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Abstract

This paper uses a multilevel logit model and a multilevel mixed linear model to simultaneously analyze the micro-level (household) and macro-level (governorate) factors that might affect the nature and social patterning of poverty in Tunisia. We find convincing evidence that the likelihood of a household being poor is positively and significantly related to household size, number of children per family and education level of household head. Macro-level analysis indicates that a greater neighborhood unemployment rate is associated with higher odds of poverty, while greater industrial agglomeration and migration balance are associated with reduced odds of poverty.

JEL Classification: J1

Keywords: Poverty; Households; Spatial context; multilevel analysis; Tunisia.

ملخص

تســتخدم هذه الورقة نموذجا logit متعدد المســتويات ونموذج خطي مختلط متعدد المســتويات لتحليل في وقت واحد على المســتوى الجزئي (الأســرة) وعلى المســتوى الكلي (محافظة) العوامل التي قد تؤثر على طبيعة الخريطة الاجتماعية للفقر في تونس. نجد أدلة مقنعة على الارتباط الإيجابي بين الأسـر كونهم فقراء والأمور المتعلقة بحجم الأسـرة وعدد الأطفال في الأسـرة ومسـتوى تعليم رب الأسرة. ويشير التحليل على المستوى الكلي أن نسبة البطالة ترتبط بارتفاع احتمالات الفقر، في حين ترتبط أكثر بالتجمعات الصناعية وتوازن الهجرة مع تقليل احتمالات الفقر.

1. Introduction

Despite the national decrease in the absolute poverty rate[1], 15.5% of the Tunisian population, (i.e., 1.6 million people), are actually living under the poverty line.[2] Poverty still remains a severe socioeconomic problem, even worsening in recent years and potentially threatening social cohesion. In addition, the decline in absolute poverty rate at the national level has masked huge differences between regions. The analysis of poverty changes across regions shows that some of them, particularly the Northwest have experienced an impressive reduction in both absolute and relative poverty[3] thanks to important public and private investments (such as the construction of the university and tourist pole in Jendouba). Still, the majority of the Middle-Western governorates, especially Sidi-Bouzid and Kasserine, have not profited from economic growth and investments. Therefore, the evolution of relative poverty rates in this disadvantaged region is even worse and living standards are either stagnant or worsening while other littoral regions (Northeast and Middle East) are getting richer. It is then not shocking that the resentments caused by the feeling of being expelled from growth benefits are one of the chief factors behind the fact that the outbreak of the Tunisian revolution initiated in these regions. It is noteworthy, thus, that targeted investment policy is a prevailing tool for poverty alleviation. Before implementing any investment, government or any policymakers must determine what kind of investment is needed for each region and which region requires it the most required.

A body of research and studies has been performed worldwide to determine factors that globally contribute to economic hardship. The major and common shortcoming of these previous studies is their inability to simultaneously consider the individual-level and macro-level factors to analyze poverty. All these studies have been limited to an analysis of one of the two levels. For the micro-level analysis, monetary and non-monetary approaches have been used to study poverty trends in Tunisia during the last three decades. Main researches focusing on poverty issues in Tunisia using income or expenditure as an indicator of household welfare, show that there has been a significant decrease in the level of poverty (Ayadi et al., 2004; Muller and Bibi 2010; World Bank 2003). Ayadi et al., (2008) developed a welfare composite index (WCI) using a set of non-monetary household living conditions indicators (ownership of durable goods, housing conditions and education) to analyze poverty trends in Tunisia between 1988 and 2001 from a multidimensional perspective. They showed that the poverty rate decreased during the period but the regional and rural/urban disparities remained unchanged. A recent study by Amara and Ayadi (2013) investigated the geographic determinants of welfare and poverty among 261 small administrative units in Tunisia from the macro-level perspective using a set of spatial tools such as exploratory spatial data analysis, spatial model and geographically weighted regression model. They found that spatial analysis techniques outperform non-spatial statistical counterparts.

In response to the weakness of former research, this study aims to consider both the micro-level and macro-level variables that are expected to influence the poverty pattern within the country. To our knowledge, this is the first empirical work that explicitly investigates the influence of both micro-level (individual and household) and macro-level (regional level) characteristics on the odds of households being in poverty. Indeed, poverty analysis should not be restricted only to individual features, but poor people and the society in which they live must

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[1] The absolute poverty is defined as the level of poverty calculated in terms of minimal requirements needed to provide minimal standards of food, clothing, health care and shelter. For a daily poverty line of US$ 2.5, the absolute poverty rate at the national level was 15.57, 11.3 and 7.0 in 1990, 2000 and 2005, respectively (Bibi, S., Castel, V., & Mejia, P. (2011). Poverty and inequality in Tunisia, Morocco and Mauritania. *Economic Brief, African Development Bank*).

[2] National Institute of Statistics (www.ins.nat.tn).

[3] Relative poverty as socially defined is a measure of income inequality. It's commonly calculated as the proportion of population with income less than some fixed proportion of median income.

also be considered. In fact, the experiences, behaviors of the affluent and poor and neighborhood's context added to various human and socio-economic factors that influence livelihoods are all involved in determination of poverty pattern of a country. Then, the contextual effects are more and more important in studying causes, patterns, natures, and consequences of poverty in most recent academic research. Multilevel modeling that takes account of such macro effects enables one's research on poverty to investigate both the micro and macro level effects by nesting personal-level units and factors into assessable context-level units. Identifying a hierarchical nexus between micro and macro dynamics in a statistical model that considers two-level error terms allows one to show individual-level associations with poverty while considering structural-level characteristics.

To this end, this paper makes use of a Hierarchical Generalized Linear Model (HGLM) (called also multilevel model) as the methodology to examine the micro-level and macro-level effects of poverty among households. This multilevel model permits a broad analysis of data that contain different levels of variables (Bryk and Raudenbush 2002). More distinctively, this model can be employed to estimate the effect of contextual factors (macro-level) on the economic status of a household while considering micro-level characteristics of the household. Since the dependent variable of the study is a dichotomous variable that specifies whether or not a household lives under the poverty threshold, the Multilevel Logit Regression model (MLR) is used. We use micro-level data for the households from the last National Survey on Households' Budget in 2010[4], and macro-level data for the 24 governorates from the population census in 2004.

The remainder of the paper is organized as follows: to begin, we briefly conduct in section 1 a comprehensive literature review in the field of predicting and understanding the dynamics of household poverty. The second section is devoted to the presentation of the data and methodology employed to estimate the contribution of each micro-level and macro-level factor in spatial variation of poverty rate. Finally, we present, in the third section, an overview of the principal results, summarize our thinking and attempt to suggest some policy recommendations for decision makers and all stakeholders.

