WPS6466

Policy Research Working Paper 6466

Estimating Quarterly Poverty Rates Using Labor Force Surveys

A Primer

Mohamed Douidich
Abdeljaouad Ezzrari
Roy Van der Weide
Paolo Verme

The World Bank
Middle East and North Africa Region
Poverty Reduction and Economic Management Department
May 2013

Abstract

The paper shows how Labor Force Surveys can be used effectively to estimate poverty rates using Household Expenditure Surveys and cross-survey imputation methods. With only two rounds of Household Expenditure Survey data for Morocco (2001 and 2007), the paper estimates quarterly poverty rates for the period 2001–2010 by imputing household expenditures into the Labor Force Surveys. The results are encouraging. The methodology is able to accurately reproduce official poverty statistics by combining current Labor Force Surveys with previous period Household Expenditure Surveys, and vice versa. Although the focus is on head-count poverty, the method can be applied to any welfare indicator that is a function of household income or expenditure, such as the poverty gap or the Gini index of inequality. The newly produced time-series of poverty rates can help researchers and policy makers to: (a) study the determinants of poverty reduction or use poverty as an explanatory factor in cross-section and panel models; (b) forecast poverty rates based on a time-series model fitted to the data; and (c) explore the linkages between labor market conditions and poverty and simulate the effects of policy reforms or economic shocks. This is a promising research agenda that can expand significantly the tool-kit of the welfare economist.

This paper is a product of the Poverty Reduction and Economic Management Department, Middle East and North Africa Region. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at pverme@worldbank.org or rvanderweide@worldbank.org.

Estimating Quarterly Poverty Rates Using Labor Force Surveys: A Primer[1]

Mohamed Douidich, Abdeljaouad Ezzrari[2], Roy Van der Weide and Paolo Verme[3]

JEL: D6, H53, I3, R13

Keywords: Poverty, cross-survey imputations, Morocco, forecasts, simulations

Sector board: Poverty (POV)

---

[1] The work was undertaken in the framework of the cooperation agreement between the World Bank and the High Commission for the Plan of Morocco. The authors are grateful to Peter Lanjouw, Tomoki Fuji , Nobuo Yoshida, Roy Katayama, Gladys Lopez and participants to several workshops in Washington and Morocco where the paper was presented for useful comments.
[2] National Observatory of Living Standards, High Commission for the Plan, Morocco
[3] The World Bank; The study has received financial support from the World Bank's Knowledge for Change Program for which the authors are grateful.

1. Introduction

The estimation of poverty in any given country relies on household surveys that contain information on income, consumption or expenditure (Household Expenditure Surveys, or HESs for short). This information is complex to collect and requires elaborated and time consuming questionnaires that result in costly surveys. For this reason, statistical agencies worldwide have taken to the practice of administering relatively small surveys (usually in between 5,000 and 10,000 households) at intervals of several years (usually every 4-5 years).

This practice is sensible from a logistics- and cost perspective but has two main drawbacks for the measurement of poverty. The first is that small surveys can provide statistically reliable statistics only for highly aggregated areas such as rural and urban areas or large sub-national regions. And the second is that poverty statistics can only be produced in conjunction with the HES surveys every several years, leaving researchers with no information on poverty for the periods between any two surveys or beyond the most recent survey.

To address these two shortcomings, we advocate the use of imputation methods to fill these data gaps. Imputation methods have a long history in statistics and economics and have been used to address a variety of missing data problems; see e.g. Rubin (1978 and 1987). While originally conceived to fill data gaps within surveys, these methods have also been extended to cross-survey imputation where one survey is used to fill data gaps of another survey belonging to the same population. A recent review of these methodologies by Ridder and Moffit (2007) shows how widespread these methodologies have become, and how they can be adapted to respond to different types of missing data problems. See also Fujii and van der Weide (2013) and the references therein.

In the context of poverty analyses, imputation methods have found numerous applications to address statistical inference problems across space and time. For example, Elbers et al. (2002, 2003, 2005) combine census and survey data to estimate poverty and inequality for areas considered too small for statistical inference with survey data alone, an exercise known as “poverty mapping”. For an overview of the statistics literature on small area estimation, see Rao (2003). One could alternatively also work with large surveys instead of censuses such as Demographic and Health Surveys (DHSs) to obtain imputation-based poverty estimates. Examples of the latter are Stifel and Christiaensen (2007) and Grosse et al. (2009) who used DHSs to respectively estimate poverty in Kenya and Bolivia. More recently, Christiaensen et al. (2012) used data from Vietnam and China to create a pseudo-panel out of repeated cross-section HESs using imputation methods.

