total annual Household Expenditure (2005/2010)

variables	mean	min	std	max
Total expenditures (2005)	1939806	36941.8	1808218	5400000
Total expenditures (2010)	2322616	57420.01	1969094	6000000

In this section we apply the methods explained previously. Both methods have given different results and are even opposed but they are very interesting.

JR- Method

When we made the estimation with the method developped by JR we found the following results summarized in Table 1 (asymptotic standard errors within parentheses):

Table 4.4 – Poverty components with and without bias corrections (α=2)

Components	Without bias corrections	with bias correction	
		Analytica	Bootstrap
Chronic poverty	0.065	0.009	0.009
	(0.0016)	(0.0017)	(0.0017)
Transient poverty	0.102	0.158	0.158
	(0.0012)	(0.0014)	(0.0013)
Total	0.167	0.167	0.167
	(0.0023)	(0.0023)	(0.0023)

asymptotic standard errors within parentheses
our computation using imputeddata (see previous section)

16. we used imputed data following the rubin approach presented in the previous section

The first comment to make is that transient poverty is more important than chronic poverty. In fact, it represents about the two thirds of total (intertemporal) poverty. We also emphasize, even with the correction selection bias, the share of the transient poverty further increased to 90% of total poverty.
We analyzed poverty with average income during period t. Therefore, indiviual in severe poverty, at t-1, can still be considered to have zero chronic poverty if their income in period t is large enough to make an average income during the periods t higher than 1 tends. An opportunity to solve this problem is to use the average of the censored income poverty as shown in table 2 (asymptotic standard errors within parentheses).

As mentioned, this does not change total poverty, but it has a considerable impact on its two components. Bias-corrected related to chronic poverty increases from 27% to 53% of total poverty. Result shown also that chronic poverty is always larger with the censored approach.

Table 4.5 – Chronic and transient poverty using censored income (α =2)

Components	Without bias corrections	with bias correction	
		Analytica	Bootstrap
Chronic poverty	0.105 (0.0021)	0.043 (0.0020)	0.073 (0.0010)
Transient poverty	0.062 (0.0020)	0.123 (0.0020)	0.094 (0.0010)
Total	0.167 (0.0023)	0.167 (0.0023)	0.167 (0.0023)

EDE-povety gap methods

The proposed method, in this section, based on the concept of EDE poverty gap. Estimation of this method allows us to have very significant results compared to the JR approach.// In Table 4 (asymptotic standard errors within parentheses) we used the same data (used in the previous section) to decompose total poverty, but this time using the EDE method, with and without bias corrections. Again, the two methods of bias correction give very similar results and increase transient poverty estimates. However, the differences with the JR approach is very important. Transient poverty now represents more than 22 % (15 % without bias corrections) of total poverty. Now the social decision-maker would be willing to spend more than the equivalent of about 22 % of total poverty to eliminate

Table 4.6 – Decomposition based on EDE poverty gap ; α= 2

Components	Without bias corrections	with bias correction	
		Analytica	Bootstrap
Cost of inequality within individuals	0.154	0.154	0.154
	(0.002)	(0.002)	(0.002)
Cost of inequality between individuals	0.084	0.062	0.062
	(0.001)	(0.001)	(0.001)
Transient poverty	0.043	0.063	0.065
	(0.001)	(0.001)	(0.001)
Chronic poverty	0.238	0.219	0.219
	(0.002)	(0.001)	(0.002)
Intertemporel	0.282	0.282	0.282
	(0.002)	(0.002)	(0.002)

intra-individual inequalities of the state of poverty. This is a very significant and important departure from the JRestimates, which suggest for the same data and the same parameter values, that transient poverty was about 53 % of total poverty.

4.5 Recursive mixed process model to poverty dynamic assessment

In this study we use the recursive bivariate probit model (Roodman, 2011) in order to take into account the interdependence of poverty status between 2005 and 2010.

4.5.1 Data sources and Descriptive Statistics

The empirics are based on the Tunisian household's expenditures surveys of 2005 an 2010. To run a multiple imputation of our interest variables (expenditures employment and regions) we have selected some characteristics that are considered sufficiently stable over time namely: the sex of individuals (1 for female), the region: Urban Great Tunisia, Rural great Tunisia, urban east, rural east, urban west and rural west [17] the educational level: illiterate (reference modality), primary level, secondary level and higher level. For age we choose four generation: individual who were born between 1984 and 1975, 1974 and 1965, 1964 and 1955, and finally, born between 1954 and 1945. We have not taken the household head as a reference since it may change from a year to another depending on the financial condition of the household. This method able also to deal with internal migration problem, which was mentioned by several researchers (Deshingkar (2006), Collinson (2010), De Haas

17. we choose this decomposition of areas since we are interested by the urban rural disparities over time. Moreover we could use any other figure

(2010)).

The data source used in our study is the National Survey of budget, consumption and living standard of households (NSCH)for the two years 2005 and 2010 (they are a quinquennial surveys). Samples are obtained using a stratified random sampling.

Table 2 describes the average sample of the used variables. This statistics show that woman dominate the sample with a percentage of 53.8%. Those individuals who were born between 1984 and 1975 represents 31.5 % of total sample, following by those who were born between 1974 and 1965 by 27.4%, those who were born between 1964 and 1955 represents 24.9% and finally those who were born between 1954 and 1945 represents 16.1%.

Individuals who are illiterate represents 21% of total sample and those who have a primary educational level represents 38.6%. Individuals who have secondary educational level represents 29.4% and those who have a higher educational level represents 10.7%.

Table 4.7 – Descriptive Statistics for expenditures variables: 2005-2010

parameters	mean	parameters	mean
sex		*Employment2010*	
men	0.461	Inactive	0.434
Women	0.538	Salaried	0.214
Generation		Independant	0.275
born between 1984 - 1975	0.315	unemployed	0.075
born between 1974 - 1965	0.274	*Region2005*	
born between 1964 - 1955	0.249	Urban Great Tunisia	0.189
born between 1954 - 1945	0.161	Rural Great Tunisia	0.043
Education		Urban East	0.278
Illiterate	0.210	Rural East	0.161
primary level	0.386	Urban West	0.179
secondary level	0.294	Rural West	0.147
higher level	0.107	*Region2010*	
Employment2005		Urban Great Tunisia	0.184
Inactive	0.392	Rural Great Tunisia	0.039
Salaried	0.165	Urban East	0.289
Independant	0.379	Rural East	0.158
unemployed	0.062	Urban West	0.195
		Rural West	0.132

Source: Own compute based on INS data

For employment and region variables, we must evaluate the statistics descriptive according to the two years. Indeed, we note that the percentage of unemployed individuals increased from 2005 to 2010. The percentage of salaried individuals increased while the

percentage of independent workers has decreased.

Descriptive statistics highlight the large size of urban East, at the two years, compared to other regions (27.8% at 2005 and 28.9% at 2010). Followed by the great Tunis at 2005 by 18.9% but at 2010 it is the urban west by 19.5% than the other regions. This proves the migration movement between regions.

In this chapter total expenditure is taken as a welfare indicator. Indeed, consumption expenditure are further characterize by their stability over time compared to income fluctuations. They provide information about the degree of satisfaction that comes from the consumption of good and services. This approach has been advocated in recent studies by Fang and Sakellariou (2013) Chamarbagwala (2010) . In addition, we consider an individual as poor if the equivalent expenditure of household is below the fixed poverty line (we define the poverty line as the 50% of the mean distribution). We fix two poverty lines for each year. Evidently we use the CPI (the Consumer Prices Index) to compare expenditure households in dinars, over time [18].

4.5.2 Econometric Modeling

In this study we use a mixed recursive bivariate model, firstly proposed by Maddala and Lee (1976) in order to take into account the interdependence of poverty status between 2005 and 2010. The main objectives of this model were twofold: On the one side, it verify if poverty causes future poverty through the introduction of "poverty 2005" variable in the first equation, and on the other side it detect unobservable effects that can be analyzed with the sign and the significance of the autocorrelation term (ρ). In this section, we use a dynamic recursive bivariate probit to estimate poverty dynamics. The model able to take into consideration the past experience of poverty. Following the specification given by Roodman (2011) and Roodman (2013) we assume that: note that $g(.)$ is the link vector-valued function where β_i represent a matrix of coefficients $(i = 1, 2)$ P_1^* and P_2^* represent are consecutively poverty of 2005 and poverty of 2010, σ, β_1 and β_2 are coefficient of the model and (v_1, v_2) the residuls vector. and $\mathbf{1}$ represent the indicator function note that ρ measure endogeneity of P_1^* in the P_2^* equation.

18. Since the CPI measures changes in the general price level, it is often used to estimate changes in purchasing power of Tunisian dinars.

$$
\begin{aligned}
&P_1^* = \theta_1 + v_1 \\
&P_2^* = \theta_2 + v_2 \\
&\theta_1 = \beta_1 x_1 \\
&\theta_2 = \gamma p_1 + \beta_2 x_2 \\
&p = g(p^*) = (1\{P_1^* > 0\}, \mathbf{1}\{P_2^* > 0\})' \\
&\epsilon = (v_1, v_2)' \sim \mathcal{N}(0, \sum) \\
&\sum = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}
\end{aligned}
\tag{4.22}
$$

Equations 21 – Recursive mixed process model

$$
\begin{aligned}
P_{2010} \quad = \quad & (\alpha_1 Women + \alpha_2 Gen_2 + \alpha_3 Gen_3 + \alpha_4 Gen_4 + \alpha_5 Educ_2 + \alpha_6 Educ_3 + \alpha_7 Educ_4 \\
& + \alpha_8 Salar_{2010} + \alpha_9 Indep_{2010} + \alpha_{10} Unemp_{2010} + \alpha_{11} RGT_{2010} + \alpha_{12} UE_{2010} \\
& + \alpha_{13} RE_{2010} + \alpha_{14} UW_{2010} + \alpha_{15} RW_{2010}) + (\alpha_1 Women + \alpha_2 Gen_2 \\
& + \alpha_3 Gen_3 + \alpha_4 Gen_4 + \alpha_5 Educ_2 + \alpha_6 Educ_3 + \alpha_7 Educ_4 \\
& + \alpha_8 Salar_{2005} + \alpha_9 Indep_{2005} + \alpha_{10} Unemp_{2005} + \alpha_{11} RGT_{2005} \\
& + \alpha_{12} UE_{2005} + \alpha_{13} RE_{2005} + \alpha_{14} UW_{2005} + \alpha_{15} RW_{2005}) + \xi_i.
\end{aligned}
\tag{4.23}
$$

In addition, the two equations of the model follow the bivariate normal distribution that is assumed by the following joint density function [19]

$$
\phi_2(v_1, v_2, \rho) = \frac{1}{2\pi\sqrt{1-\rho^2}} exp[\frac{-1}{2(1-\rho^2)}(v_1^2 + v_2^2 - 2\rho v_1 v_2)] \tag{4.24}
$$

where $E(v_1 \backslash x_1, x_2) = \lambda_1 = 0$ and $E(v_2 \backslash x_1, x_2) = \lambda_2 = 0$

$$
var(v_1 \backslash x_1, x_2) = \sigma_1^2 = 1,\ var(v_2 \backslash x_1, x_2) = \sigma_2^2 = 1
$$

$cov(v_1, v_2 \backslash x_1, x_2) = \rho \quad with \quad -1 \leq \rho \leq 1$ the likelihood function of the model is

19. suppose that x and p are normally and randomlly distributed, x$\sim \mathcal{N}(\lambda_x, \sigma_x^2)$and p$\sim \mathcal{N}(\lambda_p, \sigma_p^2)$. Thus the bivariate normal distribution is defined as: $\phi_2(v_1, v_2, \rho) = \frac{1}{2\pi\sqrt{1-\rho^2}} exp[\frac{-1}{2(1-\rho^2)}(\frac{(x-\lambda_x)^2}{\sigma_x^2} + \frac{(p-\lambda_p)^2}{\sigma_p^2} - 2\frac{(x-\lambda_x)}{\sigma_x}\frac{(p-\lambda_p)}{\sigma_p}]$

based on four parts:

$$L(\beta_1, \beta_2 \backslash x_1, x_2) = \prod p_{11}^{P_1 P_2} p_{10}^{P_1(1-P_2)} p_{01}^{(1-P_1)P_2} p_{00}^{(1-P_1)(1-P_2)} \tag{4.25}$$

where:

$$p_{11} = P_r(P_2 = 1, P_1 = 1 \backslash x_1, x_2) = \phi(x_1\beta_1 + \gamma, x_2\beta_2, \rho)$$

$$p_{10} = P_r(P_2 = 1, P_1 = 0 \backslash x_1, x_2) = \phi(x_1\beta_1, -x_2\beta_2, -\rho)$$

$$p_{01} = P_r(P_2 = 0, P_1 = 1 \backslash x_1, x_2) = \phi(-x_1\beta_1 - \gamma, x_2\beta_2, -\rho)$$

$$p_{00} = P_r(P_2 = 0, P_1 = 0 \backslash x_1, x_2) = \phi(x_1\beta_1 + \gamma, x_2\beta_2, \rho)$$

4.5.3 State Dependence

Heterogeneity of the experiences of persistent poverty and the various factors that influence it must be context specific and be sustained by the appropriate policies. According to Giraldo et al. (2002), distinguish the difference between Genuine State Dependence (GSD) and Aggregate State Dependence (ASD) (Arulampalam et al. (2000) and Cappellari and Jenkins (2004)) is crucial [20]

Aggregate State Dependence :

We follow the definition of Cappellari and Jenkins (2004) to distinguich between *Aggregate State Dependence* (ASD) and *True State Dependence* [21] (TSD). The first one (ASD) does not take into account the individual heterogeneity. It represent the difference between the conditional probability of being poor at time t given that it was poor at t-1, and the conditional probability of being poor at time t given that it was not poor at t-1. Actually, it represent the difference between poverty persistence and poverty transitory (entry). We assume:

20. For example, if chronic poverty is caused principally by GSD, monetary transfers programs might be an effective policy by increasing the income of poor individuals. Otherwise, it is not effective because they do not modify the adverse individual's characteristics.

21. called also as Genuine State Dependence (GSD), for more details see Cappellari and Jenkins (2004)

$$ASD = \frac{\frac{\sum_{s\in\{p_{st-1}=1\}} P_r(p_{st}=1\backslash p_{s,t-1}=1)}{\sum_s p_{s,t-1}}}{\frac{\sum_{s\in\{p_{st-1}=0\}} P_r(p_{st}=1\backslash p_{s,t-1}=0)}{\sum_s (1-p_{s,t-1})}} - \tag{4.26}$$

Equations 22 – Agregate State Dependence

Genuine State Dependence :

On other hand, we measure the TSD as the rising probability of being poor on t caused by the poverty on t-1, with control to the individual heterogeneity. The choosen model assume that each composant of X'_{it} (in the transition equation) may present a various impact on the status of poverty on "t" conditionally to poverty status on "t-1". Cappellari

$$GSD = N^{-1} \sum_{i=1.....N} [\hat{P}_r(p_{it} = 1\backslash p_{i,t-1} = 1) - \hat{P}_r(p_{it} = 1\backslash p_{i,t-1} = 0)] \tag{4.27}$$

Equations 23 – Genuine State Dependence

and Jenkins (2004)

4.5.4 Results

The estimation of the mixed recursive biprobit model enable us to achieve two objectives. On the one side, it verify if poverty causes future poverty through the introduction of pauvrete 2005 variable in the first equation, and on the other side it detect unobservable effects that can be analyzed with the sign and the significance of the autocorrelation term (ρ).

Regression results

The parameter ρ allows to identify the correlation of the unobservable characteristics between initial and subsequent state. In the context of our exercise, we found that this parameter is statistically significant with a negative sign. This proves that specific shocks which are not observed but can cause the poverty of individuals, increase the probability of leaving poverty in the subsequent period.

According to the Student test, the auto-correlation coefficient ρ is statistically significant with a p-value different of zero. This is mean that an individual how was poor in 2005 has a higher probability to be poor in 2010.

With regard to the parameter linked to poverty status of 2005, the marginal effect indicates that the probability of being poor at 2010 depends on the probability of being poor at 2005. This is meaning that a poor person at 2005 have a higher probability of being poor at 2010 regarding to oher persons (not poor).

With regard to the generation variables, we found that all coefficients are statistically significant and negative for the older generation. This sign indicates that the probability of being poor is greater for younger individuals. This individuals are less likely to be initially poor than the other generation. This find might be explained by the fact that this generation was more formed in terms of education system compared to others. As a result they had more chance of having an employment than others. As expected, we find that the parameter of initial condition (poverty 2005) is significantly positive; the marginal effect of this variable indicates that the probability of being poor is higher when the individual has experienced poverty in the past.

Finally, our study highlight that 61 (0.3/0.49) per cent of total observed poverty (0.49) is the origin of a stationary propension of poverty (ie. chronic condition) while 39 per cent coming from transient poverty (0.19/0.49). When we compare different poverty lines, we highlight similar results (table 2 in appendix).