2. Relevant Literature Review

The lion's share of poverty studies has a tendency to take either an individual-level approach, focusing on the socio-economic characteristics of individuals and households, or a macro-level approach, centering on the characteristics of small to large geographic units such as neighborhoods, counties, governorates and regions (Poston et al., 2010). In fact, these well-developed literatures have illustrated that the spatial-temporal poverty dynamics operate at both levels. More lately, academics have started to struggle for more holistic accounts of poverty and linked issues of well-being by considering different levels of investigation in their studies designs (e.g., Sampson et al. 1999; Cotter 2002; Cotter et al. 2007); this is the same approach that we follow in the present paper.

Micro-level theoretical orientations that have directed research on poverty comprise human capital (Becker 1964), status achievement (Blau and Duncan 1967), and the culture of poverty (Lewis 1966). The first one (i.e., the human capital approach) supposes that specific tastes, preferences, and capabilities guide inhabitants to make differential investments in education and skill development that eventually translate into important and lesser remunerations in the labor market. The second approach (i.e., status attainment tradition) has emphasized on both the attained (e.g., educational achievement) and imputed (e.g., age, race, and sex) features of persons and households, and how these characteristics are associated with outcomes like income and occupation. According to the third approach, the culture of poverty, people growing

[4] Enquête Nationale sur le Budget, la Consommation et le Niveau de Vie des ménages (EBCNV).

up poor are socialized to internalize values that preclude them from contributing to the economic mainstream and separating them from the middle class, in consequence perpetuating their misery. Though this thesis has been broadly criticized (Wilson 1987; Lee et al 2008) for missing both empirical evidence and having a misplaced accent on values over structural drawbacks, it has continued to play a part in several debates about poverty. The common implication of all these cited micro-level approaches is that there are numerous micro-level attributes that serve to make persons differentially vulnerable to poverty issues. In the present paper, we use a number of these attributes as micro-level independent variables in the estimated poverty models.

Several empirical researches have illustrated that socio-economic and demographic features of individuals, families, and households impact their poverty status. Indeed, a range of disparities across social groups have usually been shown such as that large households are associated with poverty (Lanjouw and Ravallion 1995; Cortes 1997; Ferreira et al 1998) and poverty is higher in rural areas than in urban areas (Ravallion and Sen, 1996; Duclos et al., 2006). The literature also shows that increasing the education of the poor will tend to reduce poverty (Bastos et al., 2009). Some other recent studies show that families headed by married couples have faced lower poverty than those headed by unmarried women (Snyder et al., 2006); and that poverty is more prevalent among female-headed households than among male-headed households (Bastos et al., 2009). Overall, individual characteristics of persons, families, and households influence, with little doubt, poverty status. Nevertheless, the shortcoming of concentrating on micro-level factors alone is that it tells us nothing about the impact of the structural and spatial factors that differentiate the spatial contexts in which people, families, and households are belonging.

Turning now to macro-level literature, over the last half century a chief body of poverty research has focused on location’s effects in comprehending socioeconomic stratification and, more particularly, poverty. Principally, social scholars have found enduring associations between the features of geographic location and poverty (Friedman and Lichter 1998; Poston et al. 2010; Cotter 2002; Lobao and Saenz 2002; Massey and Eggers 1990; Ravallion and Wodon 1999; Hentschel et al, 2000; Minot and Baulch 2005; Epprecht et al 2011; Baker and Grosh 1994).

A multilevel model is founded in the fact that in social sciences, concepts and data structures are regularly hierarchical. The dependent variables, in this model, depict the behavior of persons. Nevertheless, the persons themselves are assembled into larger geographical units, such as neighborhoods or counties. If the theories maintain that the outcome behavior will be affected by the individual’s or family’s features as well as those of the geographical context, subsequently the independent variables should refer to the features of both the people and the higher order spatial units (Poston et al, 2010).

These concepts are grounded in the main proposal that comprehending human behavior needs that we specify how individuals interact with their social background. Many early social scholars defied individualistic perspectives by assuming that persons help shape their society and that the communally formed social context consecutively impacts their behavior (Duncan et al., 1993). Recently, quantitative developments have permitted social scientists to statistically examine how social contextual factors have an impact on human behavior. Particularly, multilevel modeling has been used to scrutinize “spatial effects” on individual-level outcomes (see Poston and Duan 2000; Goldstein et al., 1993; Poston 2002 and Entwisle et al., 1994 for other applications of multilevel modeling such as unemployment, school assessment performance, immigrant earnings and mathematics attainment).

3. Data and Methodology

3.1 Data

In our study, we use two different sources of data: the 2010 National Survey on Households' Budget, Consumption and Standard of Living (EBCNV 2010) and the population census 2004. The EBCNV 2010 is conducted by the INS (National Statistical Institute of Tunisia) and can be downloaded from the INS or from the Economic Research Forum data portal.[5] The 2010 survey was based initially on a random sample of 13392 households representing 0.61% of total households in the country (61 surveyed household for every 10000 household). It is a representative sample distributed across 1116 districts at the national level, for both urban and rural areas, for the twenty four governorates and for the seven economic regions of the country (Great Tunis, North East, North West, Middle East, Middle West, South East and South West). The 13392 households were drawn using a two stages stratified random sampling in each governorate. In the first stage a sample of primary units (district) is drawn with probability proportional to their size (PPS) in number of households. The district was defined by the General Census of Population 2004 as a geographic area that contains on average 70 households. In the second stage of selection, 12 households are selected per primary district (sampled district). A second sample of 12 households is selected to be used as a substitutive sample if the interviewer failed to get contact with the originally selected household. During the 2010 survey, 11281 out of 13392 households were successfully interviewed, yielding a response rate of 85%. Table 1 shows the distribution of districts and households sampled by regions (see Appendix Table A1 for the distribution of districts and households governorates). The second database used in our study is the general population census 2004[6].