Cross-survey imputation techniques have also been used to resolve problems of comparability between surveys of the same type over time, for example due to changes in the questionnaires. Kijima and Lanjouw (2003) and Tarozzi (2007) have re-estimated poverty rates in India using imputed data in an effort to validate the official figures on poverty during what became known as the “great Indian poverty debate” (see e.g. Deaton and Kozel, 2005).

These latter examples show that cross-survey imputation methods can be used effectively to improve both the levels of *disaggregation* and the *frequency* at which statistics of interest may be obtained. This is of great relevance to both research and policy making. Imagine a country that may have been affected by the 2008 global financial crisis and the 2001 crisis before that. Suppose however that the only official poverty estimates that are available over this extended period are for the years 2001 and 2007, while the next official poverty estimates will not become available until 2014. This means that until 2014 policy makers will have no data on how poverty has evolved post-2007, i.e. there is no way to tell whether the recent global crisis has had any impact on poverty. By 2014, when the new official poverty estimates are published, the effects of the 2008 crisis may not be visible any longer and the window for response may have passed. The same argument can be applied to macroeconomic shocks that have occurred prior to 2007, which include the 2001 financial crisis. Relying solely on official poverty estimates derived from these household surveys does not allow us to identify any responses in poverty between survey years, which can be far apart. And poverty may exhibit important seasonal fluctuations that annual poverty estimates cannot reveal.[4]

In this paper, we build on the existing cross-survey imputation literature to improve the *frequency* of poverty estimates, i.e. to provide up-to-date estimates of poverty when official estimates are deemed outdated. We do this using quarterly Labor Force Surveys (LFSs) from Morocco, a country that represents an ideal natural experiment. Morocco implemented consumption surveys in 2001 and 2007 and is expecting to complete the next survey in 2013. Note however that much has happened since 2007 as well as between 2001 and 2007; two global financial crisis (2001 and 2008) and a number of domestic shocks which include favorable rainfall that has boosted agricultural output. Any one of these events may have had a significant impact on poverty levels. However, policy makers in Morocco do not have the data needed to verify whether poverty rates have indeed changed. The question we wish to address is whether we can use quarterly Labor Force Surveys (LFSs) to fill these gaps and, by doing so, connect the dots of poverty estimates in Morocco for the period between the last two consumption surveys (2001-2007) and beyond. To our knowledge, this is the first comprehensive experiment of cross-survey imputation that uses LFS data to estimate a series of quarterly poverty rates spanning a decade. Note that if the proposed methodology proves successful, it can be applied to countries worldwide, wherever there is a need for it, since LFSs are standard surveys that are conducted at least annually if not quarterly in almost every country.

The application of this methodology to Morocco shows encouraging results. We estimated quarterly poverty rates with LFSs for the period 2001-2007 using separately a consumption model estimated from 2001 consumption data and a consumption model estimated from 2007 consumption data. Despite the fact that the two models are 6 years apart, we found that the models produced nearly identical poverty trends over the period under consideration. We also estimated the 2001 poverty rate using the 2007

[4] A few countries have attempted to address this problem by producing statistics on poverty at an infra-annual level. For example, Peru experimented with the administration of quarterly consumption surveys while Mexico produces a proxy of income poverty every month using Labor Force Surveys. However, collecting survey data quarterly is evidently very expensive while many countries do not collect income data together with labor data making these efforts difficult to replicate elsewhere.

consumption model and, vice-versa, estimated the 2007 poverty rate using the 2001 consumption model. In both cases, we were able to closely match the official poverty rates with the imputation-based estimates. Whether we used the *forward* approach or the *backward* approach, we effectively obtained the same poverty estimates.

The application provides a number of new insights for Morocco. The imputation-based estimates show that poverty consistently declined between 2001 and 2007, and that the decline continued beyond 2007 and up to 2010. This confirms that Morocco has been able to withstand the global financial crisis, arguably due to the favorable agricultural production during that same time period. The estimates also show an urban-rural convergence in poverty, with rural poverty falling faster than urban poverty, thereby reducing the urban-rural gap. Interestingly, poverty rates in Morocco have not declined everywhere; disaggregating by region, we see both upward and downward trends in poverty that previous statistics for 2001 and 2007 were not able to capture. The quarterly poverty estimates have provided an entirely new perspective on the study of poverty in Morocco.