Table 4.8 – Results of the mixed recursive model

	Initial condition		Permanence poverty statut		Transitory poverty	
Explanatory variables	marginal effect	std. Err.	marginal effect	std. Err.	marginal effect	std. Err.
sex (Female as reference)						
Male	0.0028	0.0051	0.0002	0.0055	-0.0020	0.0045
Education (Illitirate as reference)						
primary level	0.0041	0.0071	-0.0028	0.0077	-0.0068	0.0066
Secondary level	-0.0161	0.0095*	-0.0375	0.0096*	-0.0455	0.0079*
higher level	-0.0734	.0118*	-0.1069	0.0115*	-0.1069	0.0084*
Employment (Inactive as reference)						
Salaried	0.0059	0.0060	0.0064	0.0064	0.0049	0.0050
Independant	0.0560	0.0062*	0.0594	0.0065*	0.0474	0.0055*
Unemployed	0.0378	0.0099*	0.0402	0.0104*	0.0318	0.0086*
Region (Urban Great Tunisia as reference)						
Rural Greater Tunis	0.1130	0.0148*	0.1207	0.0158*	0.0938	0.0128*
urban East	-0.0247	0.0072*	-0.0270	0.0078*	-0.0194	0.0058*
Rural East	0.1395	0.0092*	0.1485	0.0097*	0.1169	0.0090*
urban West	0.0682	0.0083*	0.0734	0.0089*	0.0556	0.0070*
Rural West	0.2344	0.0088*			0.2031	0.0101*
Generation (first generation (26 - 35 years) as reference						
Second generation	0.0446	0.0066*	0.0496	0.0071*	0.0416	0.0059*
Third generation	0.0109	0.0070	0.0115	0.0074*	0.0089	0.0060
Fourh generaion	-0.0301	0.0078*	-0.0415	0.0081*	-.0398	.0062*
poverty 2005	0.1426	0.0278*	0.1510	0.0302*	0.1221	0.0223*
ρ	-0.2383		0.000			
T	22.14		0.000			
number of observaion	51492					
Chronic poverty	0.3	Observed poverty	0.49	GSD	0.1034	ASD 0.0862

Source: Own computes based on INS data

T is the coefficients equivalence test and *** significant at 1% ,** significant at 5%,*significant at 10%

Simulation and poverty prediction

Table 4.9 shows simulated predicted values for individuals with reference to the estimated coefficients. As expected, our results highlight a highest observed poverty as well as transient poverty and chronic poverty in the rural west region. This is logical since these regions suffer from a bad social conditions and a wicked infrastructure that prevents them to escape from poverty. Regional disparities in the Tunisian labor market, have convinced many potential job seekers to change the place of residence to the great Tunis or to the urban east.

Regarding to the educational level effects, we point the similar probabilities for both

Table 4.9 – Poverty Transition: Poverty status in 2010, conditional on poverty status in 2005

	Poverty components			
Characteristics	Observed	Chronic	Transient	Transient/observed
Sexe				
Male	0.4912	0.2967	0.1945	0.3959
Female	0.4895	0.2970	0.1925	0.3932
Education				
Illiterate	0.5373	0.3188	0.2185	0.4066
primary level	0.5277	0.3160	0.2117	0.4011
Secondary level	0.4542	0.2812	0.1730	0.3808
higher level	0.3234	0.2119	0.1115	0.3447
Region				
urban Greater Tunis	0.3667	0.2287	0.1380	0.3763
Rural Greater Tunis	0.5813	0.3495	0.2318	0.3987
urban East	0.3203	0.2017	0.1186	0.3702
Rural East	0.6322	0.3772	0.2550	0.4033
urban West	0.4957	0.3021	0.1936	0.3905
Rural West	0.8161	0.4749	0.3412	0.4180

Source: Own computes based on INS data

chronic and transient poverty for individuals whose educational level is primary or illiterate (40% per cent of the observed poverty). These groups might suffer from periodical changes in their status.

For the variable sexes of Individuals, results show a slight difference for women at the level of poverty components. In fact, men present higher chronic level of poverty face to higher transient poverty for women. We can explain this find by the fact that on labor market, men are facing more difficulties to find a decent job than women. In fact according to a recent report of INS [22] the rate of women who have a high level of education exceeds that of men, while the rate of non-schooling of men exceeds that of women. These two factors may decrease the chance of getting a permanent job.

22. INS report, 2015 (rgph2014.ins.tn/fr/resultats)

To analyze the effect of internal migration on the persistence of poverty and the downward into poverty, we propose to predict some other simulated cases based on the estimated coefficients of our model (table5).

Unemployment is considered as a condition related to the concept of vulnerability to poverty rather than to a chronic poverty state. This result is justified when compared simulation (1) and (6). Such finds are expected as unemployment is theoretically approved as a transient state conditioned by the short-term situation of the national economy.

Regarding table 8, the probability of transient and chronic poverty of an individual who initially and originally lived in rural west areas decreases when he change their residence to the urban great Tunis.

When we change the educational level to secondary level for the same individuals, their probability decreases compared to basic case.

Great Tunis represent the destination of all individuals looking for a decent job. In fact, deprived cities of the great Tunis(the delicate urban environment) suffer from the degradation of school equipment Payet (2006).

Table 4.10 – The predicted transition poverty rates

	man		woman	
cases	Persistence	Transitory	Persistence	Transitory
Basic case: situation at 2005: young individual lives in rural west, not educated, unemployed	0.3397	0.2495	0.3384	0.2470
case2: same as basic case except individual change location to urban greater Tunis at 2010	0.2570	0.1663	0.2567	0.1643
case3: same as case 2 except individual educational level is secondary	0.2213	0.1266	0.2218	0.1250
case4: same as case 3 except individual change residence to urban east	0.1943	0.1064	0.1948	0.1079
case5: same as case4 except individual has a higher educational level	0.1672	0.0898	0.1678	0.0885
cas 6: same as case4 except individual has a job	0.0891	0.0363	0.0923	0.0349

Source: Own computes based on INS data

This study shows interesting results in terms of public policy. Since the proposed methodology highlight that Tunisian poverty is mainly chronic, an effective policy to reduce poverty must involve a multi-sectorial reform with a constructively program of income inequality distribution and reduce regional disparities is required. Such programs able the improvement of infrastructure in rural areas, facilitates access to information, labor market

and public services.

4.6 Conclusion and Recommendation

Most works on poverty dynamics, in developing country, consisted in measuring and identifying correlated variables to chronic and transient poverty. Further research are necessary to understand what causes chronic poverty and why some groups of individuals are not able to accumulate assets that generate sufficient income to increase consumption expenditures above a minimum acceptable level (i.e. poverty line). To execute such analysis panel data are recommended. However, as in most developing countries, penalized data about individual's well-being conditions does not exist. As a result, researchers does not able to conduct a *ex-post* dynamic analysis of poverty.

This chapter, propose to use potential outcomes approach as a particulary case of missing data to impute potential variables and, in a second step, to run a dynamic poverty analysis. The main objectives of our study were, first of all, the analysis of poverty dynamics by analyzing its chronic and transitory characteristics in order to improve knowledge about this phenomenon. Secondly, we identify more efficient policy measurements in favor of population suffering from persistent poverty.

Our finding emphasize that poverty is unequally distributed by regions, urban East and greater Tunis have the lowest rate of poverty. Poverty decreased from 2005 to 2010, but this decrease faces to a higher consumption disparities with an economic inequalities, asserts that the GDP growth was biased towards the non-poor. Until now, the adopted economic and social development does not correspond to good regional governance objectives that Tunisia should achieve. Results show also, that there is always a negative relation between poverty components and education. This proves the role of education in the fight against poverty. *Ceteris paribus*, more we are graduated more we are able to improve our well-being. Moreover, simulation results enable the prediction of the probability of downward into poverty and the persistence in poverty by taken into account internal migration between regions. The results of our methodology demonstrate that individuals who are the most affected by chronic poverty are the less educated and who reside in rural west.

These finds are encouraging in terms of public policy since it suggests a new approach to poverty dynamics analysis in the case of non-panelized data. Potential extensions of this new methodology may include larger database about poverty dynamic within the framework of a deeper vision of multidimensional poverty dynamic concept.

Chapter 5

General Conclusion

The principal objective of this thesis was to analyze poverty profile in Tunisia. We have, throughout our research, provide answers to the general question "why some people do not get out from the trap of ptoverty and why some regions are much poorer than the other? We have replied to this question in three steps.

In the first part we focused on the measure of poverty according to several socio-economic variables related to household's welfare. To that purpose we use monetary approach to analyze the profile of poverty. In the second part, we are interested in the welfare gap between rural and urban areas. Finally, in the third part, we focused on the dynamics of poverty and its extent over time.

The main approaches that are presented in the first chapter, to analyze poverty, were twofold: The first one, the classic approach, according to this approach we fix, on the one hand, a poverty line which enable us to classify households into poor and not poor. On the other hand, using FGT indices and logit model, we have measured poverty and analyzed household welfare by selecting variables that would influence the well-being of these households. The second one, the fuzzy approache which enables a gradual analysis of poverty. Both, FGT indexes and logit model attest the importance of some variables such as education and regional location on household's welfare and the probability of entry-exit to poverty. These findings was approved by some subsequent searches in Tunisia (Belhadj and Matoussi (2007), Belhadj (2011a), Jemmali and Amara (2015)). On the other hand, we have proposed a new methodology for measuring poverty using fuzzy set approach. The idea was to propose a logit membership function enable to compare logit model with fuzzy approach. The application of this methodology in the Tunisian case leds to some conclusions. First of all, result show that 19.4% of Tunisian households are poor. In addition, the decomposition of the fuzzy index by regions shows that fuzzy proportion of poor households is higher in rural areas especially in the west region. Finally, decomposition according to the sex of household head indicates that households headed by a man, have on average lower deprivation than other.

Although these three methods differ in the methodology for analyzing and measuring poverty, but they leads to the same results that it has a strong regional disparity in terms of poverty rates. Finally, stochastic dominance and sensitivity test reveal the robustness of these results.

The second contribution in this PhD thesis designed to explain the welfare gap between rural and urban areas in Tunisia. We used a new decomposition approach developed

by Chernozhukov et al. (2013) to explain this gap. The originality of our work is the estimation of disaggregated expenditure per quantiles using censored and uncensored quantiles regressions for disaggregated consumption expenditures. Consequently this study enable us to dissect out whether observed differences are due to household characteristics or due to returns to those characteristics. We find that both covariate and return effects are larger at the higher quantile. Moreover, for poor households, the causes that make urban one better than rural households is essentially due to difference in characteristics, whereas for the non-poor households, the gap is rather due to the returns of their characteristics. This results conduct us to bring some explanations. First of all, investing a lot more in education, health and other characteristics, enable us to create economic growth and to have a more equitable society. However, it can generate much more inequality between rural and urban households, as the last one is characterized by greater returns of these characteristics. Therefore, if the reasons of this gap are not addressed, more resources (more qualified teachers, well equipped hospitals, computers, etc.) must be allocated to the rural areas in order to avoid urban-biased development. Decomposing the gap between urban and rural area, this study shows that the problem is not only about equality but also it is an equity issue. Such equity, implies that resources should be allocated with regard to the quality. Therefore, the counterfactual decomposition used in this study may be an appropriate tool that can help policymaker to reduce regional inequality by encouraging positive discrimination policy in favour marginalized areas.

In the third contribution we looked at the evolution of poverty over time. Nevertheless, in Tunisia, like the most developing countries, information are incomplete through time and surveys are not in form of panel data. This study presents a contribution to the extant literature by proposing a new approach enable to panelized the used data base. In fact, we consider an alternative "potential outcomes" (or "counterfactual" approach) combined with multiple imputation to get around this problem. Our proposition is to impute potential variables enable to run a longitudinal analysis. The method allows multiple imputation of an entire blocs of interest variables. The second step of this study consist to assess poverty dynamics and examines his trajectories based on the distinction between chronic and transient poverty. Static and econometric approach are used. The first one based on the Jalan-Ravallion and the EDE poverty gap methods to decompose poverty into chronic and transient components. Following Duclos e al. (2006), in the case of a small number of

periods, we use statistical procedure for correct expected bias when we estimate chronic and transient poverty. For the econometric anlysis we perform a recursive biprobit model. This model enables us to deal with bias selection as it takes into consideration the initial poverty state. Results show that between 2005 and 2010, about 61 per cent of relative poverty in Tunisia is chronic and the principal cause of this persistence is due to the initial condition of past poverty. The proposed method was designed fundamentally to keep track of variation to poverty at different time periods by computing each components. In fact, the significance of the depth component proposes that when comparing individual groups, information regarding poor individuals over time are important in accurately identifying individual poverty. One other point illustrated by this study was the crucially of depth aspect concerning the breadth of deprivation in Tunisia, asserting that poverty remains chronic.

Furthermore, this exercise represent an important step on the path that aims to improve policies against poverty and inequality. Results allow policy makers to improve mechanisms and tools against these scourges. First of all, we suggest that strategy of fighting against poverty should be based on how to break the circle of successive poverty. Besides, they should focus on individual's characteristics (improving employability with education, supporting households with children, etc). In addition, we should know that the development of social groups and deprived regions inevitably involves a strategy to reduce regional disparities. Indeed, this work has demonstrate that Building hospital, school and university is an important step but it is not enough. They must address the necessary resources for the development of this area (qualified teachers, competent, doctors computers, internet, etc.). Results highlight that it will not serve to implement projects and invest if these areas without a human capital capable of leading the development. In light of these results, we suggest an effective policy to reduce poverty based on a multi-sectoral reform with a constructively program of income inequality distribution and reduce regional disparities. Such programs able the improvement of infrastructure in rural areas, facility access to information, labor market and public services.

This PhD thesis opens the way towards new research questions and empirical applications. With regard to the disparities between rural and urban areas we suggest gap measurements over time. We suggest to use quantile regression for panel data, such model enable us to introduce fixed effects in order to control unobserved covariate. This method is required as it allows a dynamic assessment of this disparity and so a better target measures against

this scourges. In addition, for a dynamic measure of poverty, running a panel data seems to be useful. Therefore, we suggest to use a panel data model using other household surveys if there are available. In addition we can use a recursive biprobit model with a larger data base, according to this model, poverty of 2010 depends on poverty of 2005 which itself depends on poverty of 2000, etc.

On the other hand, it is required to change efforts to measure poverty dynamics beyond the simple income and consumption definition to more multidimensional assessment and concepts of poverty. This is very current in static analyses but it is rare in poverty dynamics studies. In fact, multidimensionality is essential when analyzing social phenomenon. It's time to exit from the hole of income/consumption measurement. Poverty dynamics analysis can be performed differently when we use non-income measures, and these are essential as a cross-check on movement in income measures, as well as giving us a wider figure on how well-being in all its aspects moves over time. Multidimensional poverty dynamic assessment remain our next challenge of research.

Otherwise, conversation about poverty shows a separation, between economist's and other scientist's researchers (sociology, politics, etc.). However, it also shows that there is a desire to bridge this separation. We hope that this volume will support that process, encourage others to take part in the debate, and to fight against conceptual and methodological obstacles that still to be overcome.

Bibliography

Aassve, A., S. Mazzuco, and L. Mencarini (2005). Childbearing and well-being: a comparative analysis of european welfare regimes. *Journal of European Social Policy 15*(4), 283–299.

Achia, T. N., A. Wangombe, and N. Khadioli (2010). A logistic regression model to identify key determinants of poverty using demographic and health survey data. *European Journal of Social Sciences 13*(1), 38–45.

Adams, W. M., R. Aveling, D. Brockington, B. Dickson, J. Elliott, J. Hutton, D. Roe, B. Vira, and W. Wolmer (2004). Biodiversity conservation and the eradication of poverty. *Science 306*(5699), 1146–1149.

Albrecht, J., A. Van Vuuren, and S. Vroman (2009). Counterfactual distributions with sample selection adjustments: Econometric theory and an application to the netherlands. *Labour Economics 16*(4), 383–396.

Alkire, S., A. Conconi, and J. M. Roche (2014). Multidimensional poverty index 2014: Brief methodological note and results. *University of oxford, Department of International Development, oxford Poverty and Human Development Initiative, oxford, UK*.

Alkire, S., J. E. Foster, S. Seth, M. E. Santos, et al. (2015). Multidimensional poverty measurement and analysis: Chapter 10-some regression models for af measures. Technical report, Queen Elizabeth House, University of Oxford.

Araar, A. (2012). Expected poverty changes with economic growth and redistribution.

Araar, A. and J.-Y. Duclos (2007). Poverty and inequality components: a micro framework.

Araar, A., J.-Y. Duclos, M. Audet, and P. Makdissi (2009). Testing for pro-poorness of growth, with an application to mexico. *Review of income and wealth 55*(4), 853–881.

Araar, A., J.-Y. Duclos, and C. PEP (2013). User manual dasp version 2.2.

Arndt, C., R. Benfica, F. Tarp, J. Thurlow, and R. Uaiene (2010). Biofuels, poverty, and growth: a computable general equilibrium analysis of mozambique. *Environment and Development Economics 15*(01), 81–105.