We use the household's poverty status as the dependent variable. An individual or a household is considered as poor if its per capita expenditure (or income) falls below a minimum level poverty line. The World Bank defines three different methods to construct poverty lines: the cost of basic needs, food energy intake, and subjective evaluations (see chapter 3 in Haughton and Khandker, 2009). The cost of basic needs (or the CBN approach) is the most commonly used method for almost all countries including Tunisia to identify poverty line. For the Tunisia case, the poverty line is defined by the National Institute of Statistics (INS) according to the World Bank's methodology. For each of the three strata defined in the Tunisian household surveys (big cities, small and medium towns and rural areas), a specific poverty threshold was estimated taking into account Tunisian modes of consumption and cost of living in the various places of residence. The INS estimates at the first step the food poverty line representing the cost (the median cost of the poorest 20% of Tunisians or reference group) of a basket of food items (reference food basket).[7] With information on the caloric content of each food items, the INS estimates the total calories consumed by an individual who consumes this reference food basket (taking into account their physical activity and their location). Then, the food poverty line was calculated by multiplying the median cost of one kcal of the reference group of households by the recommended energy need for each stratum. In the second step, a nonfood poverty line is added to food poverty line in order to obtain an overall poverty line (food plus nonfood). The nonfood poverty line represents the cost of essential nonfood requirements of the reference group of households (see INS for technical details). Table 2 gives poverty lines, median cost of 1000 Kcal for reference group as well as recommended energy requirement for each stratum in 2010. The INS also published the annual extreme poverty line per capita. It is

[5] The 2010 and 2005 National Survey on Households' Budget, Consumption and Standard of Living can be downloaded from the National Institute of Statistics (www.ins.nat.tn) or from the Economic Research Forum data portal: (www.erfdataportal.com).

[6] See http://www.ins.nat.tn for more details.

[7] For more details, see "Measuring poverty, Inequality and polarization in Tunisia 2000-2010" (INS, 2012).

about TND 757 (Tunisian Dinars) in the cities, TND 733 in small towns and TND 571 in non-communal areas (rural areas).

The independent variables include socio-demographic (the area of residence, the size of the household, household composition, the gender of the household head) and socio-economic characteristics (the educational level of the household head and the household head's main occupation). We expect poverty to rise with household size and that more educated members and a large number of earners in a household reduce poverty. It is also widely believed that the gender of the household head significantly influences poverty (males used as the reference category). The education level of the household head was divided into three categories: no education (reference category); primary, lower secondary and secondary level and post-secondary, university and postgraduate level. Finally, working status of the household head was assessed by four separate binary variables: employed (reference category); unemployed or student; homemaker and pensioner or retired.

Governorate-level variables used in this study were the poverty rate, the unemployment rate, the urbanization rate, the percentage of the labor force engaged in manufacturing, the proportion of the labor force employed in agriculture and the migration balance. The poverty rate, which measures the proportion of extremely poor people at the governorate-level, was included to investigate whether the level of poverty at the regional level is associated with the household or individual poverty status. We believe that the place of residence can impact the probability of households being poor. Indeed, the concentration of underprivileged populations results in the 'impoverishment' of a region. In addition, because it accumulates social and economic difficulties, an underprivileged region could in itself become a potential factor in the welfare reduction of its occupants (Blokland, 2003; Van Eijk, 2010; Cameron, 2005; Hillier, 2007). The unemployment rate was used to measure the level of employment opportunity on poverty. The proportion of the labor employed in manufacturing was included to test how manufacturing agglomeration can affect the household's probability of being poor. In fact, the most empirical studies on poverty in Tunisia showed that households living in manufacturing areas are less likely to be poor than those living in agricultural areas (Amara and Ayadi, 2013). In addition, we test the effect of the migration balance on household poverty status. The migration-poverty relationship may highlight the existence of poverty-linked labor immobility at the governorate level. Such labor immobility, in turn, may contribute to persistence of poverty in certain unprivileged region. The impact can be positive, negative or zero.

Table 3 presents the descriptive data for the dependent variables, and the level-1 and level-2 independent variables. Among the 11,281 households, 04.1% of them are in extreme poverty and 14.4% are in poverty. About 85% of the total households are headed by males. At the governorate-level, the unemployment rate is equal to 15%, the proportion of the labor employed in industry and in agriculture represents, respectively, 19% and 18%.

3.2 Methodology

In this study, we employed multilevel logit modelling that exploits the hierarchical structure of the data in order to determine the direct effect of the individual (or household) and group (governorate) explanatory variables, as well as the interactions between levels (Snijders and Bosker 1999; Goldstein 2011). A multilevel logit model, also known as mixed logit model, was used to predict a dichotomous variable y_{ij} indicating whether the household i nested in region j is poor or not. The multilevel logit model establishes that the dependent variable, y_{ij}, follows a binomial distribution (y_{ij} Binomial$(1, p_{ij})$) with conditional variance var$(y_{ij} \mid p_{ij})$ = $p_{ij}(1-p_{ij})$, where p_{ij} is the probability that the household i from region j is poor (the probability that y_{ij} takes the value 1).

As a first step, it is interesting to estimate a null model (also called empty model) where the response variable is a function of an intercept and random effects at each level. The null model provides the probability that the reference household would consider as poor, assuming that it did not vary with the household or regional characteristics. In addition, the empty model allows the decomposition of the total variance of the outcome into different variance components for each hierarchical level.

Level 1: For a household i corresponding to the jth region, the log-odds (or the logit of the probability of observing y_{ij} = 1) is:

$$\log(\frac{p_{ij}}{1-p_{ij}}) = \text{logit}(y_{ij}) = \beta_{0j} \tag{1}$$

Level 2: For that household, the second-level (regional level) equation is

$$\beta_{0j} = \gamma_{00} + \mu_{0j} \tag{2}$$

Thus, the combined model follows:

$$\log(\frac{p_{ij}}{1-p_{ij}}) = \text{logit}(y_{ij}) = \gamma_{00} + \mu_{0j} \tag{3}$$

Where γ_{00} is the overall average log-odds and $\mu_{0j} \sim N(0, \sigma^2_{\mu 0})$ is the random variation in the level-1 intercepts across regions.

As a second step, the log-adds for households can be a function of household and regional characteristics. Hence, (eq. 3) can be extended to consider P ($p = 1,...,P$) household covariates (x_{pij}) and Q ($q = 1,...,Q$) regional variables (z_{qj}).

Level 1:

$$\log(\frac{p_{ij}}{1-p_{ij}}) = \text{logit}(y_{ij}) = \beta_{0j} + \sum_{p=1}^{P} \beta_{pj} x_{pij} \tag{4}$$

Level 2:

$$\beta_{0j} = \gamma_{00} + \sum_{q=1}^{Q} \beta_{0q} z_{qj} + \mu_{0j} \quad \text{and} \quad \beta_{pj} = \gamma_{p0} + \sum_{q=1}^{Q} \beta_{pq} z_{qj} \tag{5}$$

Thus, the combined model follows:

$$\log(\frac{p_{ij}}{1-p_{ij}}) = \text{logit}(y_{ij}) = \gamma_{00} + \sum_{p=1}^{P} \beta_{p0} x_{pij} + \sum_{q=1}^{Q} \beta_{0q} z_{qj} + \sum_{p=1}^{P} \sum_{q=1}^{Q} \beta_{pq} x_{pij} z_{qj} + \mu_{0j} \tag{6}$$

Where β_{pj} in equation (eq. 4) is the regression coefficient (slope) of the pth household characteristics in region j which is allowed to randomly vary across regions by adding the Q regional variables. However, it is possible to assume fixed regression slopes (β_{pj} are equal to the average slope across regions γ_{p0} without the regional variables in equation (eq. 5)), and the model in this case is denoted as *variance component* model. The double sum in equation (eq. 6) captures possible cross-level interactions between variables at different levels.