The potential for extensions and applications of this work is also promising. The estimated quarterly poverty series can be used for further cross-section and panel econometric work, for forecasting, and for simulation of policy reforms and economic shocks. These applications have the potential to substantially expand the toolkit of the welfare economist.

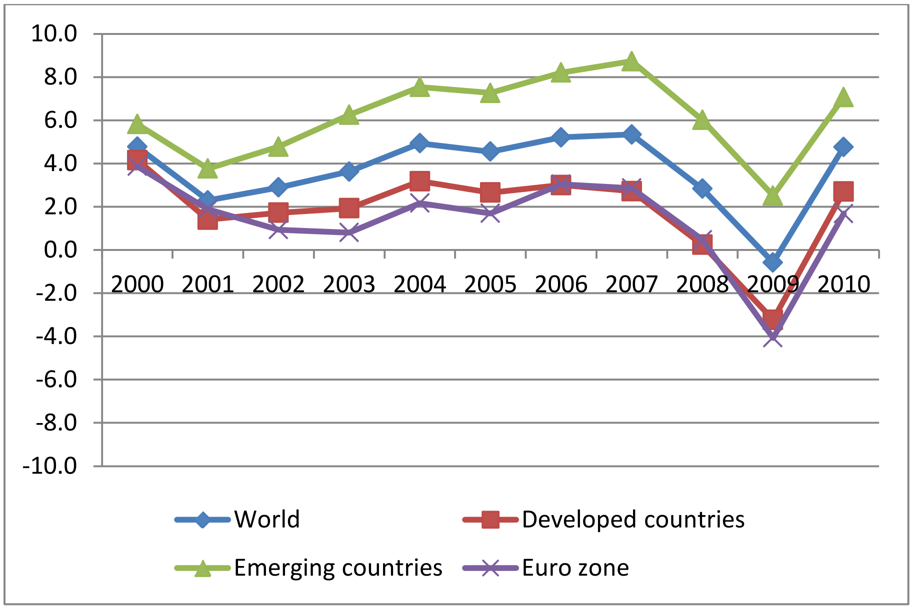
The paper is organized as follows. The next section describes the macroeconomic context, poverty trends and government policies in Morocco over the period 2000-2010. Section three illustrates the cross-survey imputation methodology adopted. Section four explains the HESs and LFSs data used. Section five, shows the empirical model, section six carries out some validation tests and section seven discusses the poverty estimations obtained. Section eight discusses possible extensions and applications of the methodology proposed and section nine concludes.

2. Growth, poverty and policies 2000-2010

As an emerging economy that has increasingly opened to trade during the last decade, Morocco has become more dependent on the global economy. Global shocks that include the 2001 and 2007-2008 financial crises and the global increases in food and commodities prices in 2008 set the background for better understanding the performance of the domestic economy and the evolution of poverty between 2000 and 2010.

As shown in Figure 1, at the outset of the decade world growth rates were around 5% on average with relatively small differences between developed and emerging economies. The 2001 financial crisis is seen to be associated with a visible decline in world output affecting all groups of countries and reducing average growth rates by about 2-3 percentage points. We then see an exceptional period between 2001 and 2007 where all groups of countries experience increasing growth rates. During this period, we also observe a divergence between developed and emerging economies with the emerging economies clearly outpacing developed economies. The euro zone, which includes some of the major trade partners of Morocco, was the worst performer among the group of countries considered in terms of average growth.

Figure 1 - World GDP growth 2000-2010

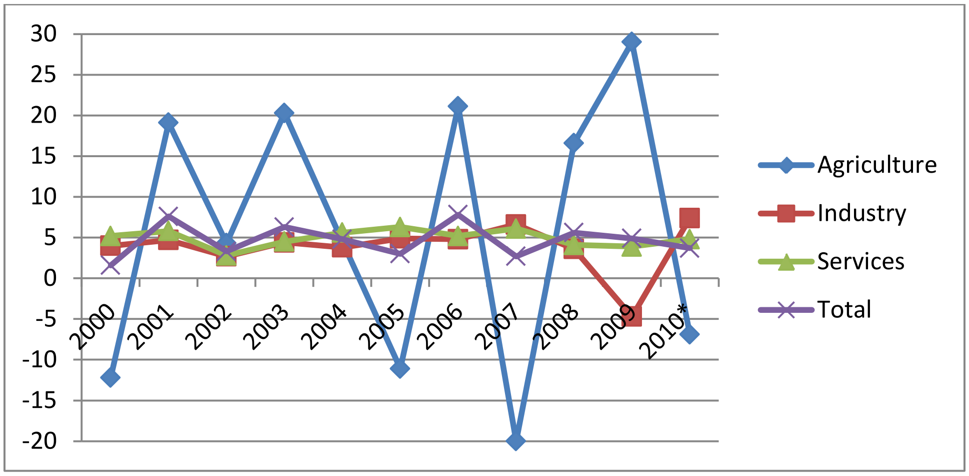


Source: Morocco Tableau de Bord (2000-2010)