Arrow, K. J. (1971). A utilitarian approach to the concept of equality in public expenditures. *The Quarterly Journal of Economics 85*(3), 409–415.

Arulampalam, W., A. L. Booth, and M. P. Taylor (2000). Unemployment persistence. *Oxford Economic Papers 52*(1), 24–50.

Ashenfelter, O. and R. Oaxaca (1987). The economics of discrimination: Economists enter the courtroom. *The American Economic Review*, 321–325.

Atkinson, A. B. (1970). On the measurement of inequality. *Journal of economic theory 2*(3), 244–263.

Atkinson, A. B. and F. Bourguignon (1982). The comparison of multi-dimensioned distributions of economic status. *The Review of Economic Studies 49*(2), 183–201.

Atkinson, M. and R. Bilger (1992). Effects of water velocity on phosphate uptake in coral reef-hat communities. *Limnology and Oceanography 37*(2), 273–279.

Ayadi, M., A. El Lahga, and N. Chtioui (2007). Pauvreté et inégalités en tunisie: une approche non monétaire. Technical report, PEP-PMMA.

Ayadi, M., C. Naouel, and A. El Lahga (2005). Analyse multidimensionnelle de la pauvreté en tunisie entre 1988 et 2001 par une approche non monétaire. In *PEP, a paper presented during the 4th PEP Research Network General Meeting.*

Ayeb, H. (2011). Social and political geography of the tunisian revolution: the alfa grass revolution. *Review of African Political Economy 38*(129), 467–479.

Babu, S., S. N. Gajanan, and P. Sanyal (2014). *Food security, poverty and nutrition policy analysis: statistical methods and applications.* Academic Press.

Bane, M. J. and D. T. Ellwood (1986). Slipping into and out of poverty: The dynamics of spells. *The Journal of Human Resources 21*(1), 1–23.

Barouni, M. and S. Broecke (2014). The returns to education in africa: Some new estimates. *The Journal of Development Studies 50*(12), 1593–1613.

Basu, K. (2006). Globalization, poverty, and inequality: What is the relationship? what can be done? *World Development 34*(8), 1361–1373.

Belhadj, B. (2011a). New fuzzy indices of poverty by distinguishing three levels of poverty. *Research in Economics 65*(3), 221–231.

Belhadj, B. (2011b). A new fuzzy poverty index by distinguishing three levels of poverty. *Research in Economics 65*(3), 221–231.

Belhadj, B. and M. S. Matoussi (2007). Proposition d'un indice flou de pauvreté en utilisant une fonction d'information. *International conference: Sciences of Electronic, Technologies of Information and Telecommunications (SETIT 2007)*.

Betti, G., B. Cheli, A. Lemmi, and V. Verma (2006). Multidimensional and longitudinal poverty: an integrated fuzzy approach. In *Fuzzy set approach to multidimensional poverty measurement*, Volume 3, pp. 115–137. Springer.

Biewen, M. (2005). The covariance structure of east and west german incomes and its implications for the persistence of poverty and inequality. *German Economic Review 6*(4), 445–469.

Biewen, M. (2009). Measuring state dependence in individual poverty histories when there is feedback to employment status and household composition. *Journal of Applied Econometrics 24*(7), 1095–1116.

Blackwell, M., J. Honaker, and G. King (2015). A unified approach to measurement error and missing data: Overview and applications. *Sociological Methods & Research*.

Blinder, A. S. (1973). Wage discrimination: reduced form and structural estimates. *Journal of Human resources 8*(4), 436–455.

Blocker, C. P., J. A. Ruth, S. Sridharan, C. Beckwith, A. Ekici, M. Goudie-Hutton, J. A. Rosa, B. Saatcioglu, D. Talukdar, C. Trujillo, et al. (2013). Understanding poverty and

promoting poverty alleviation through transformative consumer research. *Journal of business research 66*(8), 1195–1202.

Bourguignon, F. (1993). Croissance, distribution et ressources humaines: comparaison internationale et spécificités régionales. *Revue d'économie du développement 4*(93), 3–35.

Bourguignon, F. (2003). The growth elasticity of poverty reduction: explaining heterogeneity across countries and time periods. *Inequality and growth: Theory and policy implications*, 3–26.

Bourguignon, F. (2004). The poverty-growth-inequality triangle. *Poverty, Inequality and Growth 69*, 1–344.

Bourguignon, F., F. H. Ferreira, and P. G. Leite (2008). Beyond oaxaca–blinder: Accounting for differences in household income distributions. *The Journal of Economic Inequality 6*(2), 117–148.

Bourguignon, F., F. H. Ferreira, and M. Menendez (2007). Inequality of opportunity in brazil. *Review of Income and Wealth 53*(4), 585–618.

Breen, R, L. R. M. W. and P. R (2010). Long-term trends in educational inequality in europe: Class inequalities and gender differences. *European Sociological Review 26*(1), 31–48.

Breuer, A., T. Landman, and D. Farquhar (2015). Social media and protest mobilization: Evidence from the tunisian revolution. *Democratization 22*(4), 764–792.

Brinkerhoff, D. W. and A. A. Goldsmith (2003). How citizens participate in macroeconomic policy: International experience and implications for poverty reduction. *World Development 31*(4), 685–701.

Cantó, O. (2003). Finding out the routes to escape poverty: the relevance of demographic vs. labor market events in spain. *Review of Income and Wealth 49*(4), 569–588.

Cappellari, L. and S. P. Jenkins (2002). Who stays poor? who becomes poor? evidence from the british household panel survey. *The Economic Journal 112*(478), C60–C67.

Cappellari, L. and S. P. Jenkins (2004). Modelling low income transitions. *Journal of applied econometrics 19*(5), 593–610.

Carr-Hill, R., S. Jenkins-Clarke, P. Dixon, and M. Pringle (1998). Do minutes count? consultation lengths in general practice. *Journal of health services research & policy 3*(4), 207–213.

Chamarbagwala, R. (2010). Economic liberalization and urban–rural inequality in india: a quantile regression analysis. *Empirical Economics 39*(2), 371–394.

Chang, H.-H. (2012). Consumption inequality between farm and nonfarm households in taiwan: a decomposition analysis of differences in distribution. *Agricultural Economics 43*(5), 487–498.

Charnoz, P., E. Coudin, and M. Gaini (2013). Une diminution des disparités salariales en france entre 1967 et 2009. In *Insee Références-Édition 2013, Emploi et salaires*.

Chernozhukov, V., I. Fernandez-Val, S. Han, and A. Kowalski (2012). Cqiv: Stata module to perform censored quantile instrumental variables regression. *Statistical Software Components*.

Chernozhukov, V., I. Fernández-Val, and A. E. Kowalski (2015). Quantile regression with censoring and endogeneity. *Journal of Econometrics 186*(1), 201–221.

Chernozhukov, V., I. Fernández-Val, and B. Melly (2013). Inference on counterfactual distributions. *Econometrica 81*(6), 2205–2268.

Chernozhukov, V. and H. Hong (2002). Three-step censored quantile regression and extramarital affairs. *Journal of the American Statistical Association 97*(459), 872–882.

Chu Ng, Y. and S. K. Li (2000). Measuring the research performance of chinese higher education institutions: an application of data envelopment analysis. *Education Economics 8*(2), 139–156.

Collinson, M. A. (2010). Striving against adversity: the dynamics of migration, health and poverty in rural south africa. *Global Health Action 3*.

Cornec, M. (2014). Constructing a conditional gdp fan chart with an application to french business survey data. *OECD Journal: Journal of Business Cycle Measurement and Analysis 2013*(2), 109–127.

Cremin, P. and M. G. Nakabugo (2012). Education, development and poverty reduction: A literature critique. *International Journal of Educational Development 32*(4), 499–506.

Cutler, D. M. and L. F. Katz (1992). Rising inequality? changes in the distribution of income and consumption in the 1980s. Technical report, National Bureau of Economic Research.

Davidson, R. and J.-Y. Duclos (2000). Statistical inference for stochastic dominance and for the measurement of poverty and inequality. *Econometrica 68*(6), 1435–1464.

Davidson, R. and J.-Y. Duclos (2013). Testing for restricted stochastic dominance. *Econometric Reviews 32*(1), 84–125.

De Haas, H. (2010). The internal dynamics of migration processes: a theoretical inquiry. *Journal of ethnic and migration studies 36*(10), 1587–1617.

De vincenti, A. (2001). La zone grise: travailler aux frontières du salariat et du travail indépendant. *Actes des VIIIe Journées de Sociologie du Travail*, 105–112.

Deaton, A. (1997). *The analysis of household surveys: a microeconometric approach to development policy*. World Bank Publications.

Deaton, A. and M. Irish (1984). Statistical models for zero expenditures in household budgets. *Journal of Public Economics 23*(1), 59–80.

Deaton, A. and S. Zaidi (2002). *Guidelines for constructing consumption aggregates for welfare analysis*. World Bank Publications.

Deaton, A. S. (1974). The analysis of consumer demand in the united kingdom, 1900-1970. *Econometrica: Journal of the Econometric Society 42*(2), 341–367.

Dempster, A. P., N. M. Laird, and D. B. Rubin (1977). Maximum likelihood from incomplete data via the em algorithm. *Journal of the royal statistical society. Series B (methodological) 39*(1), 1–38.

Deshingkar, P. (2006). Internal migration, poverty and development in asia: Including the excluded. *IDS Bulletin 37*(3), 88–100.

Dolton, P. J., G. H. Makepeace, and W. Van der Klaauw (1989). Occupational choice and earnings determination: The role of sample selection and non-pecuniary factors. *Oxford Economic Papers 41*(3), 573–594.

Duclos, J.-Y., A. Araar, and C. Fortin (2003). Dad: A software for distributive analysis/analyse distributive. *MIMAP programme, International Development Research Centre, Government of Canada, and Université Laval (www. mimap. ecn. ulaval. ca)*.

Duclos, J.-Y., D. E. Sahn, and S. D. Younger (2006). Robust multidimensional poverty comparisons. *The economic journal 116*(514), 943–968.

Duncan, G. J. and W. Rodgers (1991). Has children's poverty become more persistent? *American Sociological Review 56*(4), 538–550.

Duncan, M. (1983). Generalised cabibbo angles in supersymmetric gauge theories. *Nuclear Physics B 221*(2), 285–299.

Dutta, S. (2015). Identifying single or multiple poverty trap: An application to indian household panel data. *Social Indicators Research 120*(1), 157–179.

Efron, B. (1992). Bootstrap methods: another look at the jackknife. *Springer Series in Statistics*, 569–593.

Engel, A. (1896). Nouvelles et correspondance. *Revue archéologique* (29), 204–229.

Fang, Z. and C. Sakellariou (2013). Evolution of urban–rural living standards inequality in thailand: 1990–2006. *Asian Economic Journal 27*(3), 285–306.

Fesselmeyer, E. and K. T. Le (2010). Urban-biased policies and the increasing rural–urban expenditure gap in vietnam in the 1990s. *Asian Economic Journal 24*(2), 161–178.

Filmer, D. and L. Pritchett (1999). The effect of household wealth on educational attainment: evidence from 35 countries. *Population and development review 25*(1), 85–120.

Firpo, S., N. M. Fortin, and T. Lemieux (2011). Occupational tasks and changes in the wage structure.

Fortin, N., T. Lemieux, and S. Firpo (2011). Decomposition methods in economics. *Handbook of labor economics 4*(A), 1–102.

Foster, J., J. Greer, and E. Thorbecke (1984). A class of decomposable poverty measures. *Econometrica: Journal of the Econometric Society 52*(3), 761–766.

Gelman, A. (2011). Causality and statistical learning1. *American Journal of Sociology 117*(3), 955–966.

Gelman, A., J. B. Carlin, H. S. Stern, and D. B. Rubin (2014). *Bayesian data analysis*, Volume 109. Taylor and Francis.

Giraldo, F. X., J. S. Hesthaven, and T. Warburton (2002). Nodal high-order discontinuous galerkin methods for the spherical shallow water equations. *Journal of Computational Physics 181*(2), 499–525.

Graham, J. W., A. E. Olchowski, and T. D. Gilreath (2007). How many imputations are really needed? some practical clarifications of multiple imputation theory. *Prevention Science 8*(3), 206–213.

Greer, J. and E. Thorbecke (1986a). Food poverty profile applied to kenyan smallholders. *Economic Development and Cultural Change 35*(1), 115–141.

Greer, J. and E. Thorbecke (1986b). A methodology for measuring food poverty applied to kenya. *Journal of Development Economics 24*(1), 59–74.

Gupta, S., M. Verhoeven, and E. R. Tiongson (2002). The effectiveness of government spending on education and health care in developing and transition economies. *European Journal of Political Economy 18*(4), 717–737.

Hagenaars, A. J., K. De Vos, M. A. Zaidi, and Eurostat (1995). *Statistiques relatives à la pauvreté à la fin des années 80: recherche saappuyant sur les microdonnées*. OPOCE.

Hamdène, Z. and L. Benhassen (2012). L'éradication du fléau de la pauvreté en tunisie: acquis et défis. *Centre de recherche en éthique de l'UdeM (CRÉUM)*.

Hassine, N. B. (2015). Economic inequality in the arab region. *World Development 66*, 532–556.

Hauser-Davis, R. A., T. F. de Oliveira, A. M. Da Silveira, J. M. B. Protázio, and R. L. Ziolli (2012). Logistic regression and fuzzy logic as a classification method for feral fish sampling sites. *Environmental and ecological statistics 19*(4), 473–483.

Heckman, J. J. (1978). Simple statistical models for discrete panel data developed and applied to test the hypothesis of true state dependence against the hypothesis of spurious state dependence. In *Annales de l'INSEE*, Number 30/31, pp. 227–269. JSTOR.

Herrera, J. and F. Roubaud (2003). Dynamique de la pauvreté urbaine au pérou et à madagascar 1997-1999: une analyse sur données de panel. Technical report, Discussion papers//Ibero America Institute for Economic Research.

Honaker, J., G. King, M. Blackwell, et al. (2011). Amelia ii: A program for missing data. *Journal of Statistical Software 45*(7), 1–47.

Honoré, B. E. and J. L. Powell (1994). Pairwise difference estimators of censored and truncated regression models. *Journal of Econometrics 64*(1), 241–278.

Honzík, P., L. Krivan, P. Lokaj, R. Lábrová, Z. Nováková, B. Fiser, and N. Honzíková (2010). Logit and fuzzy models in data analysis: estimation of risk in cardiac patients. *Physiological Research 59*, S89.

Horowitz, J. L. (1988). The asymptotic efficiency of semiparametric estimators for censored linear regression models. *Empirical Economics 13*(3-4), 123–140.

Hossain, S. I. (1996). Making education in china equitable and efficient. *Social sector expenditure review*.

Hulme, D. and A. Shepherd (2003). Conceptualizing chronic poverty. *World development 31*(3), 403–423.

Irz, X., L. Lin, C. Thirtle, and S. Wiggins (2001). Agricultural productivity growth and poverty alleviation. *Development policy review 19*(4), 449–466.

Jalan, J. and M. Ravallion (1998). Transient poverty in postreform rural china. *Journal of Comparative Economics 26*(2), 338–357.

Jemmali, H. and M. Amara (2015). Assessing inequality of human opportunities: A new approach for public policy in tunisia. *Applied research in quality of life 10*(2), 343–361.

Jenkins, S. P. and P. J. Lambert (1997). Three 'i's of poverty curves, with an analysis of uk poverty trends. *Oxford Economic Papers 49*(3), 317–327.

Jenkins, S. P., J. A. Rigg, and F. Devicienti (2001). *The dynamics of poverty in Britain*. Department for Work and Pensions (United Kingdom) press.

Jensen, C. (2011). Capitalist systems, deindustrialization, and the politics of public education. *Comparative Political Studies 44*(4), 412–435.

Kapteyn, A., P. Kooreman, and R. Willemse (1988). Some methodological issues in the implementation of subjective poverty definitions. *Journal of Human Resources 23*(2), 222–242.

Kaur, D. and H. Pulugurta (2008). Comparative analysis of fuzzy decision tree and logistic regression methods for pavement treatment prediction. *WSEAS Transactions on Information Science and Applications 5*(6), 979–990.

Kennedy, P. E. (1981). Estimation with correctly interpreted dummy variables in semilogarithmic equations [the interpretation of dummy variables in semilogarithmic equations]. *American Economic Review 71*(4).

Koenker, R. and G. Bassett Jr (1978). Regression quantiles. *Econometrica: journal of the Econometric Society 46*(1), 33–50.

Koenker, R. and G. Bassett Jr (1982). Robust tests for heteroscedasticity based on regression quantiles. *Econometrica: Journal of the Econometric Society 50*(2), 43–61.

Kolm, S.-C. et al. (2007). Editorial : Serge kolm's "the optimal production of social justice". *The Journal of Economic Inequality 5*(2), 213–234.

Lachaud, J.-P. (1995). *Pauvreté et marché du travail au Bénin: quelques éléments d'analyse.* Centre d'économie du développement, Université Bordeaux I, working paper.