4. Results

4.1 Empty model results

We start our analysis by fitting a two-level empty model, also called the 'Random intercept-model,' the 'null model' or the 'intercept-only' model. The empty model predicts the level 1 (household) intercept of the dependent variable as a random effect of the level 2 (governorate) grouping variable, with no other factors at level 1 or 2. The purpose of this step is to test for significant intercept variance, which is a test of the need for mixed modelling. If the intercept variance is not significant, it can be fixed for future steps. Table 4 shows the results of the empty model for the two dependent variables: 'extremely poor' household and 'poor' household. The LR tests indicate that multilevel logit model is more appropriate than simple logit model (the LR tests are significant at the 0.01 level), which allows us to justify the use of this multilevel modelling approach. The between governorate variance ($\sigma_{\mu 0}^{2}$) is non-zero for both 'extremely poor' and 'poor' households. This finding is supported by the intraclass correlation coefficients (ICCs) that revealed considerable clustering of household ('extremely poor' or 'poor') within governorates. Indeed, the ICCs indicated that 23.6% and 27.2% of the total variance of the 'extremely poor' and 'poor' household could be, respectively, accounted for by governorate-level effects. The clustering effect, detected at the empty model indicated that which governorate the household resides in has an important impact on the probability of escaping poverty.

According to the empty model, the average extreme poverty rate across governorates (odds ratio) is estimated to be 2.8%, while the average poverty rate is equal to 14.1%. Also, the mean probability of living in extreme poverty is about 0.027 and it is estimated to be 0.124 for living in poverty.

The variations across governorates in random intercept, for both extreme poverty and poverty, are presented respectively in Fig. 1 and Fig. 2. The non-coastal governorates, such as Jendouba (1.10), El Kef (1.31), Sidi Bouzid (1.43) and Kasserine (2.09), have comparatively higher levels of extreme poverty, while coastal governorates (for example Monastir (-1.51), Nabeul (-1.46), Ben Arous (-1.3) and Manouba (-0.93)) have relatively lower extreme poverty rates (Fig. 1). Figure 2 ranks the 24 governorates from low to high predicted random intercept. Compared to Fig. 1, the ranking is almost the same. The extremely poor governorates are also the poorest ones, more specifically: Jendouba (0.78), Sidi Bouzid (0.79), El Kef (0.92), and Kasserine (1.60).

4.2 Fixed effects results with only household characteristics

The results regarding the impact of household characteristics (level 1) on poverty status are shown in Table 5. Four specifications are estimated: the first (model 1) consists of estimated fixed effects of only household covariates for the extreme poverty status. The second specification (model 2) includes household factors to estimate the log-odds of the household being in poverty. The results show that almost all explanatory variables (the fixed effects) have significant coefficients. As presented in Table 5, the extremely poor households are more likely to live in rural areas, while poor households live in urban areas. Both household size and the household composition (the number of adults and children in the household) increase the likelihood of extreme poverty and poverty in Tunisia. If the household size increases by one person, the odds of being extremely poor will be increased by 48%. The gender of the household head is also a significant factor associated with the odds of being poor (it is not significant for the extremely poor households). More specifically, male-headed households are 34% less likely to be extremely poor than female-headed households. The relationship between the number of earners per household and poverty is also evident. Controlling for other factors and compared to a household without earners, the odds of escaping extreme poverty increases 0.36 times for each additional earner, while the comparable figures for a household with two earners and for the one with three or more earners are respectively 0.19 and 0.16. These effects are almost the same for model 3 and model 4. A strong inverse relationship is also evident between household head's education and poverty or extreme poverty status. In addition, the odds of a household headed by unemployment or student of being extremely poor is about 1.95 times the odds for household with employed head. However, households headed by a retired or homemaker person are negatively and significantly associated with poverty (model 2 in Table 5).

When controlled for individual factors, the governorate level variations for all specifications were lower than those in the empty model. More specifically, for the extremely poor households, the inter-governorate variance is reduced from 1.018 to 0.664 (65%) after controlling for household characteristics.

4.3 Fixed effects results with both household and governorate characteristics

Models in Table 6 combine the household-level variables with the governorate-level variables in order to predict the likelihood that household will be extremely poor (column 1) or poor (column 3). Among the governorate-level variables, the unemployment rate at the governorate-level has a statistically significant positive effect on poverty status of the household. Specifically, one additional percentage point of unemployment rate is expected to increase a household's odds of living in extreme poverty by 11% (column 1 in Table 6). However, one additional percentage point of the proportion of the labor employed in industry is expected to reduce the household's adds of being in extreme poverty by 6%. A lower regional unemployment rate means that households have a greater likelihood of being employed and are at a lower risk of extreme poverty (giving that we find a negative and significant relationship between the number of earners and the extreme poverty at the household-level (Table 5)). As other recent studies (such as Amara and Ayadi, 2013) on the relationship between industrial agglomeration and poverty, our results show that poverty is higher and more persistent in the non-industrial areas. Amara and Ayadi (2013) showed that greater distance from the business districts such as Great Tunis and Sfax may negatively affect the per capita expenditure, resulting in increased poverty rates. As shown in Figure 1 and Figure 2, extremely poor and poor households are more concentrated in the non-coastal areas (more specifically, the Middle West and North West regions of Tunisia), while coastal areas (Greater Tunis, Monastir, Sousse and Sfax) have relatively lower extreme poverty rates and remain the main industrial zones of the country. Indeed, the concentration of infrastructure and human capital in the coastal zones has facilitated the development of industrial structures and consequently the relatively fast growth of the Tunisian economy. The share of manufacturing firms reaches 84% in the coastal area compared to 16% in the interior area. Similarly, the coastal areas absorbed 88% of manufacturing jobs in 2010 against only 12% for the interior areas (Amara and Ayadi, 2014). All those factors can explain the negative relationship between industrial agglomeration and poverty.

Compared to fixed effects model in Table 5, we find that the estimated coefficients of the household-level variables are relatively stable with minor fluctuation. All of the coefficients retain their sign and level of statistical significance. However, the variation at the level 2 (governorate-level) has decreased from 0.664 (Table 5) to 0.065 and becomes insignificant when controlling for both household and governorate level factors to predict the likelihood that family will be extremely poor. The inter-governorates variation has also decreased from 0.475 (column 3 in Table 5) to 0.105 (column 3 in Table 6) but it remains statistically different from zero.