During the same period, Morocco experienced significant annual changes in GDP growth (Figure 2) but remained in line with world growth overall, with a growth rate hovering around 4-5% a year. The significant annual fluctuations in the output of the Moroccan economy are explained by the volatile performance of the agricultural sector. Despite accounting for only about 15% of GDP, the agricultural sector accounts for a much larger share of the annual variations in GDP. For example, growth in agricultural production accounted for 27% of total growth in 2003 and 35% in 2009.[5] Interestingly, Morocco has been able to counter balance the effects of the 2001 and 2007-2010 global crises thanks to exceptional agricultural years that happened in conjunction with (or following) the two global crises; as shown in Figure 2, the agricultural sector exhibits exceptional growth rates in 2001, 2008 and 2009.

[5] Our estimates based on official statistics (Tableau de Bord, High Commission for the Plan, 2012, mimeo).

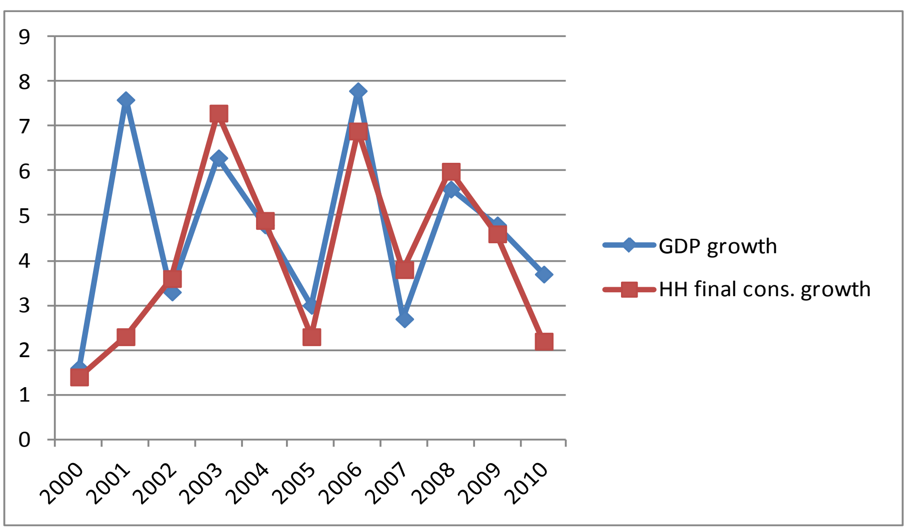
Figure 2 - Morocco GDP growth by Economic Sector 2000-2010



Source: Morocco Tableau de Bord 2000-2010

Macro indicators would suggest that GDP growth has trickled down to households. According to national accounts, household final consumption growth has closely followed the evolution of GDP growth (Figure 3) and this is in line with developments in the labor market. Despite a growing working age population, Morocco has been able to increase marginally the employment rate and decrease unemployment from 13.4% in 2000 to 9.1% in 2010. While low female and youth labor market participation and the large urban-rural divide continue to pose a problem to the Moroccan economy, the main macroeconomic trends over the past decade have been positive.