Lachaud, J.-P. (2000). Echelles d'équivalence et différentiel spatial de pauvreté et d'inégalité au burkina faso. *Documents de travail 46.*

Laderchi, C. R. and Q. E. House (2000). *The monetary approach to poverty: a survey of concepts and methods.* Queen Elizabeth House.

Laderchi, C. R., R. Saith, and F. Stewart (2003). Does it matter that we do not agree on the definition of poverty? a comparison of four approaches. *Oxford development studies 31*(3), 243–274.

Leibbrandt, M. and J. Levinsohn (2011). Fifteen years on: Household incomes in south africa. *NBER Working Paper* (16661), 1–35.

Leibbrandt, M., I. Woolard, A. Finn, and J. Argent (2010). Trends in south african income distribution and poverty since the fall of apartheid.

Lemieux, T. (2006). Increasing residual wage inequality: Composition effects, noisy data, or rising demand for skill? *The American Economic Review 96*(3), 461–498.

Lillard, L. A. and R. J. Willis (1978). Dynamic aspects of earning mobility. *Econometrica: Journal of the Econometric Society 46*(5), 985–1012.

Lipton and Ravallion (1995). Poverty and policy. *Handbook of Development Economics 3*.

Lipton, M. (1977). Why poor people stay poor: urban bias in world development.

Lipton, M. and M. Ravallion (1993). *Poverty and policy*, Volume 1130. World Bank Publications.

Little, R. J. and D. B. Rubin (2014). *Statistical analysis with missing data*. John Wiley and Sons press.

Machado, J. A. and J. Mata (2005). Counterfactual decomposition of changes in wage distributions using quantile regression. *Journal of applied Econometrics 20*(4), 445–465.

Maddala, G. and L.-F. Lee (1976). Recursive models with qualitative endogenous variables. In *Annals of Economic and Social Measurement*, Volume 5, pp. 525–545. NBER.

McCulloch, N. and B. Baulch (1999). Tracking pro-poor growth. new ways to spot the biases and benefits. *Insights* (31), 3.

McKay, A. and D. Lawson (2002). *Chronic poverty: a review of current quantitative evidence*. Chronic Poverty Research Centre, working paper.

Mehta, A. K. and A. Shah (2001). Chronic poverty in india: overview study. *Chronic Poverty Research Centre Working Paper* (7).

Melly, B. (2005). Decomposition of differences in distribution using quantile regression. *Labour Economics 12*(4), 577–590.

Miller, P. W. (1987). The wage effect of the occupational segregation of women in britain. *The Economic Journal 97*(388), 885–896.

Moon, C. G. (1989). A monte carlo comparison of semiparametric tobit estimators. *Journal of Applied Econometrics 4*(4), 361–382.

Morrisson, C. (2002). Health, education and poverty reduction.

Nelson, R. R. and E. S. Phelps (1966). Investment in humans, technological diffusion, and economic growth. *The American economic review 56*(1/2), 69–75.

Neuman, S. and R. L. Oaxaca (2004). Wage decompositions with selectivity-corrected wage equations: A methodological note. *The Journal of Economic Inequality 2*(1), 3–10.

Newey, W. K. et al. (1990). *Efficient estimation of semiparametric models via moment restrictions*. Econometric Research Program, Princeton University.

Nguyen, B. T., J. W. Albrecht, S. B. Vroman, and M. D. Westbrook (2007). A quantile regression decomposition of urban–rural inequality in vietnam. *Journal of Development Economics 83*(2), 466–490.

Nicolson, G. L. (1976). Transmembrane control of the receptors on normal and tumor cells: I. cytoplasmic influence over cell surface components. *Biochimica et Biophysica Acta (BBA)-Reviews on Biomembranes 457*(1), 57–108.

Oaxaca, R. (1973). Male-female wage differentials in urban labor markets. *International economic review 14*(3), 693–709.

OECD (2015). Tunisia: A reform agenda to support competitiveness and inclusive growth.

Paarsch, H. J., H. Hong, et al. (2006). An introduction to the structural econometrics of auction data. *MIT Press Books 1*.

Patlagean, E. (1977). *Pauvreté économique et pauvreté sociale à Byzance, 4e-7e siècles*, Volume 48. Walter de Gruyter press.

Payet, J.-P. (2006). Les écoles en milieu défavorisé dans le grand tunis. un regard ethnographique. *L'Année du Maghreb* (I), 395–398.

Pfeffer, F. T. (2008). Persistent inequality in educational attainment and its institutional context. *European Sociological Review 24*(5), 543–565.

Piesse, A., L. Alvarez-Rojas, and D. Judkins-Westat (2010). Causal inference using semiparametric imputation. In *Proceedings of the Section on Survey Research Methods of the American Statistical Association*, pp. 1085–1096.

Pieters, J. (2011). Education and household inequality change: a decomposition analysis for india. *Journal of Development Studies 47*(12), 1909–1924.

Pourahmad, S., S. M. T. Ayatollahi, S. M. Taheri, and Z. H. Agahi (2011). Fuzzy logistic regression based on the least squares approach with application in clinical studies. *Computers & Mathematics with Applications 62*(9), 3353–3365.

Powell, J. L. (1984). Least absolute deviations estimation for the censored regression model. *Journal of Econometrics 25*(3), 303–325.

Powell, J. L. (1986a). Censored regression quantiles. *Journal of econometrics 32*(1), 143–155.

Powell, J. L. (1986b). Symmetrically trimmed least squares estimation for tobit models. *Econometrica: Journal of the Econometric Society 54*(6), 1435–1460.

Ravallion, M. (1988). Expected poverty under risk-induced welfare variability. *The Economic Journal 98*(393), 1171–1182.

Ravallion, M. (1994). *Poverty comparisons*, Volume 56. Taylor and Francis press.

Ravallion, M. (1998). *Poverty lines in theory and practice*, Volume 133. World Bank Publications.

Ravallion, M. (2011). On multidimensional indices of poverty. *The Journal of Economic Inequality 9*(2), 235–248.

Ravallion, M. and B. Bidani (1994). How robust is a poverty profile? *The World Bank Economic Review 8*(1), 75–102.

Ravallion, M. and G. Datt (2002). Why has economic growth been more pro-poor in some states of india than others? *Journal of development economics 68*(2), 381–400.

Ravallion, M. and J. Jalan (1996). Growth divergence due to spatial externalities. *Economics Letters 53*(2), 227–232.

Ravallion, M. and M. Lokshin (2002). Self-rated economic welfare in russia. *European Economic Review 46*(8), 1453–1473.

Rendtel, U., R. Langeheine, and R. Berntsen (1998). The estimation of poverty dynamics using different measurements of household income. *Review of Income and Wealth 44*(1), 81–98.

Roodman, D. (2011). Fitting fully observed recursive mixed-process models with cmp. *The Stata Journal 11*(2).

Roodman, D. (2013). An expanded framework for mixed process modeling in stata. In *German Stata Users' Group Meetings 2013*, Number 02. Stata Users Group.

Royston, P. (2004). Multiple imputation of missing values. *Stata Journal 4*(3), 227–241.

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of educational Psychology 66*(5), 688.

Rubin, D. B. (1987). The calculation of posterior distributions by data augmentation: Comment: A noniterative sampling/importance resampling alternative to the data augmentation algorithm for creating a few imputations when fractions of missing information are modest: The sir algorithm. *Journal of the American Statistical Association 82*(398), 543–546.

Sarangi, N., K. Abu-Ismail, H. El-Laithy, and R. Ramadan (2015). Towards better measurement of poverty and inequality in arab countries: A proposed pan-arab multipurpose survey.

Schafer, J. L. (1997). *Analysis of incomplete multivariate data*. CRC press.

Schluter, C. (1998). Statistical inference with mobility indices. *Economics Letters 59*(2), 157–162.

Schultz, T. W. (1961). Investment in human capital: reply. *The american economic review 51*(5), 1035–1039.

Sen, A. (1976a). Poverty: an ordinal approach to measurement. *Econometrica: Journal of the Econometric Society 44*(2), 219–231.

Sen, A. (1976b). Poverty: an ordinal approach to measurement. *Econometrica: Journal of the Econometric Society 44*(2), 219–231.

Sen, A. (1979). Personal utilities and public judgements: or what's wrong with welfare economics. *The economic journal 89*(355), 537–558.

Sen, A. (1985). Well-being, agency and freedom: the dewey lectures 1984. *The journal of philosophy 82*(4), 169–221.

Skoufias, E. and R. S. Katayama (2011). Sources of welfare disparities between and within regions of brazil: evidence from the 2002–2003 household budget survey (pof). *Journal of Economic Geography 11*(5), 897–918.

Smith, R. (2012). Why nations fail: The origins of power, prosperity, and poverty. *The RUSI Journal 157*(5), 96–97.

Splawa-Neyman, J., D. Dabrowska, T. Speed, et al. (1990). On the application of probability theory to agricultural experiments. essay on principles. section 9. *Statistical Science 5*(4), 465–472.

Stevens, A. H. (1999). Measuring the persistence of poverty over multiple spells: Climbing out of poverty falling back. *Journal of Human Resources 34*(3), 557–588.

Stevens, M. L., E. A. Armstrong, and R. Arum (2008). Sieve, incubator, temple, hub: Empirical and theoretical advances in the sociology of higher education. *Annu. Rev. Sociol 34*, 127–151.

Tarabini, A. (2010). Education and poverty in the global development agenda: Emergence, evolution and consolidation. *International Journal of Educational Development 30*(2), 204–212.

Tarabini, A. and J. Jacovkis (2012). The poverty reduction strategy papers: An analysis of a hegemonic link between education and poverty. *International Journal of Educational Development 32*(4), 507–516.

Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica: journal of the Econometric Society 26*(1), 24–36.

Townsend, P. (1979). *Poverty in the United Kingdom: a survey of household resources and standards of living*. Univ of California Press.

Townsend, P. (1985). A sociological approach to the measurement of poverty–a rejoinder to professor amartya sen. *Oxford Economic Papers 37*(4), 659–668.

Van Buuren, S. (2012). *Flexible imputation of missing data*. CRC press.

Van de Werfhorst, H. G. and J. J. Mijs (2010). Achievement inequality and the institutional structure of educational systems: A comparative perspective. *Annual review of sociology 36*, 407–428.

Van Praag, B. (1971). The welfare function of income in belgium: An empirical investigation. *European Economic Review 2*(3), 337–369.

Visaria, P. (1980). Poverty and living standards in asia. *Population and Development Review 6*(2), 189–223.

Wedgwood, R. (2007). Education and poverty reduction in tanzania. *International Journal of Educational Development 27*(4), 383–396.

Whitmore, G. A. (1970). Third-degree stochastic dominance. *The American Economic Review 60*(3), 457–459.

Working, H. (1943). Statistical laws of family expenditure. *Journal of the American Statistical Association 38*(221), 43–56.

Yeo, R. and K. Moore (2003). Including disabled people in poverty reduction work:"nothing about us, without us". *World Development 31*(3), 571–590.

Yun, M.-S. (2004). Decomposing differences in the first moment. *Economics letters 82*(2), 275–280.

Yun, M.-S. (2009). Wage differentials, discrimination and inequality: A cautionary note on the juhn, murphy and pierce decomposition method. *Scottish Journal of Political Economy 56*(1), 114–122.

Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning—i. *Information sciences 8*(3), 199–249.

Zedini, A. and B. Belhadj (2015). A new approach to unidimensional poverty analysis: Application to the tunisian case. *Review of Income and Wealth 61*(3), 465–476.

Appendix A

A.1 Share of food expenditure

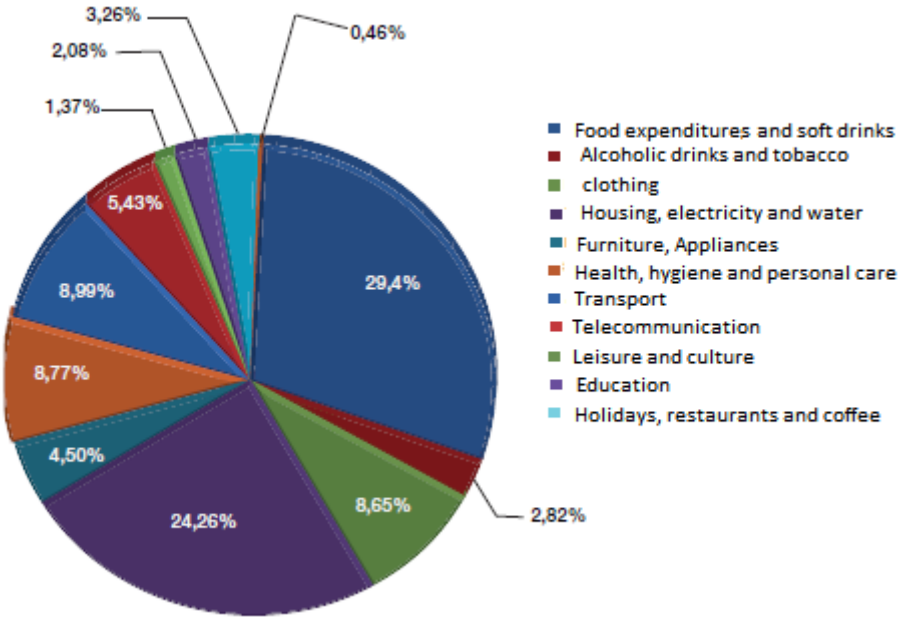


Figure A.1 – Share of food expenditure in household consumption - 2010 in%

Appendix B

B.1 Histograms of the different expenditure transformations

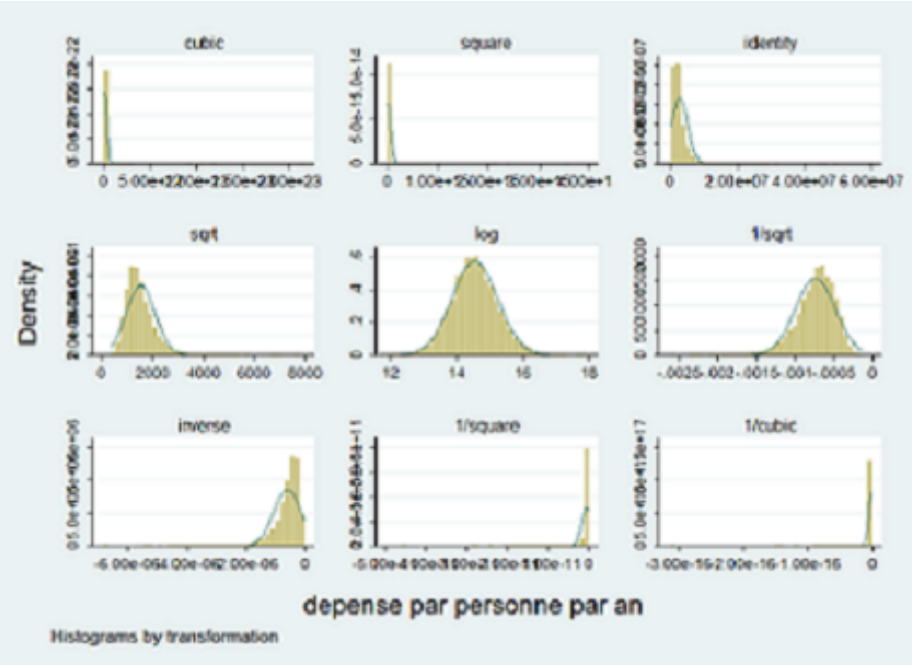
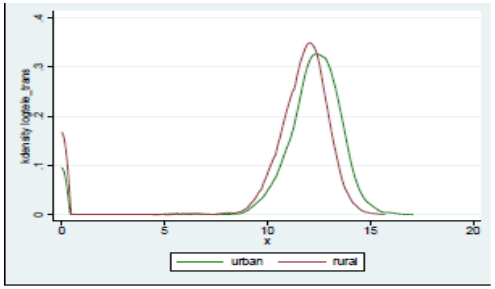
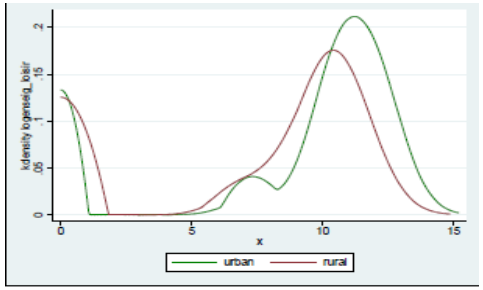


Figure B.1 – Histograms of the different expenditure transformations

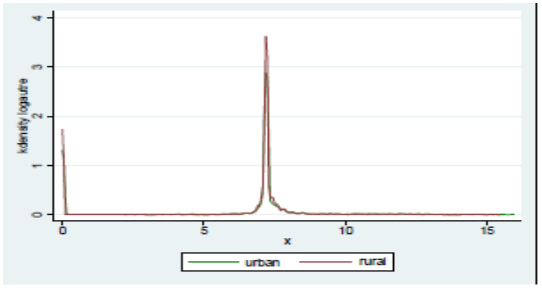
B.2 Kernel densities of the urban-rural desaggregate expenditures