Table 7 was similar to Table 6, but it included a fixed interaction effect between household and governorate characteristics (cross-level fixed effects) in addition to all main effects variables. More specifically, we test how the number of possible wage earners in the household living in poorest governorate can improve the odds of escaping poverty. Indeed, promoting employment and fighting poverty in lagging areas is one of the major challenges facing the Tunisian government today. One of the solutions followed by the government, especially after the January 14 Revolution, is to recruit from each poor household living in a lagging area one unemployed member. Such an initiative can directly contribute to poverty reduction since each income earner typically supports several other non-working household members in addition to themselves (which is the case for most countries with high dependency ratio). To this end, we test the effect of three new variables on household poverty status: household with one earner living in poor governorate (one earner×poverty); household with two earners living in poor governorate (two earners×poverty) and household with three or more earners living in poor governorate (three or more earners×poverty).

The models with cross-level interactions find that, under controls, the odds of being in extreme poverty or in poverty for a household with two earners and living in poorest governorate decreases by 5%. The estimated coefficients of the household and regional level variables are relatively stable with minor fluctuation.

5. Further Robustness Checks

In the body of the paper, we used a multilevel logistic model to estimate the log odds of being in poverty by using a binary dependent variable. It would be a good robustness check to estimate a mixed linear model by using the 'welfare ratio' given by total household expenditure or consumption as a proportion of the poverty line. The distribution of this measure determines the level of absolute poverty. Table 8 presents two robustness checks for the results in Table 7. We estimate a mixed linear model with governorate specific random intercepts using the logarithm of the welfare ratio for the first and the second poverty line ($\ln\_w\,ratio1$ and $\ln\_w\,ratio2$) (column 1 and column 2 in Table 8, respectively).

The household-level and governorate-level effects have the expected sign and almost all of them are in accordance with our previous results. Larger households are more likely to be poor than smaller households. The gender of the household head's variable has a positive and significant impact on both $\ln\_w\,ratio1$ and $\ln\_w\,ratio2$, which confirms the previous results of the multilevel logit model that female households are poorer compared to male headed households. The welfare ratio was also highest among household heads who are more educated, but it decreased considerably for households with more children. The welfare ratio of household with two earners is twice as important that household with one earner.

With regard to governorate-level characteristics, the poverty and unemployment rates negatively impact the household's welfare ratio, while governorates with positive internal migration balance have a positive impact (significant at 10% for the $\ln\_w\,ratio1$ and at 5% for $\ln\_w\,ratio2$). These results can be explained by the fact that a large share of industrial capital in Tunisia is concentrated principally in a very small number of urban centers in coastal area (Great Tunis in the North; Sfax, Sousse and Monastir in the Middle East). As a result, rich areas attract professionals and skilled workers, which can help to improve their productivity. Thus, migration can directly and indirectly increase income and consumption and decrease poverty in the home area (Nguyen et al, 2010). The cross-level effects are also positive and significant at the level of 1% and show that households with one or more earners within poorest are have the highest welfare ratio than households without earners.

6. Conclusions and Policy Implications

This paper has presented empirical evidence for the existence of potential household as well as governorate contextual effects on the log-odds to being in poverty or in extreme poverty in Tunisia. The results of the multilevel logit model show that the household size, household occupation (more specifically households with three or more children), the number of earners per household and the level of education of the household head are statistically significant in explaining the log-odds of households to be living in poverty or in extreme poverty. The results show, however, that the impact of urban/rural variable is not the same for all households. More specifically, extremely poor households are more likely to live in rural areas, while poor households live in urban areas.

At the contextual level, the macro-level predictors included the urbanization rate, the unemployment rate, the rate of poverty, the part of industrial jobs, the part of agriculture jobs and the migration balance. Among those macro-level or governorate-level variables, the effect of unemployment rate is positive and statistically significant, supporting the idea that households living in governorates with less employment opportunity are more likely to be poor. However, households living in governorates with a higher proportion of industrial jobs are more likely to have escaped poverty. Our results show also that some cross-level interaction effects exist and can explain household poverty. More specifically, we find that an additional earner in a given household living in the poorest area has a significant effect to reduce this poverty level. By introducing the household-level, governorate-level variables and cross-level interaction effects, the variance at the macro-level detected in the empty model has significantly reduced and has disappeared in the same case.

In our opinion, taking into account the multilevel structure of the household survey as well as the micro-level, the contextual-level and the cross-level interaction effects can help policy makers to identify principal determinants of household poverty. Public policy can act to reduce household poverty directly by providing a good education and household occupation or indirectly by providing employment opportunity and strengthening industrial agglomeration in lagging areas of the country. Although Tunisia has achieved enormous progress in poverty and inequality reduction during the last 50 years, the effect of these programs during this period has not been reached in the Northwest and Middle West regions (more specifically the governorates of Kesserine, Kairouan, Siliana, Jendouba, El Kef and Sidi Bouzid). It is important to emphasize that both researchers and policy makers need to abandon the idea that poverty is a micro-level problem only related to household characteristics. Poverty reduction policy in Tunisia should have a regional dimension where region-specific policies need to be formulated and implemented.

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Figure 1: Random Intercept Predictions and Approximate 95% Confidence Intervals for Extreme Poverty in Tunisia