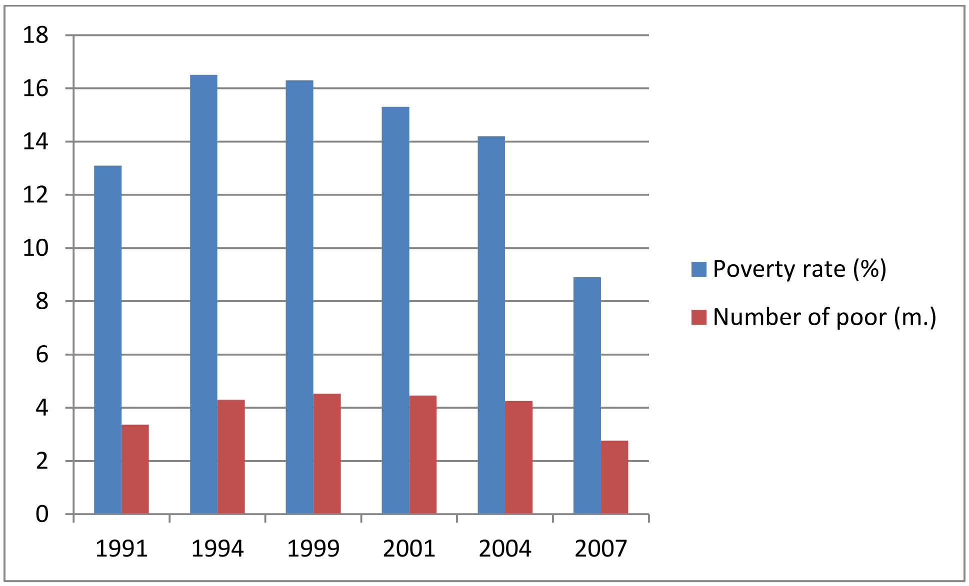
Figure 3 - GDP and household consumption growth 2000-2010



Source: HCP National Accounts (2000-2010), various publications

This macro picture is also supported by micro data. The Moroccan High Commission for the Plan (HCP) estimates that household consumption in real terms has increased at an average rate of 2.8 percent a year between 1999 and 2007 as compared to -1.8 percent for the previous decade. The same institution estimates that the poverty rate has declined at an annual rate of -7.3 percent as compared to a rate of +2.8 percent for the previous decade.[6] Comparing the 2001 and 2007 household consumption surveys shows that the poverty rate has declined from 15.3% to 8.9% and this has resulted in an effective reduction in the number of the poor from 3.4 million in 2001 to 2.7 million in 2007. In sum, one could argue that growth over the past decade has been pro-poor as well as pro-rural areas vis-à-vis the previous decade (Figure 4).

Figure 4 – Official Poverty Rates Estimates 1991-2007



Source: HCP (2012). 1994 and 2004 are population census estimates made with poverty mapping techniques.

This change in fortunes for the poor can be traced back to a combination of public policies that have been implemented over the years. Starting from the mid-1990s, the government has launched ambitious macroeconomic reforms coupled with stabilization measures. The macroeconomic policies include regulatory and institutional improvements to attract foreign investments, price liberalizations, acceleration of the privatization process, better competition laws, a better framework for SME development and a progressive opening of the economy to global trade. The country joined the WTO and signed bilateral trade agreements with the US, the EU, and several non-EU Mediterranean countries. Stabilization policies aimed at consolidating public finance, controlling inflation, and reducing the debt/GDP ratio. All of these objectives have been largely achieved by 2010. A large program of

[6] The poverty line in 2007 was set at 3,834 MAD per person per year for urban areas and at 3,569 MAD per person per year for rural areas. In 2007, this was equivalent to 1.25 USD per person per day in urban areas and 1.16 USD per person per day in rural areas (non-PPP).

infrastructure development accompanied these reforms with the aim of closing the gap between urban and rural areas, and developing the growth potential of more remote areas.

On the social and microeconomic side, a number of programs with the objective of reducing poverty have also been launched. These include the 2000-2004 development plan, the fund for the fight against droughts and desertification, the fight against analphabetism, the work of the foundation Mohamed V for solidarity, the work of the agency for social development and the national agency for employment and skills promotion, several initiatives for microcredits promotion and the national charts for education and health. In addition, the launch of the National Initiative for Human Development (NIHD) in 2005 – an ambitious national plan to develop the poorest areas of the country – marked an important step forward in addressing the wider spectrum of deprivation.

To our knowledge, none of these measures and programs has been fully evaluated, in part because it is difficult to tease out the impact that any particular program had on poverty. Moreover, estimates of poverty for the full period are simply not available. It is believed that Morocco has responded well to the 2007-2009 global shocks thanks to the countercyclical agricultural performance, but poverty estimates are available only for 2001 and 2007 (the two years for which household consumption surveys are available). This leaves policy makers unable to assess whether their policies have been effective in sustaining economic growth and poverty reduction against the backdrop of the global crises. This motivates the use of cross-survey imputations using Labor Force Surveys (LFSs) to fill this vacuum.

3. Methodology

We adopt a standard imputation approach that is commonly used in the case of missing data. If a variable in a data set is missing altogether, but is available in a second data set representative of the same population, this second data set can be used to estimate the missing variable in the first data set. A prerequisite is that the two data sets share a set of regressors that are sufficiently correlated with this missing variable.