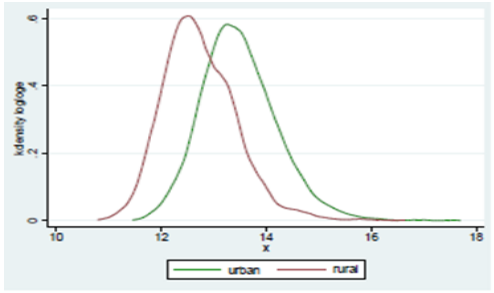
Log of transport expenditures



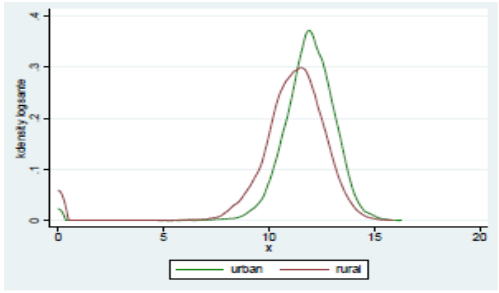
Log of education and leisure



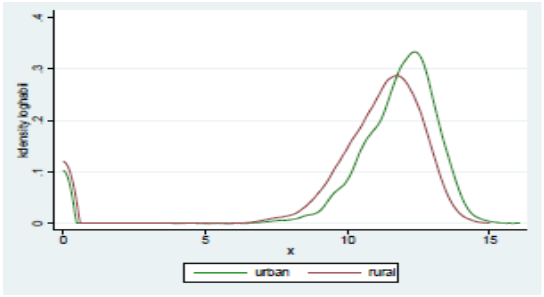
Log of other expenditures



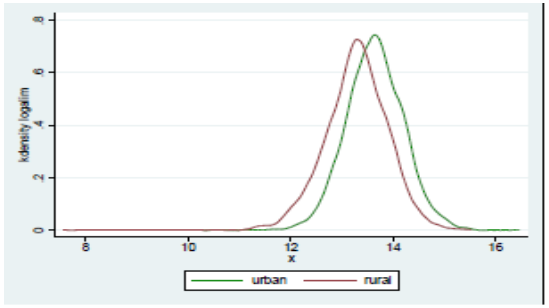
Log of housing expenditures



Log of health expenditures

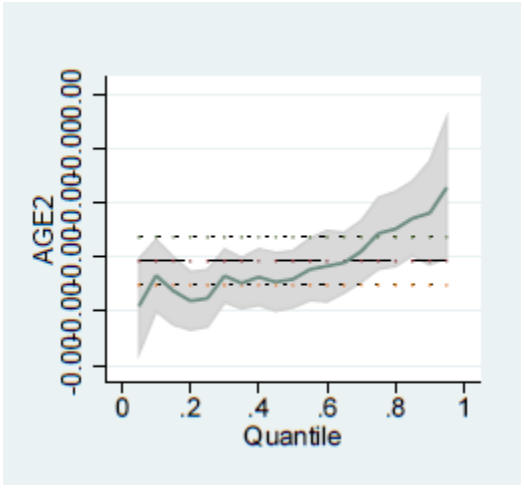


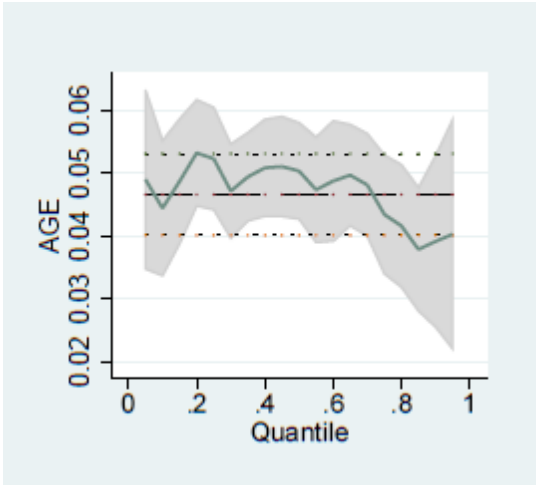
Log of clothing expenditures

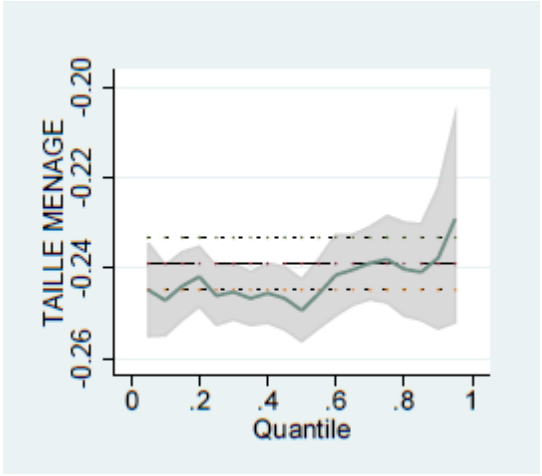


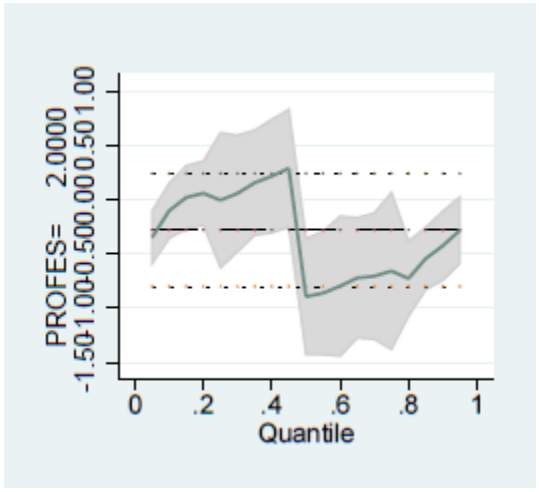
Log of food expenditures

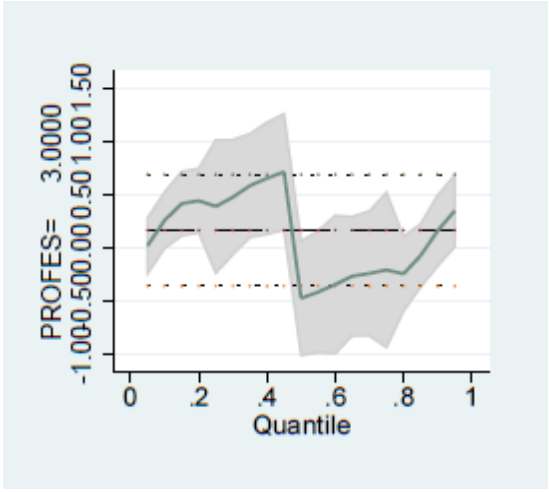
B.3 Quantile estimates

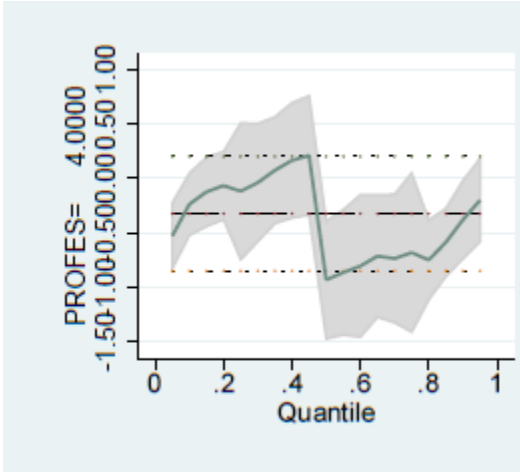

AGE2
-0.000 -0.000 -0.000 -0.000 -0.000 -0.000
0 .2 .4 .6 .8 1
Quantile

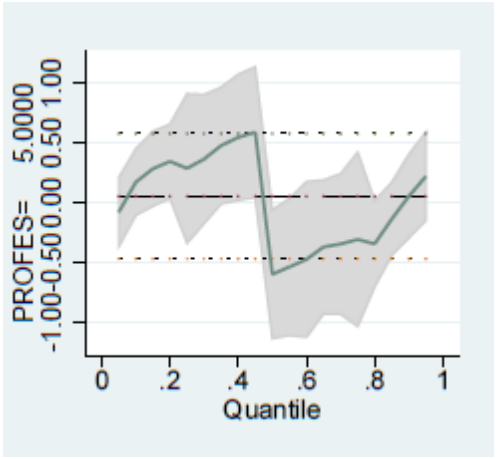

AGE
0.02 0.03 0.04 0.05 0.06
0 .2 .4 .6 .8 1
Quantile

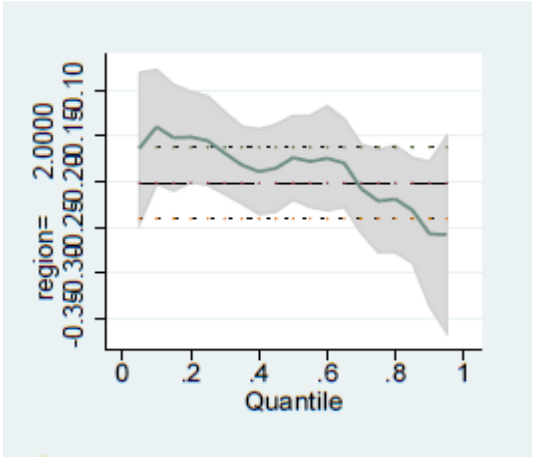

TAILLE MENAGE
-0.26 -0.24 -0.22 -0.20
0 .2 .4 .6 .8 1
Quantile

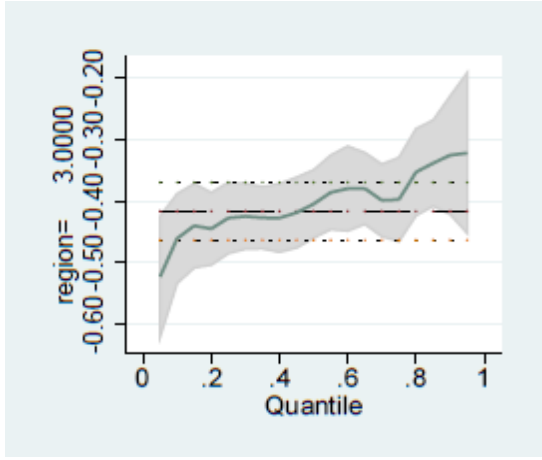

PROFES= 2.0000
-1.50 -1.00 -0.500.000.501.00
0 .2 .4 .6 .8 1
Quantile

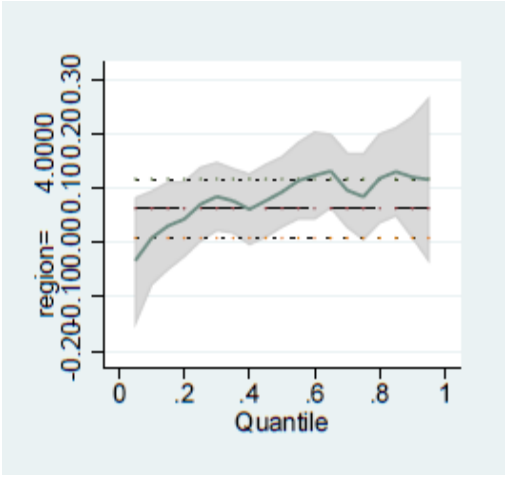

PROFES= 3.0000
-1.00 -0.500.000.501.001.50
0 .2 .4 .6 .8 1
Quantile

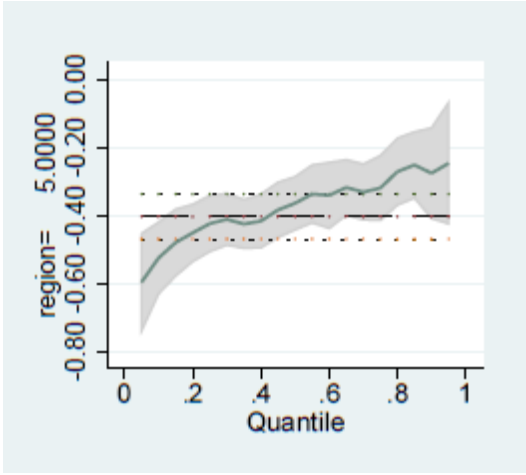

PROFES= 4.0000
-1.50 -1.00 -0.500.000.501.00
0 .2 .4 .6 .8 1
Quantile

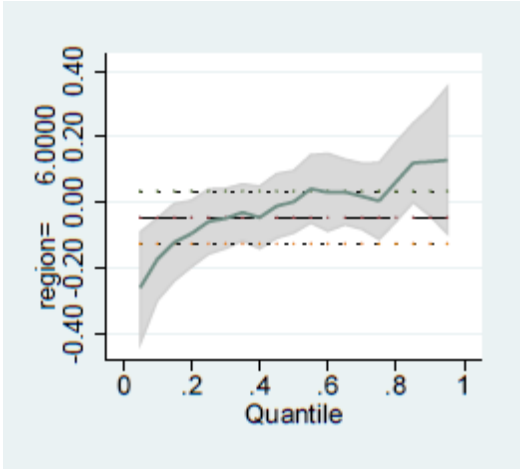

PROFES= 5.0000
-1.00 -0.50 0.00 0.50 1.00
0 .2 .4 .6 .8 1
Quantile

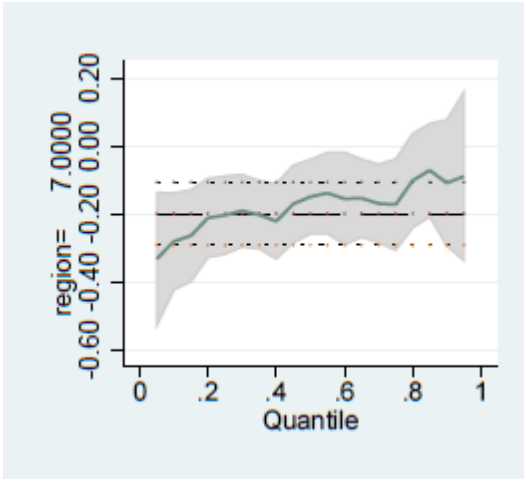

region= 2.0000
-0.35 -0.30 -0.25 -0.20 -0.15 -0.10
0 .2 .4 .6 .8 1
Quantile

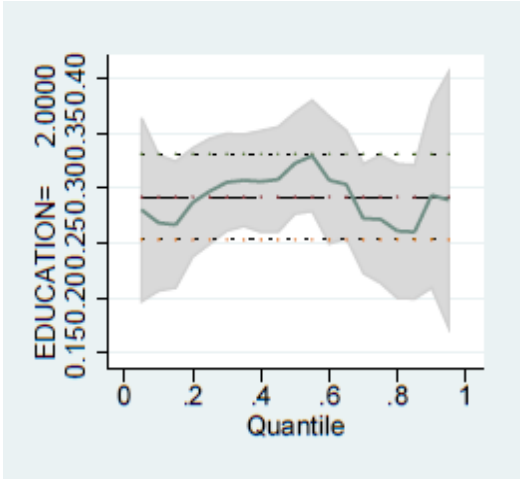

region= 3.0000
-0.60 -0.50 -0.40 -0.30 -0.20
0 .2 .4 .6 .8 1
Quantile

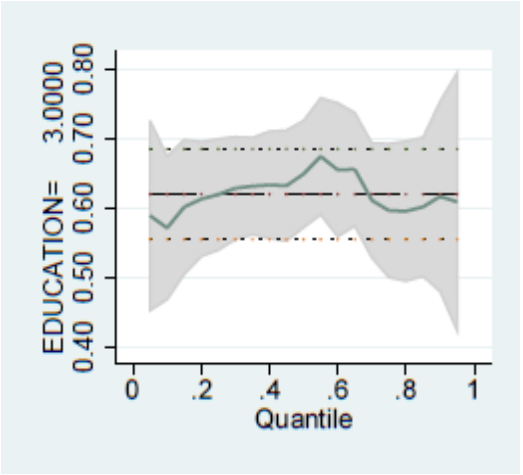

region= 4.0000
-0.20 -0.10 0.00 0.10 0.20 0.30
0 .2 .4 .6 .8 1
Quantile

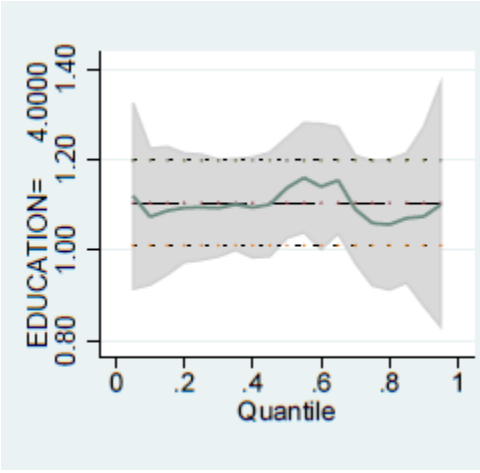

region= 5.0000
-0.80 -0.60 -0.40 -0.20 0.00
0 .2 .4 .6 .8 1
Quantile

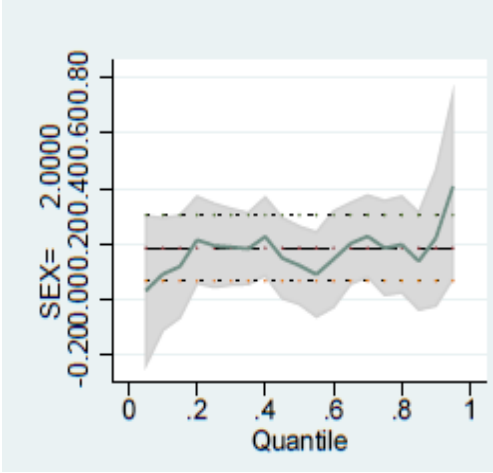

region= 6.0000
-0.40 -0.20 0.00 0.20 0.40
0 .2 .4 .6 .8 1
Quantile


region= 7.0000
-0.60 -0.40 -0.20 0.00 0.20
0 .2 .4 .6 .8 1
Quantile


EDUCATION= 2.0000
0.15 0.20 0.25 0.30 0.35 0.40
0 .2 .4 .6 .8 1
Quantile


EDUCATION= 3.0000
0.40 0.50 0.60 0.70 0.80
0 .2 .4 .6 .8 1
Quantile


EDUCATION= 4.0000
0.80 1.00 1.20 1.40
0 .2 .4 .6 .8 1
Quantile


SEX= 2.0000
-0.20 0.00 0.20 0.40 0.60 0.80
0 .2 .4 .6 .8 1
Quantile

B.4 Detailed RIF decomposition method

Table 1: Urban-Rural welfare gap (RIF-regression)