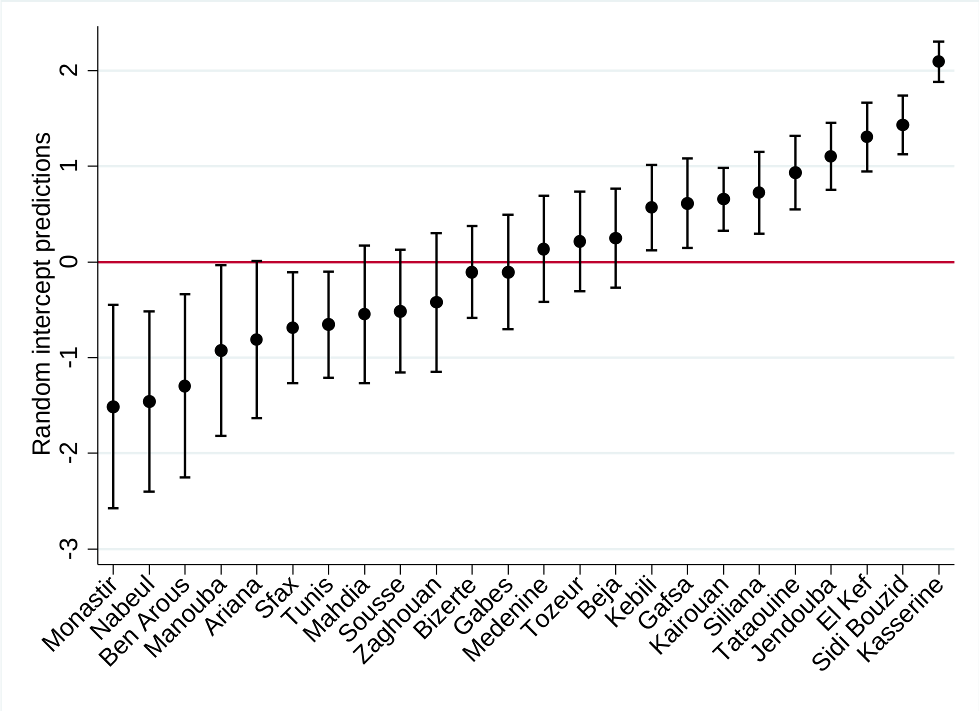

Figure 2: Random Intercept Predictions and Approximate 95% Confidence Intervals for Poverty in Tunisia

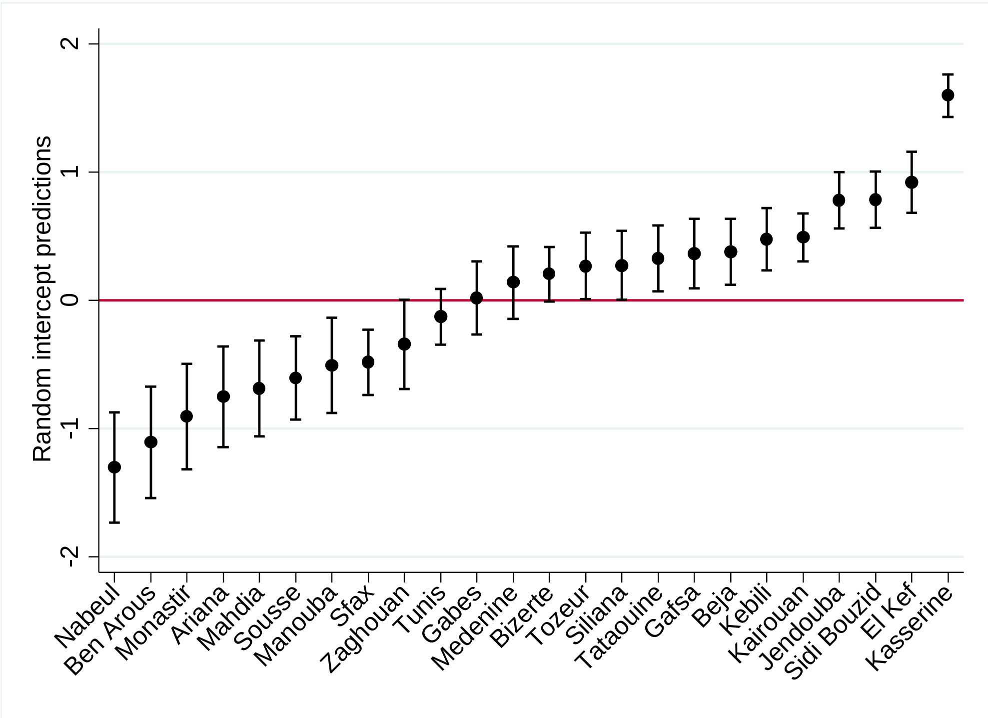

Table 1: Distribution of Districts and Households Sampled by Regions

Region	Total		Sample size		
	District	Households	District	Households	Household sample percent (%)
Great Tunis	7863	533996	240	2880	0.54
North East	4446	316199	156	1872	0.59
North West	3821	269016	144	1728	0.64
Centre East	7379	503248	216	2592	0.52
Centre West	3871	264142	144	1728	0.65
South East	2711	186278	108	1296	0.7
South West	1644	112960	108	1296	1.15
Total	31735	2185839	1116	13392	0.61

Source: The National Institute of Statistics-Tunisia (INS).

Table 2: Caloric Requirements and Annual Per Capita Poverty Line in 2010

Stratum	Recommended Energy requirement	Median cost of 1000 Kcal for reference group (in Thousands)	Food poverty line (in TND)	Annual per capita poverty line (in TND)
Cities	2273	576	478	1277
Small towns	2304	553	465	1158
Non-communal Areas	2327	438	373	820

Source: INS, 2012.

Table 3: Summary Description of the Variables

	Type	Mean	stdv (range)
Dependent variables			
(poverty Status and welfare ratio)			
Extremely Poor	Dichotomous	0.041	
Poor	Dichotomous	0.144	
logarithme of the welfare ratio 1	Continuous	1.055	0.612 (-1.353-3.616)
logarithme of the welfare ratio 2	Continuous	0.616	0.598 (-1.716-3.159)
Independent variables: Individual level			
Urban/rural (urban = 1; rural = 0)	Dichotomous	0.644	
Household size	Categorical	4.465	1.885 (1-15)
Gender of the household head	Categorical	0.849	
(male as reference category)			
Household composition	Categorical		
(1-2 adults, no child reference category)			
1-2 adults, 1-2 children		0.177	
1-2 adult, 3 or more children		0.139	
3 adults or more, 0-1 child		0.373	
3 adults or more, 2-3 children		0.138	
3 adults or more, 4 children or more		0.026	
Number of earners	Categorical		
(no earner reference category)			
household with 1 earner		0.535	
household with 2 earners		0.247	
household with 3 or more earners		0.100	
Household head's education	Categorical		
(None reference category)			
primary/lower secondary and secondary		0.118	
post secondary, university and postgraduate		0.079	
Household head's occupation	Categorical		
(employed as reference)			
unemployed or student		0.024	
Homemaker		0.080	
pensioners or retired		0.265	
Regional level			
urbanization rate (%)	Continuous	61.412	22.541 (24.3-100)
Poverty rate (%)	Continuous	14.006	6.771 (4.823-28.476)
Unemployment rate (%)	Continuous	14.847	3.651 (7.6-21.9)
part of industrial jobs (%)	Continuous	18.599	9.422 (6.170-42.790)
part of agricultural jobs (%)	Continuous	18.286	11.126 (0.86-39.16)
migration balance (Thousand)	Continuous	-1,204	16.556 (-27.2- 37.896)
N(Regions)		7	
N(Governorates)		24	
N(Clusters)		480	
N(Household)		11281	

Note: The governorate-level variables are from the general population census (2004) except for the poverty rate variable which is calculated from the EBCNV 2005.

Table 4: Null Model Results

	Extremely poor		Poor	
Parameters	**Empty model**	**Empty model using MCMC estimation**	**Empty model**	**Empty model using MCMC estimation**
Intercept (γ_{00})	-3.588***	-3.614***	-1.960***	-2.014***
Standard error	0.218	0.293	0.149	0.154
$\sigma_{\mu 0}^2$	1.018***	1.230***	0.510***	0.589***
Standard error	0.328	0.472	0.154	0.201
Odds ratio = exp (γ_{00})	0.028	0.027	0.141	0.133
Probability (p_{ij})	0.027	0.026	0.124	0.118
Intraclass Correlation Coefficient (ICC)	0.236	0.272	0.134	0.152
LR test	350.95***		576.71***	

Notes: The intraclass correlation coefficient (ICC) is the proportion of the variance of the governorate-level random effect out of the total variance. Giving that the unobserved individual latent variable follows a logistic distribution with individual level variance equal to ($\pi^2/3$), the ICC is calculated as: ICC = ($\sigma_{\mu 0}^2$)/($\sigma_{\mu 0}^2 + \pi^2/3$).

Table 5: Estimated Multilevel Logit with Random Intercept and Household Characteristics

	Extremely Poor		Poor	
Covariates	**Model (1)**	**Odds ratio (OR) For model (1)**	**Model (2)**	**Odds ratio (OR) For model (2)**
Intercept	-4.554***	(0.011)	-2.871***	(0.057)
Individual level				
Urban/rural (urban = 1; rural = 0)	-0.460***	(0.631)	0.132*	(1.141)
Household size	0.392***	(1.480)	0.352***	(1.422)
Gender of the household head	-0.345	(0.708)	-0.409***	(0.664)
Household composition				
1-2 adults, 1-2 children	0.722**	(2.059)	0.862***	(2.368)
1-2 adult, 3 or more children	1.456***	(4.289)	1.443***	(4.233)
3 adults or more, 0-1 child	0.293	(1.340)	0.530***	(1.699)
3 adults or more, 2-3 children	0.709**	(2.032)	0.958***	(2.606)
3 adults or more, 4 children or more	1.355***	(3.877)	1.559***	(4.754)
Number of earners				
Household with 1 earner	-1.018***	(0.361)	-1.049***	(0.350)
Household with 2 earners	-1.671***	(0.188)	-1.510***	(0.221)
Household with 3 or more earners	-1.812***	(0.163)	-1.841***	(0.159)
Household head's education				
Primary/lower secondary and secondary	-1.193***	(0.303)	-1.168***	(0.311)
Post secondary, university and postgraduate	-0.967***	(0.380)	-1.784***	(0.168)
Household head's occupation				
Unemployed or student	0.669**	(1.952)	0.259	(1.296)
Homemaker	-0.278	(0.757)	-0.860***	(0.423)
Pensioners or retired	-0.101	(0.904)	-0.210**	(0.811)
$\sigma^2_{\mu 0}$	0.664***	0.786**	0.475***	0.545***
Standard error	0.240	0.309	0.145	0.190
Log likelihood	-1467		-3733	
LR test	167.14***		398.38***	
Bayesian DIC		2934.25		7447.77

Notes: Odds ratio in parentheses. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 6: Estimated Multilevel Logit with Household and Governorate Characteristics

Covariates	Model (1) with governorate Attributes	Odds Ratio (OR)	Model (2) with governorate Attributes	Odds Ratio (OR)
Intercept	-4.181***	(0.015)	-3.966***	(0.019)
Individual level				
Urban/rural (urban = 1; rural = 0)	-0.419***	(0.658)	0.148**	(1.160)
Household size	0.381***	(1.464)	0.349***	(1.418)
Gender of the household head	-0.337	(0.714)	-0.408***	(0.665)
Household composition				
1-2 adults, 1-2 children	0.735**	(2.085)	0.866***	(2.377)
1-2 adult, 3 or more children	1.472***	(4.358)	1.451***	(4.267)
3 adults or more, 0-1 child	0.309	(1.362)	0.534***	(1.706)
3 adults or more, 2-3 children	0.728**	(2.071)	0.966***	(2.627)
3 adults or more, 4 children or more	1.356***	(3.881)	1.554***	(4.730)
Number of earners				
household with 1 earner	-1.016***	(0.362)	-1.050***	(0.350)
Household with 2 earners	-1.652***	(0.192)	-1.503***	(0.222)
Household with 3 or more earners	-1.781***	(0.168)	-1.832***	(0.160)
Household head's education				
primary/lower secondary and secondary	-1.183***	(0.306)	-1.165***	(0.311)
Post secondary, university and postgraduate	-0.944***	(0.389)	-1.781***	(0.168)
Household head's occupation				
unemployed or student	0.701**	(2.016)	0.273	(1.314)
Homemaker	-0.299	(0.742)	-0.863***	(0.422)
Pensioners or retired	-0.100	(0.905)	-0.210**	(0.811)
regional level (governorate)				
Urbanization rate (%)	-0.009	(0.991)	0.005	(1.005)
Poverty rate (%)	0.026	(1.026)	0.021	(1.021)
Unemployment rate (%)	0.100***	(1.105)	0.065***	(1.067)
Part of industrial jobs (%)	-0.065***	(0.937)	-0.031***	(0.969)
Part of agricultural jobs (%)	-0.030	(0.970)	0.002	(1.002)
Migration balance (Thousand)	-0.001	(0.999)	-0.010	(0.990)
$\sigma^2_{\mu 0}$	0.065		0.105***	
Standard error	0.041		0.038	
Log likelihood	-1447		-3717	
LR test	8.31***		70.77***	

Notes: Odds ratio in parentheses. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 7: Estimated Multilevel Logit with Household and Governorate Characteristics and Interaction Effects