	10^{th} percentile		50^{th} percentile		90^{th} percentile	
	estimated	%	estimated	%	estimated	%
Reference Group: Urban Coef.						
Estimated log expenditure gap: E[RIF_q (ln(Exp^u))]-E[RIF_q(ln(Exp^r))]	-0.633***	(0.023)	-0.564***	(0.018)	-0.614***	(0.025)
Age	0.010	(0.008)	0.005	(0.004)	0.003	(0.005)
Age2	-0.015	(0.009)	-0.009	(0.006)	-0.007	(0.008)
gender	-0.0031	(0.0061)	0.001	(0.007)	0.002	(0.001)
household size	-0.063***	(0.008)	-0.059	(0.007)	-0.052***	(0.007)
foreign transfer	-0.0083	(0.006)	-0.007	(0.006)	-0.001	(0.001)
logement (as reference)						
logement	-0.001	(0.018)	-0.008	(0.012)	-0.019	(0.019)
logement	0.006	(0.008)	0.002	0.003	0.003	(0.005)
West region	-0.070***	(0.011)	-0.077***	(0.007)	-0.056***	(0.011)
Education	-0.116***	(0.020)	-0.117***	(0.013)	-0.156***	(0.020)
Illiterate (as reference)						
Primary educational level	0.004*	(0.002)	0.002	(0.001)	0.009	(0.009)
Secondary educational level	-0.076***	(0.011)	-0.053***	(0.008)	-0.060***	(0.011)
High educational level	-0.044**	(0.015)	-0.066***	(0.010)	-0.098***	(0.015)

Table 1 - *continued*

Employment	-0.029**	(0.013)	-0.034**	(0.009)	-0.035**	(0.014)
Inactive (as reference)						
Salaried	-0.019*	(0.007)	-0.012**	(0.005)	-0.013*	(0.007)
Independant	-0.050***	(0.009)	-0.026***	(0.006)	-0.010	(0.009)
Unemployed	0.041***	(0.011)	0.004	(0.008)	-0.011	(0.011)
Agregated characteristics effects	-0.297***	(0.030)	-0.314***	(0.021)	-0.614***	(0.025)
Regional structure effects attributable to						
Age	0.719	(0.620)	-0.423	(0.435)	-0.209	(0.686)
Age2	-0.272	(0.303)	0.093	(0.213)	-0.192	(0.335)
gender			-0.018	(0.039)	0.068	(0.062)
household size	0.055	(0.055)	0.245	(0.039)	0.261***	(0.061)
foreign transfer	-0.001	(0.003)	0.003	(0.002)	0.005**	(0.003)
logement (as reference)						
logement	0.011	(0.021)	0.019	(0.014)	0.029	(0.021)
logement	-0.003	(0.004)	0.004	(0.003)	-0.008	(0.005)
West region	0.031**	(0.013)	0.003	(0.009)	0.017	(0.014)
Education	-0.116***	(0.020)	-0.084**	(0.033)	-0.148***	(0.051)
Illiterate (as reference)						
Primary educational level	0.030	(0.021)	-0.022	(0.015)	-0.074***	(0.023)
Secondary educational level	0.009	(0.022)	-0.048***	(0.015)	-0.062**	(0.024)
High educational level	0.005	(0.017)	-0.013	(0.012)	-0.011	(0.018)

Table 1 - *continued*

Employment	0.075**	(0.031)	0.041*	(0.021)	0.040	(0.033)
Inactive (as reference)						
Salaried	0.002	(0.016)	-0.002	(0.010)	0.032**	(0.016)
Independant	0.057**	(0.020)	0.041**	(0.014)	0.014	(0.022)
Unemployed	0.015***	(0.003)	0.003	(0.002)	-0.006	(0.004)
Constant	-0.0936***	(0.330)	-0.073	(0.232)	-0.117	(0.366)
Agregated coefficient effect	-0.335***	(0.036)	-0.249***	(0.024)	-0.277***	(0.037)

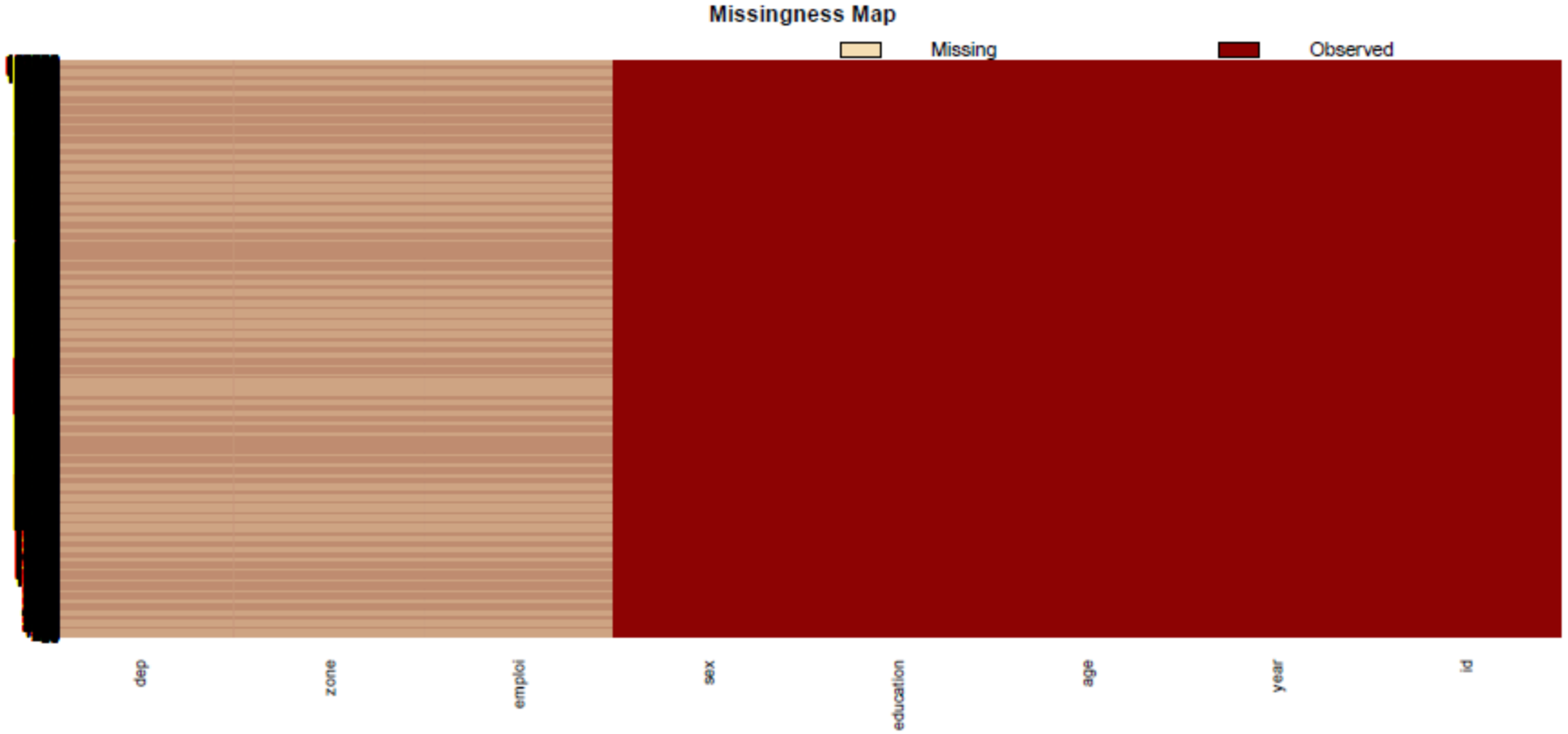
our computing usind households well-being data 2010

standard errors are in parentheses, *** significant at 1% ,** significant at 5%,*significant at 10%

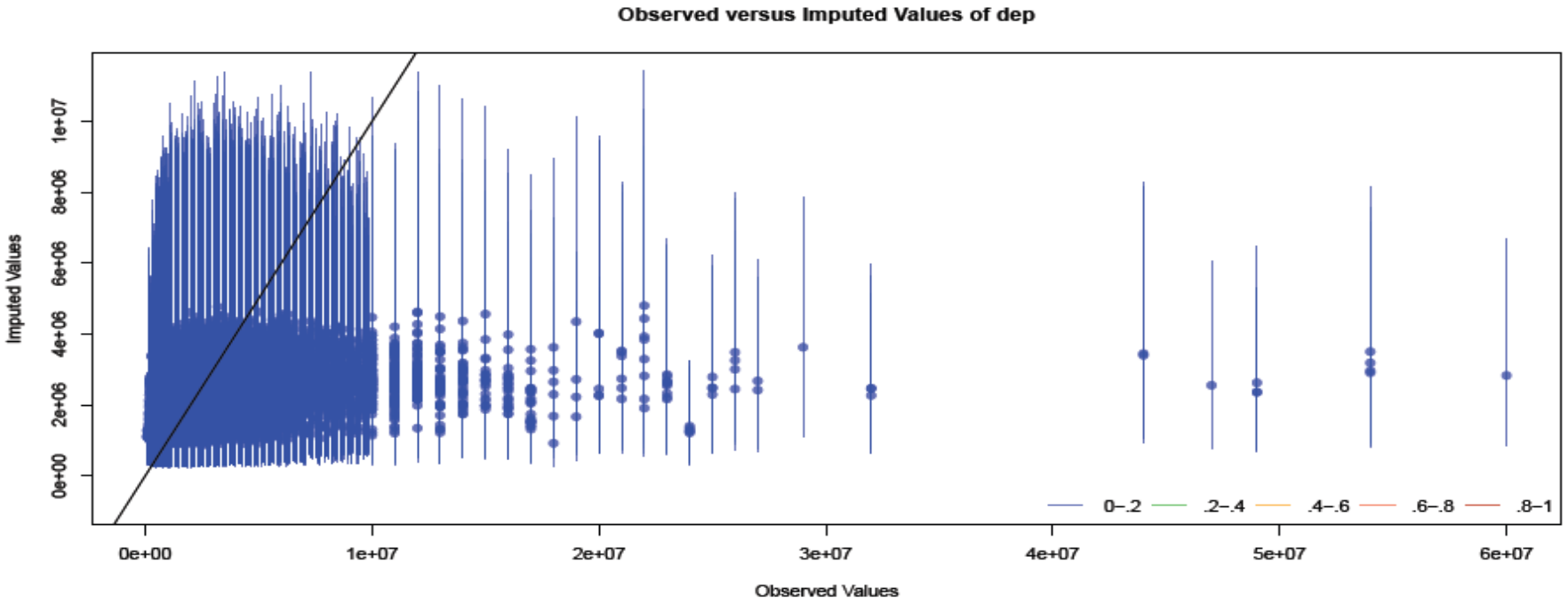
Appendix C

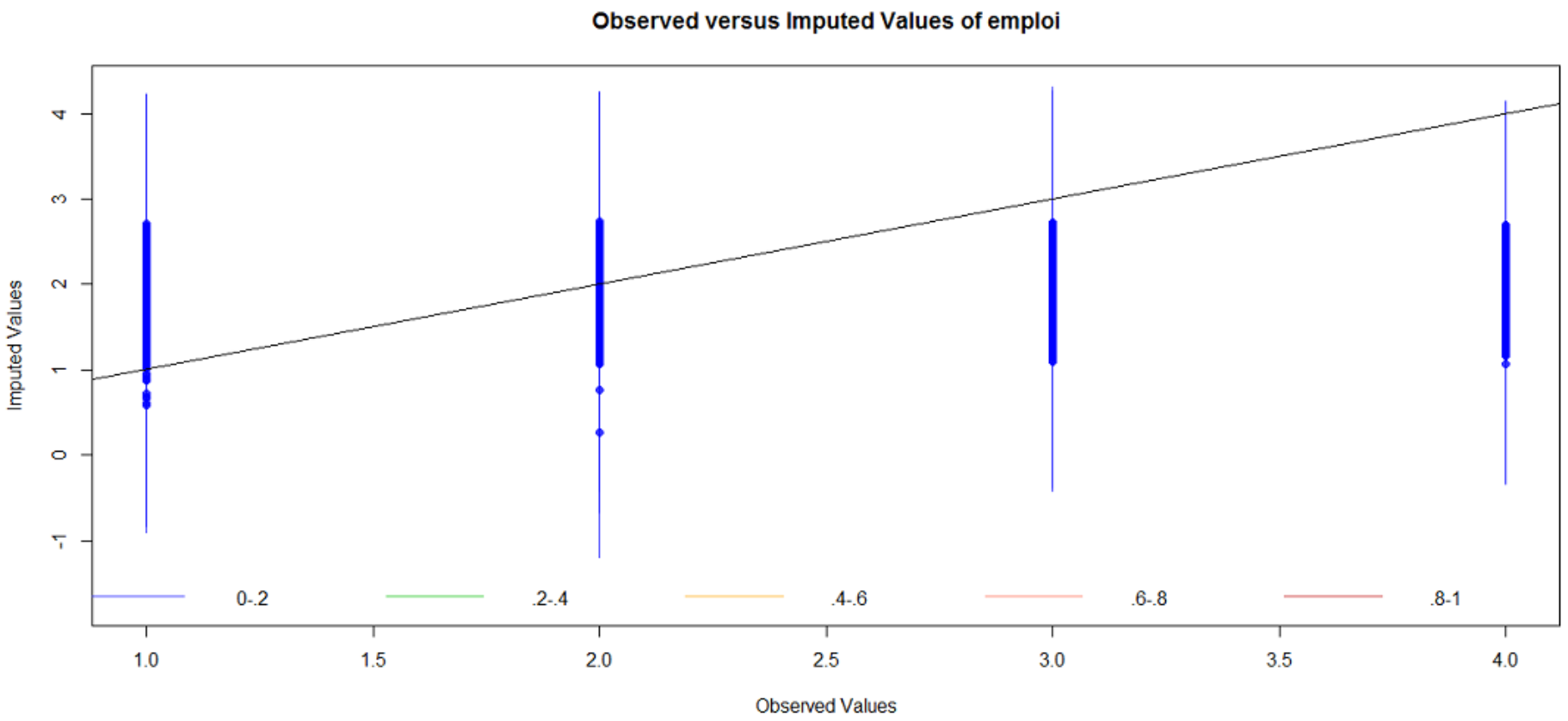
C.1 Robustness cheks of the imputed data