Covariates	**Model (1) with Household and governorate Attributes And interaction**	**Model (3) with Household and governorate Attributes And interaction**	**Model (2) with Household and governorate Attributes**	**Model (4) with Household and Governorate Attributes**
Intercept	-4.374***	(0.013)	-4.564***	(0.010)
Individual level				
Urban/rural (urban = 1; rural = 0)	-0.413***	(0.662)	-0.460***	(0.631)
Household size	0.384***	(1.468)	0.385***	(1.470)
Gender of the household head	-0.344	(0.709)	-0.344	(0.709)
Household composition				
1-2 adults, 1-2 children	0.717**	(2.048)	0.718**	(2.050)
1-2 adult, 3 or more children	1.448***	(4.255)	1.441***	(4.225)
3 adults or more, 0-1 child	0.289	(1.335)	0.288	(1.334)
3 adults or more, 2-3 children	0.702**	(2.018)	0.700**	(2.014)
3 adults or more, 4 children or more	1.343***	(3.831)	1.330***	(3.781)
Number of earners				
household with 1 earner	-0.817*	(0.442)	-0.821*	(0.440)
Household with 2 earners	-0.804	(0.448)	-0.804	(0.448)
Household with 3 or more earners	-1.148*	(0.317)	-1.156*	(0.315)
Household head's education				
primary/lower secondary and secondary	-1.186***	(0.305)	-1.187***	(0.305)
Post secondary, university and postgraduate	-0.954***	(0.385)	-0.939***	(0.391)
Household head's occupation				
unemployed or student	0.703**	(2.020)	0.703**	(2.020)
Homemaker	-0.317	(0.728)	-0.326	(0.722)
Pensioners or retired	-0.124	(0.883)	-0.127	(0.881)
regional level (governorate)				
Urbanization rate (%)	-0.010	(0.990)	-0.008	(0.992)
Poverty rate (%)	0.039*	(1.040)	0.039*	(1.040)
Unemployment rate (%)	0.102***	(1.107)	0.108***	(1.114)
Part of industrial jobs (%)	-0.066***	(0.936)	-0.065***	(0.937)
Part of agricultural jobs (%)	-0.031	(0.969)	-0.030	(0.970)
Migration balance (Thousand)	-0.001	(0.999)	-0.002	(0.998)
Interaction effects				
one earner×poverty	-0.010	(0.990)	-0.010	(0.990)
two earners×poverty	-0.047*	(0.954)	-0.047*	(0.954)
three or more earners×poverty	-0.037	(0.964)	-0.037	(0.964)
$\sigma^2_{\mu 0}$	0.062		0.103***	
Standard error	0.039		0.037	
Log likelihood	-1445		-3713	
LR test	7.37***		68.06***	

Notes: Odds ratio in parentheses. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Table 8: Robustness checks: Multilevel Mixed Linear Model with Both Household, Governorate and Interaction Effects

Covariates	Welfare ratio In log As dependent Variable (first poverty line)	Standard Error	Welfare ratio In log As dependent Variable (second poverty line)	Standard Error
Intercept	1.965***	(0.302)	1.544***	(0.286)
Individual level				
Urban/rural (urban = 1; rural = 0)	0.025	(0.022)	-0.085***	(0.021)
Household size	-0.120***	(0.008)	-0.119***	(0.008)
Gender of the household head	0.058***	(0.021)	0.059***	(0.021)
Household composition				
1-2 adults, 1-2 children	-0.265***	(0.025)	-0.266***	(0.025)
1-2 adult, 3 or more children	-0.373***	(0.033)	-0.372***	(0.033)
3 adults or more, 0-1 child	-0.128***	(0.022)	-0.128***	(0.022)
3 adults or more, 2-3 children	-0.203***	(0.022)	-0.204***	(0.022)
3 adults or more, 4 children or more	-0.282***	(0.048)	-0.283***	(0.048)
Number of earners				
household with 1 earner	0.085*	(0.046)	0.081*	(0.046)
Household with 2 earners	0.183***	(0.056)	0.179***	(0.056)
Household with 3 or more earners	0.201***	(0.066)	0.196***	(0.065)
Household head's education				
primary/lower secondary and secondary	0.281***	(0.013)	0.279***	(0.014)
Post secondary, university and postgraduate	0.481***	(0.031)	0.478***	(0.031)
Household head's occupation				
unemployed or student	-0.071**	(0.031)	-0.071**	(0.030)
Homemaker	0.208***	(0.029)	0.209***	(0.029)
Pensioners or retired	0.030*	(0.016)	0.031*	(0.016)
regional level (governorate)				
Urbanization rate (%)	-0.001	(0.002)	-0.001	(0.002)
Poverty rate (%)	-0.014***	(0.005)	-0.013***	(0.005)
Unemployment rate (%)	-0.018***	(0.007)	-0.019***	(0.006)
Part of industrial jobs (%)	0.002	(0.003)	0.003	(0.003)
Part of agricultural jobs (%)	-0.006	(0.004)	-0.005	(0.004)
Migration balance (Thousand)	0.002*	(0.001)	0.002**	(0.001)
Interaction effects				
one earner×poverty	0.010***	(0.003)	0.010***	(0.003)
two earners×poverty	0.014***	(0.004)	0.014***	(0.004)
three or more earners×poverty	0.016***	(0.005)	0.016***	(0.005)
$\sigma_{\mu 0}^2$	0.007	(0.002)	0.007	(0.002)
σ_{ε}^2	0.222	(0.009)	0.221	(0.009)
Log likelihood	-7550		-7536	
LR test	250***		232***	

Notes: Standard Error in parentheses. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01.

Appendix A

Table A1: Distribution of Districts and Households Sampled by Governorates

Governorate	Population		Sample		
	District	Household	District	Household	Household sample percent (%)
Tunis	3628	244018	96	1152	0.47
Ariana	1536	101327	48	576	0.57
Ben Arous	1691	117901	60	720	0.61
La Manouba	1008	70750	36	432	0.61
Great Tunis	**7863**	**533996**	**240**	**2880**	**0.54**
Nabeul	2174	162691	60	720	0.44
Zaghouan	473	33532	36	432	1.29
Bizerte	1799	119976	60	720	0.6
Northeast	**4446**	**316199**	**156**	**1872**	**0.59**
Beja	972	68584	36	432	0.63
Jendouba	1307	92877	36	432	0.47
El Kef	876	59107	36	432	0.73
Siliana	666	48448	36	432	0.89
Northwest	**3821**	**269016**	**144**	**1728**	**0.64**
Sousse	1876	124519	60	720	0.58
Monastir	1480	100967	48	576	0.57
Mahdia	1201	79197	36	432	0.55
Sfax	2822	198565	72	864	0.44
Middle East	**7379**	**503248**	**216**	**2592**	**0.52**
Kairouan	1572	107923	60	720	0.67
Kasserine	1186	79448	48	576	0.73
Sidi Bouzid	1113	76771	36	432	0.56
Middle West	**3871**	**264142**	**144**	**1728**	**0.65**
Gabes	975	69703	36	432	0.62
Mednine	1328	90000	36	432	0.48
Tataouine	408	26575	36	432	1.63
Southeast	**2711**	**186278**	**108**	**1296**	**0.7**
Gafsa	959	65926	36	432	0.66
Tozeur	302	20485	36	432	2.11
Kebili	383	26549	36	432	1.63
Southwest	**1644**	**112960**	**108**	**1296**	**1.15**
Tunisia	**31735**	**2185839**	**1116**	**13392**	**0.61**

Source: INS