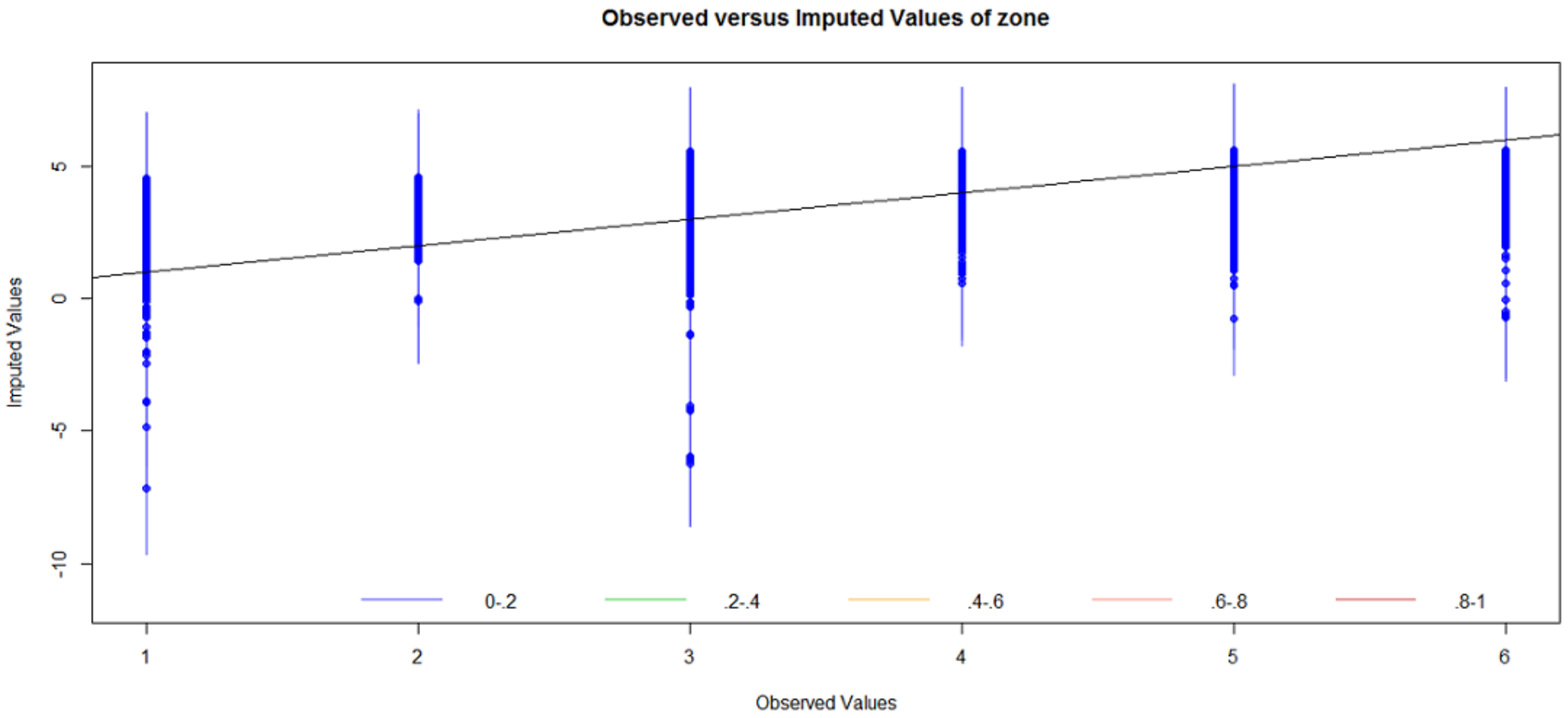
C.1.1 map


Missingness Map
Missing
Observed
dep
zone
emploi
sex
education
age
year
id

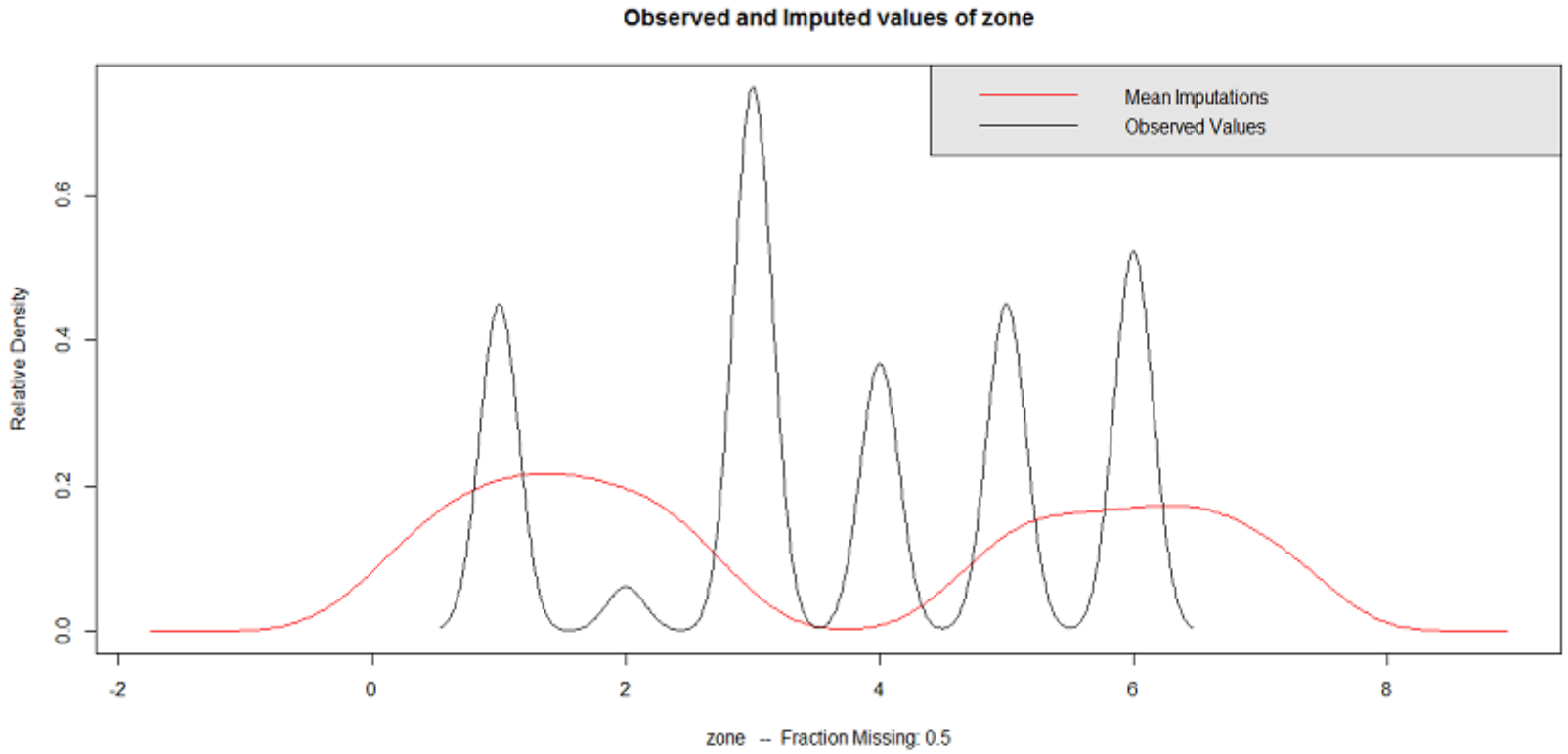
C.1.2 overimpute test

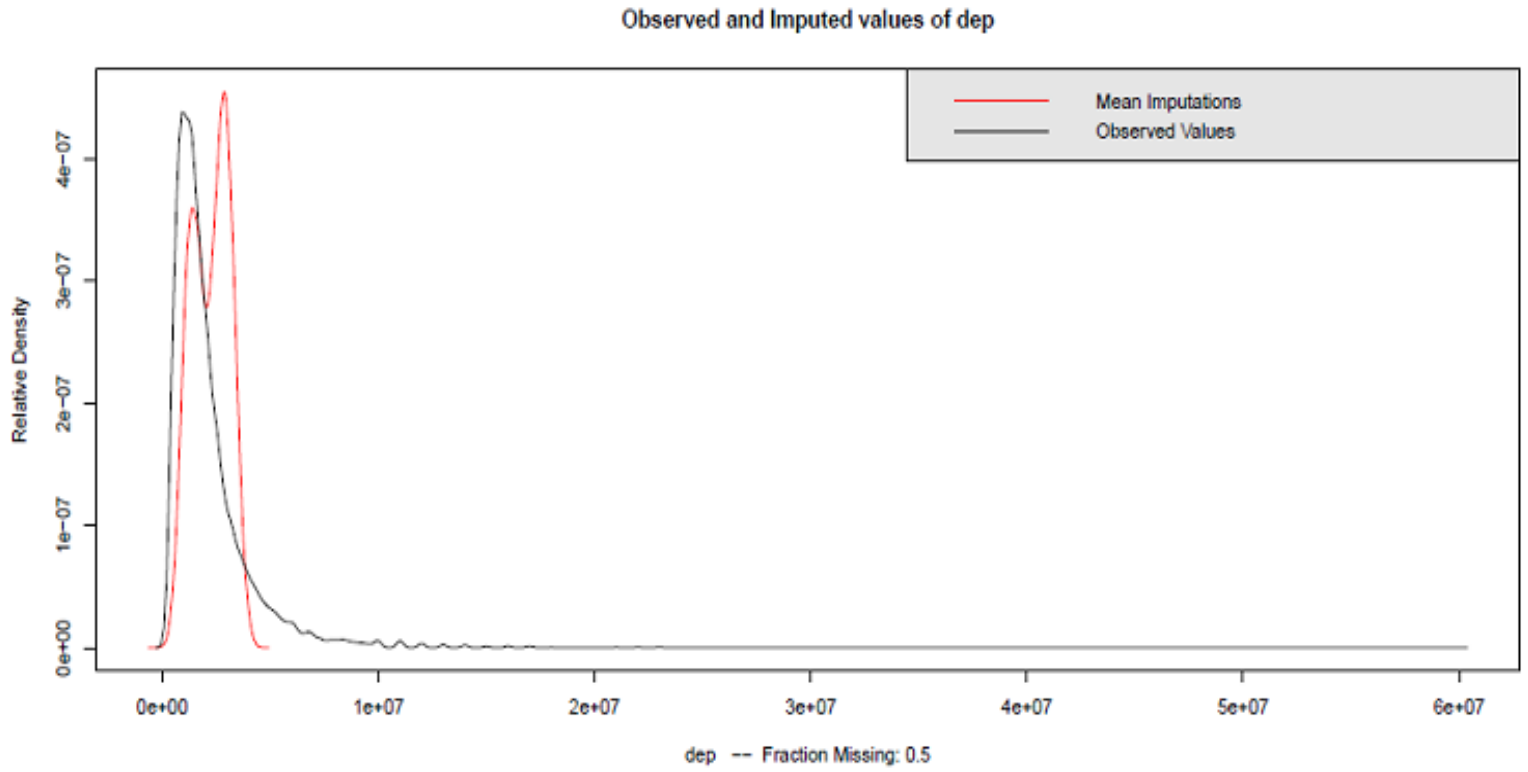

Observed versus Imputed Values of dep
Imputed Values
0e+00
2e+06
4e+06
6e+06
8e+06
1e+07
0e+00
1e+07
2e+07
3e+07
4e+07
5e+07
6e+07
Observed Values
0–.2
.2–.4
.4–.6
.6–.8
.8–1


Observed versus Imputed Values of emploi
Imputed Values
-1
0
1
2
3
4
0-.2
.2-.4
.4-.6
.6-.8
.8-1
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Observed Values


Observed versus Imputed Values of zone
Imputed Values
5
0
-5
-10
0-.2
.2-.4
.4-.6
.6-.8
.8-1
1
2
3
4
5
6
Observed Values

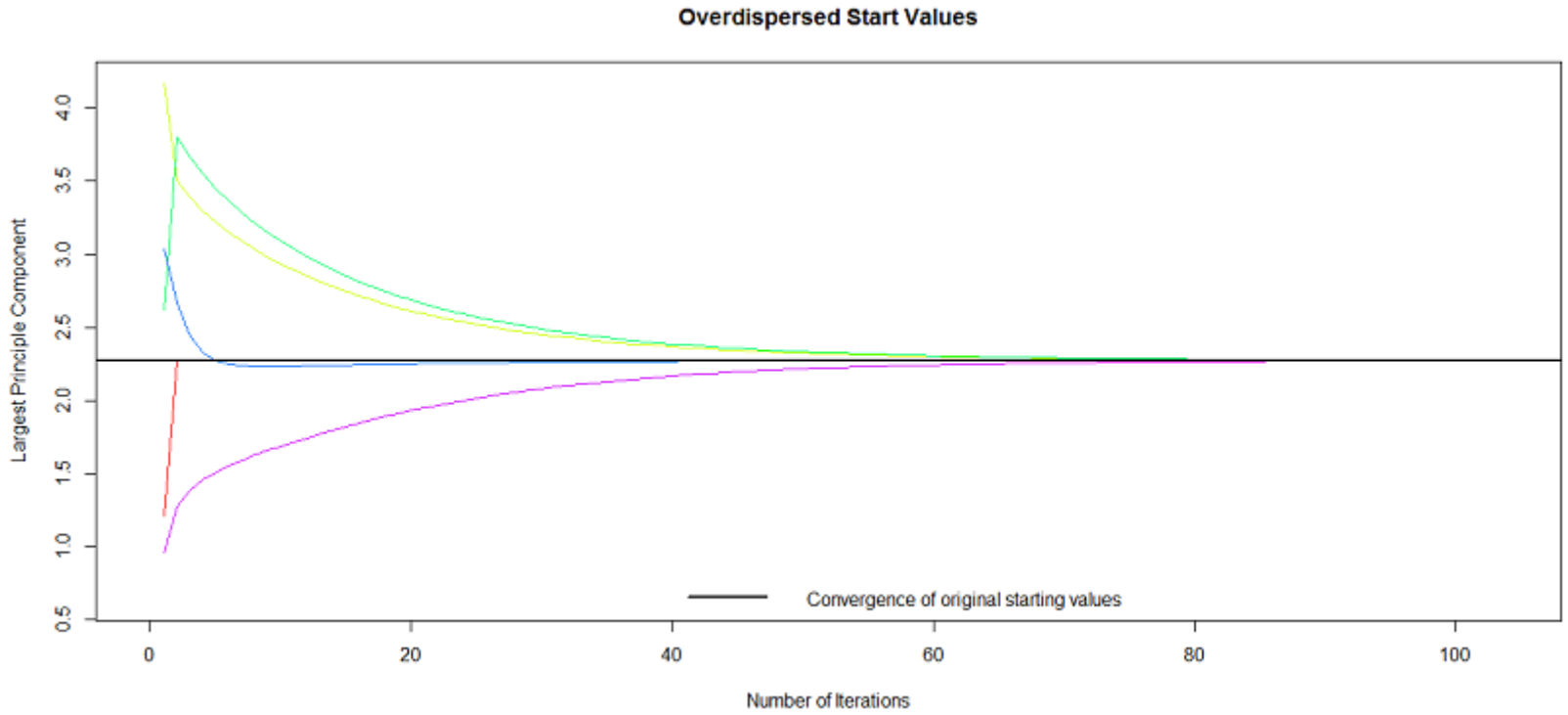
C.1.3 comparing densities


Observed and Imputed values of zone
Mean Imputations
Observed Values
Relative Density
0.0
0.2
0.4
0.6
-2
0
2
4
6
8
zone -- Fraction Missing: 0.5

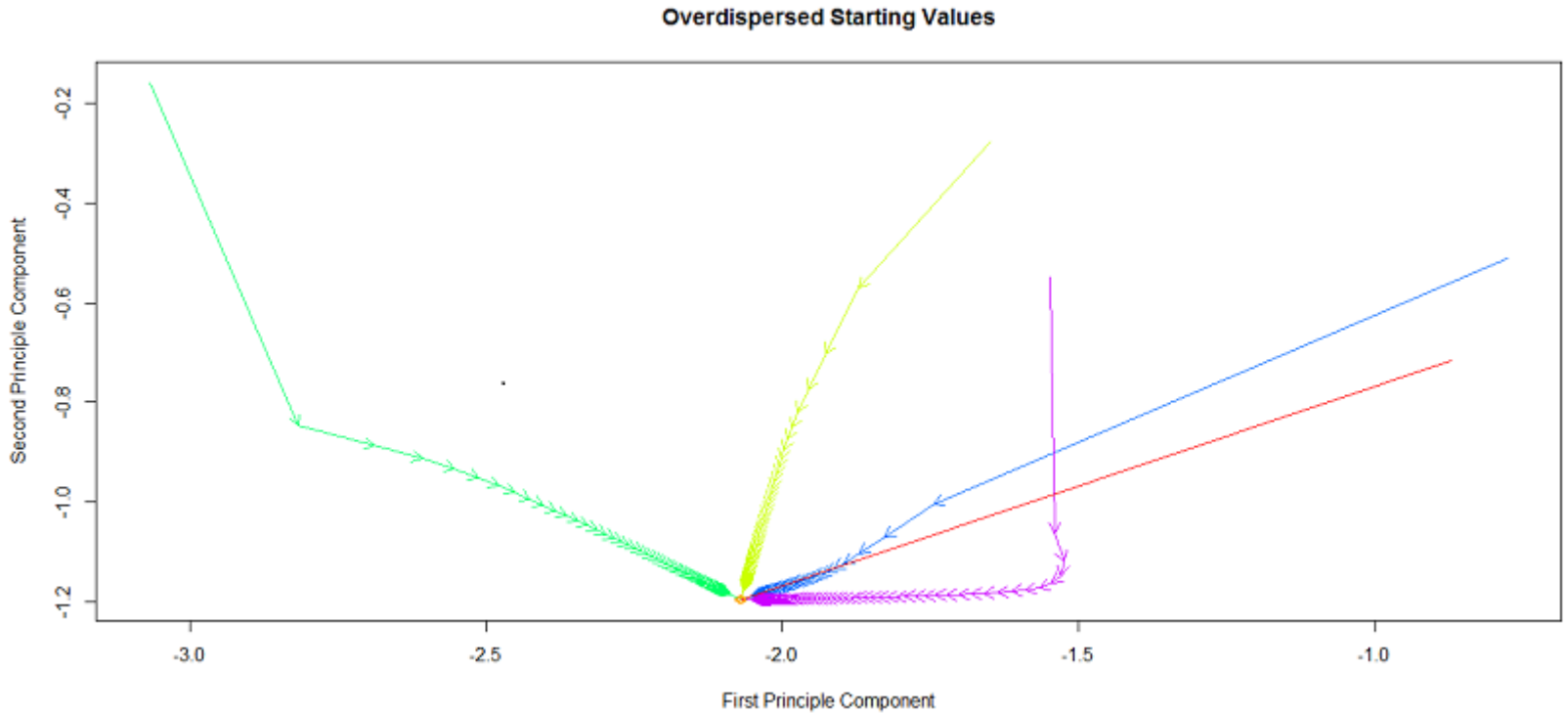

Observed and Imputed values of dep
Mean Imputations
Observed Values
Relative Density
0e+00
1e−07
2e−07
3e−07
4e−07
0e+00
1e+07
2e+07
3e+07
4e+07
5e+07
6e+07
dep -- Fraction Missing: 0.5

C.1.4 Overdispersed Starting Value

One Dimension


Overdispersed Start Values
Largest Principle Component
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
0
20
40
60
80
100
Number of Iterations
Convergence of original starting values

Two Dimension


Overdispersed Starting Values
Second Principle Component
-0.2
-0.4
-0.6
-0.8
-1.0
-1.2
-3.0
-2.5
-2.0
-1.5
-1.0
First Principle Component

C.2 Recursive mixed process model (RMPM)

Mathematic development of the RMPM

$$\begin{cases} P_1^* = \theta_1 + v_1 \\ P_2^* = \theta_2 + v_2 \\ \theta_1 = \beta_1 x_1 \\ \theta_2 = \gamma p_1 + \beta_2 x_2 \end{cases} \tag{C.1}$$

$$\Leftrightarrow$$

$$P_2^* = \gamma(\theta_1 + v_1) + \beta_2 x_2 + v_2 \tag{C.2}$$

$$\Leftrightarrow$$

$$P_2^* = \gamma(\beta_1 x_1 + v_1) + \beta_2 x_2 + v_2 \tag{C.3}$$

$$\Leftrightarrow$$

$$P_2^* = \gamma\beta_1 x_1 + \gamma v_1 + \beta_2 x_2 + v_2 \tag{C.4}$$

$$\Leftrightarrow$$

$$P_2^* = \alpha' x_1 + \beta_2 x_2 + \xi \tag{C.5}$$

with $\alpha' = \gamma\beta_1$ and $\xi = \gamma v_1 + v_2$

Robustness test

TABLE 1 – Poverty transition according to various poverty thresholds

Initial condition	40% median EXP	50% median EXP	60% median EXP	70% median EXP	80% median EXP
sex (Female as reference)					
Male	0.0028	0.0032	0.0052	0.004	0.006
Education (Illitirate as reference)					
primary level	-0.0041	-0.0116	-0.0049	-0.0042	-0.002
Secondary level	-0.0161*	-0.0514*	-0.0302*	-0.0309*	-0.027**
higher level	-0.0734**	-0.1278***	-0.0911***	-0.0899***	-0.092***
Employment (Inactive as reference)					
Salaried	0.0059	0.0169*	0.0176*	0.0175*	0.018*
Independant	0.0560*	0.0673*	0.0642*	0.0648*	0.063***
Unemployed	0.0378*	0.0479*	0.0488*	0.0493*	0.044***
Region (Urban Great Tunisia as reference)					
Rural Great Tunisia	0.1130*	0.1345*	0.1446*	0.1424*	0.130***
urban East	-0.0247*	-0.0276*	-0.0222*	-0.0245*	-0.022**
Rural East	0.1395*	0.1633*	0.1798*	0.1843*	0.167***
urban West	0.0682*	0.0856*	0.0999*	0.1035*	0.093***
Rural West	0.2344*	0.2675*	0.2898*	0.2823*	0.273***
Generation (first generation as reference)					
Second generation	0.0446*	0.0523*	0.0597*	0.0582*	0.052***
Third generation	0.0109	0.0099	0.0160*	0.0137*	0.014*
Fourh generaion	-0.0301*	-0.0539*	-0.0459*	-0.0476*	-0.042***
poverty 2005	0.1426***	0.0217***	0.1122***	0.1158***	0.122***

Table 1 - *continued*

permanence in poverty					
sex (Female as reference)					
Male	0.0002	0.0011	0.0021	0.0017	0.0014
Education (Illitirate as reference)					
primary level	-0.0028	-0.0077	-0.0101	-0.0087	-0.005
Secondary level	-0.0375*	-0.0441*	-0.0492*	-0.0496*	-0.041***
higher level	-0.1069*	-0.1221*	-0.1245*	-0.1246*	-0.121***
Employment (Inactive as reference)					
Salaried	0.0064	0.0177*	0.0179*	0.0173*	0.016**
Independant	0.0594*	0.0679*	0.0646*	0.0637*	0.069***
Unemployed	0.0402*	0.0483*	0.0492	0.0486*	0.050
Region (Urban Great Tunisia as reference)					
Rural Great Tunisia	0.1207*	0.1365*	0.1465*	0.1410*	0.145***
urban East	-0.0270*	-0.0286*	-0.0230*	-0.0250*	-0.025**
Rural East	0.1485*	0.1661*	0.1813*	0.1811*	0.176***
urban West	0.0734*	0.0889*	0.1019*	0.1032*	0.097***
Rural West	0.2344*	0.2687*	0.2876*	0.2728*	0.279***
Generation (first generation as reference)					
Second generation	0.0496*	0.0540*	0.0609*	0.0575*	0.055***
Third generation	0.0115*	0.0122	0.0146*	0.0113	0.014**
Fourh generaion	-0.0415*	-0.0529*	-0.0580*	-0.0602*	0.056***
poverty 2005	0.1510***	0.1415***	0.1134***	0.1145***	0.146***

Table 1 - *continued*

transition to poverty					
sex (Female as reference)					
Male	-0.0020	-0.0011	0.0004	0.0001	-0.0009
Education (Illitirate as reference)					
primary level	-0.0068	-0.0106	*-0.0121*	-0.0104	-0.011
Secondary level	-0.0455*	-0.0529*	-0.0574	-0.0581*	-0.056***
higher level	-0.1069*	-0.1323*	-0.1394*	-0.1428*	-0.138***
Employment (Inactive as reference)					
Salaried	0.0049	0.0157*	0.0173*	0.0174*	0.017**
Independant	0.0474*	0.0612*	0.0633*	0.0648*	0.060***
Unemployed	0.0318*	0.0433*	0.0480*	0.0493*	0.042***
Region (Urban Great Tunisia as reference)					
Rural Great Tunisia	0.0938*	0.1213*	0.1421*	0.1423*	0.122***
urban East	-0.0194*	-0.0239*	-0.0214*	-0.0242*	-0.020**
Rural East	0.1169*	0.1491*	0.1773*	0.1847*	0.159***
urban West	0.0556*	0.0776*	0.0977*	0.1032*	0.087***
Rural West	0.2031*	0.2502*	0.2892*	0.2850*	0.264***
Generation (first generation as reference)					
Second generation	0.0416*	0.0502*	0.0605*	0.0591*	0.053***
Third generation	0.0089	0.0103	0.0135*	0.0106	0.012*
Fourh generaion	-.0398*	-0.0546*	-0.0620*	-0.0659*	-0.057***
poverty 2005	0.1221*	0.1282*	0.1109*	0.1161*	0.117***
ρ	-0.2383*	-0.2052*	-0.1569*	-0.1593*	-0.1809*
observed poverty	0.4902	0.5352	0.5822	0.6252	
chronic poverty	0.2968	0.3418	0.3888	0.4318	

Source : Own computes based on INS data and *** significant at 1% ,** significant at 5%,*significant at 10%

TABLE 2 – Evolution of average expenditures per person and per milims - by Region - Tunisia 2010

catégorie	Urban Area	Rural Area	National
Alimentation	938783	641905	836763
Clothing	264728	147610	224481
Housing	794323	330726	635008
Health	270883	144704	227522
Transport	283962	137040	233473
Telecommunication	176135	73491	140862
Leisure and Culture	46663	14270	35531
Education	69468	24354	53964
Hotels and Restaurants	106818	42393	84618
Others	12587	10450	11853
Total	3102085	1643488	2600782

Source : The National Institute of Statistics-Tunisia 2010 (INS)

ANALYSE MICRO-ECONOMETRIQUE DE LA PAUVRETE: CAS DE LA TUNISIE

Résumé

Cette thèse est composée de trois essais empiriques qui visent à analyser la pauvreté en Tunisie. La première partie est consacrée à une étude unidimensionnelle et multidimensionnelle de la pauvreté. Nous mesurons de la pauvreté en fonction de l'indice composite FGT (Foster-Greeck-Thorbecke) et la régression logistique et nous introduisons une nouvelle approche basée sur la logique floue. A la fin de ce chapitre, nous testons la robustesse de notre travail et de notre choix de la ligne de pauvreté, en introduisant le concept de dominance stochastique et le test de sensibilité. La réduction de la pauvreté et de l'inégalité dans les pays en voie de développement est un sujet courant de nos jours. En particulier en Tunisie les efforts se sont concentrés sur la réduction de l'inégalité et l'écart en terme de bien être entre les zones rurales et les zones urbaines. Malgré toutes les procédures prises par l'Etat, l'écart est toujours profond. Les études antérieures ont mis en valeur le rôle crucial de certaines variables à savoir l'éducation pour réduire le gap entre les deux zones. Le deuxième chapitre vise à vérifier ce résultat, à distinguer les déterminants de bien être dans les deux zones, et à décortiquer l'origine de la persistance de cet écart en utilisons la regression par quantile et quantile censuré pour identifier les déterminant de bien etre dans les zones rurales et les zones urbaines. Et pour décortiquer l'écart entre les deux zones et vérifier si la persistance de cet écart est dû à l'effet caractéristiques ou bien à l'effet rendement de ces caractéristiques, nous utilisons la decomposition RIF proposée par Firpo et al. (2011) et une nouvelle approche de décomposition contrefactuelle proposée par Chernozhukov et al. (2013). Mener une étude dynamique nous amène à penser aux données de panel. Malheureusement, dans les pays en voie de développement, et spécialement en Tunisie, ce genre de base de données sur le bien être des individus n'est pas disponibles. Afin de contourner ce problème, plusieurs chercheurs ont eu recours à la technique de pseudo panel (citons à titre d'exemple Ben Rejeb (2008)), mais cette méthode a été délaissée car elle ne prend pas en considération la pauvreté *between*-individus de la même cohorte. Nous proposons ainsi une nouvelle approche, qui nous permet d'effectuer ce genre d'analyse, basée sur l'inférence causale et l'imputation multiple. Les résultats de cette étude ont contribué aux travaux existants concernant l'analyse de la pauvreté en Tunisie. Par rapport aux études antérieures, notre analyse met en évidence le facteur migration interne entre les régions. Ce point nous permet de prédire plusieurs scénarios concernant le changement de résidence des individus et son influence sur les différentes composantes de la pauvreté. Au total cette étude permet de dégager plusieurs conclusions et de proposer quelques recommandations pour l'amélioration des politiques de lutte contre la pauvreté.

Mots clés: Estimation semi-paramétrique ; régression quantile; pauvreté dynamique; décomposition urbaine-rurale; dominance stochastique; l'approche floue; inférence causale; imputation multiple; modèle bi-probit récursif; l'approche "potential outcome"; pauvreté chronique; pauvreté transitoire; Jalan-Ravallion approche; migration interne

A MICRO-ECONOMETRIC ANALYSIS OF POVERTY: EVIDENCE FROM TUNISIA

Abstract

This dissertation is comprised of three empirical essays dealing with some aspects of poverty analysis. The first one combines both unidimensional and multi-dimensional approaches to analyze poverty. First of all, through the Foser-Greer-Thorbeek index we present a first analysis of the Tunisian poverty profile. Secondly, we estimate a classic logit model using the same variables. Finally, we introduce a new approach based on fuzzy logic (Zadeh, 1975) able a comparison between logit model and fuzzy approach by building a membership function based on the logistic function. The execution of this models require the choice of well-being indicator, generally, the income or he consumption. In this PhD thesis, we favor the reel per capita consumer expenditures of households. The principal reasons of this choice are twofold: The first one, income is hardly observable due to a bad quality of data. The second reason is that consumer expenditures are stable over time comparing to income. Finally, we test the robustness of our work and he choice of the poverty line using sensitivity test and the concept of stochastic dominance. The second essay, focuses on the determinants of household welfare in Tunisia. Welfare is measured by real per capita household expenditure (income). We examine the inequality gap in consumption and education in rural and urban areas. Our empirical analysis relies on the Tunisian Living Standards Surveys of 2010. Our paper makes two original empirical contributions to the literature compared to previous. In order to analyze the gap between the two regions, we apply the RIF- regression advanced by Firpo et al. (2011) and the new counterfactual decompositions developed by Chernozhukov et al. (2013). We also use censored and uncensored quantiles regressions for disaggregate consumption expenditures. This study offers another analysis of the influence of some indicators such as health, food expenditures and especially education on regional disparities in developing countries. It also examines the relationship between these indicators and development disparities across the two areas. The third essay of this thesis aims to explain the determinants of poverty dynamics. Unfortunately in Tunisia, as in most developing countries, panel data are not available. We introduce a new approach able us to execute a dynamic analysis of poverty using potential outcomes approach and multiple imputation. In fact, the study based on two steps. First of all, we use a Bayesian algorithm which combines the two approach, cited previously, in order to penalize the data base. In the second step, we assess poverty dynamics through two different methods. On the one hand, we use static measurement of poverty through the Jalan-Ravallion and the Equally-Distributed Equivalent Poverty Gaps approaches. On the other hand, we execute an econometric procedure by estimating a recursive bivariate probit model. This model allows to treat the initial condition of poverty as endogenous which avoids a probable bias-selection.

Key words: Semi-parametric estimation; Quantile regression; Expenditure regression; Dynamic poverty; urban-rural decomposition; Stochastic Dominance; causal inference; poential outcomes approach; chronic poverty; transient poverty; inetrnal migration; Fuzzy Approach; Jalan-Ravallion approach; EDE Poverty Gaps

PhD Thesis

Amal JMAII

A Micro-econometric Analysis of Poverty: Evidence from Tunisia

Analyse micro-économétrique de la pauvreté: Cas de la Tunisie

Resumé

La lutte contre la pauvreté et l'inégalité régionale sont des enjeux politiques et socio-économiques forts. De nombreuses politiques tentent de limiter la persistance de pauvreté dans les régions marginalisées et surtout les zones rurales. Pour appréhender la question de la pauvreté et l'inégalité, il est nécessaire de comprendre quels sont les mécanismes en œuvre dans le choix de politiques de lutte contre la pauvreté. Nous utilisons la régression par quantile et quantile censuré pour analyser l'écart entre les régions rurales et urbaines. Ensuite, nous appliquons une nouvelle approche de décomposition contrefactuelle qui vise à analyser l'origine du gap entre les deux régions. Finalement, pour compléter notre étude nous proposons une nouvelle approche pour analyser la dynamique de la pauvreté basée sur deux étapes. Premièrement, nous transformons la base des données sous la forme de données de panel via un algorithme bayésien d'imputations multiples. Ensuite, nous utilisons l'approche de Ravallion et le modèle bi-probit récursif pour l'analyse de la pauvreté. Les modèles développés dans cette thèse permettent de mettre en évidence différents résultats jugés intéressants pour l'amélioration des politiques de lutte contre la pauvreté.

Mots Clés

pauvreté dynamique, inégalité régionale, Amelia II, modèle bi-probit récursif, inférence causale, régression quantile, méthode de décomposition countrefactuelle

Abstract

Poverty and regional inequality are a major political and socio-economic issue. Many policies are designed to limit the persistence of poverty in marginalized regions. In order to address the poverty issue correctly, it is necessary to understand the mechanisms driving policies against poverty choices. The purpose of this work is to provide a strong empirical framework, which would allow giving keys for better understanding of the reasons involved in poverty persistent on the one hand, and the failure of national policies to combat poverty. For this purpose, we use quantile and censored quantile regression to analyze regional welfare gap. To complete our analysis we use a new decomposition approach to dissect the gap between urban and rural areas. Finally, for a dynamic assessment of poverty we propose a new approach based on Rubin causal model and multiple imputation that enable to penalised the database. In a second step we use the ravallion's approach and a mixed recursive biprobit model to analyze poverty in Tunisia. The models developed in this thesis are used to highlight different results considered interesting for improving policies against poverty.

Key Words

poverty dynamic, regional inequality, Amelia II, recursif biprobit model, causal inference, quantile regression, Counterfactual decomposition method

University of Tunis El Manar