Consider the following standard linear model for household log expenditure:

$$\ln(y_{ti}) = x_{ti}^T\beta_t + u_{ti}, \quad (1)$$

where x denotes a vector of independent variables (e.g. variables on demographics, education, employment, housing conditions, asset ownership) including the constant, u denotes a zero expectation error term, and where the subscripts i and t indicate household i and time t. The superscript 'T' indicates matrix transpose.

We have two types of data sets: Household Expenditure Survey (HES) data and Labor Force Survey (LFS) data. Both types of surveys contain the regressors x but only the HES contains the household expenditure y, and only for selected years. In our case, we will consider the period 2001-2010 for which we have two years of the HES (2001 and 2007) and the full period of the LFS. The objective is to use model (1), estimated using the 2001 and 2007 HESs, to impute household expenditure into the LFSs for all available years (2001 to 2010), and then use the imputed expenditure data to estimate poverty for the entire 2001-2010 period.

We will be relying on a number of assumptions:

Assumption 1: *The model is time-invariant, i.e.* $\beta_t = \beta$.

This assumption cannot be avoided, since we are looking to apply the model for imputing data into years other than the year for which the model can be estimated. This has the potential to introduce a bias if the two different time periods are in fact associated with different models. This bias can only be ruled out if *Assumption 1* holds true. Note that this assumption can be tested both directly and indirectly. For a direct test one could use any test statistic that evaluates the difference between the estimate for β_{2001} and the estimate for β_{2007}. An indirect test can be obtained by estimating the model for one of the two HES years and then apply this model to obtain an imputed poverty rate for the other year. Since both years also allow us to compute the actual poverty rates based on observed data, we are able to verify how well the observed data compares to the imputed data. See section six for the test results.

Remark 1: The assumption of a time-invariant model also means we have to be careful with the choice of units in which both the dependent and the independent variables will be measured. One may want to avoid including independent variables that are expressed in time *t* monetary value; we will be working with quantities and dummy variables for our model. This prevents potential model inconsistencies. Let us refer to the model parameters as betas. If one variable measures the monetary value of owned bicycles, while another variable simply checks whether the household has a car or not by equaling one or zero, then this could become problematic. The beta associated with the car ownership will measure the monetary value added of the car to the total household expenditure. The beta associated with the bicycles on the other hand has no dimension but instead simply passes on (by some factor) the monetary value of the bicycles to the value of total household expenditure. To see how this may yield an inconsistency, suppose that the dependent variable is measured in time *t* prices (i.e. household expenditure over time is not measured at constant prices). Then, the beta attached to the car ownership will be expressed in time *t* prices, which goes against the assumption of constant betas. Now suppose that the dependent variable is measured in constant prices. In that case, the beta attached to the bicycles will have to convert the monetary value added of the bicycles from time *t* prices into the constant reference prices. This too is in conflict with the assumption of time-invariant betas.

Assumption 2: *The error term u is homoscedastic and normal.*

This assumption is not strictly necessary, and can thus be relaxed, but is adopted for ease of exposition. The model is found to perform surprisingly well as our empirical results for Morocco will show, despite these simplifying assumptions.

Since our variable of interest is the poverty rate (the probability that a randomly selected household has an expenditure level below the poverty line), we will transform the imputed consumptions into household probabilities of being poor conditional on the information contained in *x*. Let *F* denote the probability distribution function for a standard normal random variable, and let z_{it} denote the poverty line for household *i* and time *t*. The conditional probability of being poor is seen to solve:

$$Prob[\ln(y_{it}) < \ln(z_{it})|x_{it}] = Prob\left[u_{it} < ln(z_{it}) - x_{it}^T\beta\right] = F\left(\frac{z_{it} - x_{it}^T\beta}{\sigma}\right)$$

where σ^2 denotes the variance of *u*. The unknown model parameters will in practice be replaced by estimates, so that the estimated poverty rate solves:

$$\hat{H} = \frac{1}{n}\sum_i F\left(\frac{z_{it} - x_{it}^T\hat{\beta}}{\hat{\sigma}}\right).$$

Remark 2: It is important to note that the imputation-based poverty estimate will be subject to both sampling error and model error. Standard errors can be estimated accurately by means of bootstrapping, which will be our method of choice in the empirical section of this paper. The HES will be bootstrapped to capture the model error, and the LFS will be bootstrapped to capture the sampling error, see Fujii and van der Weide (2012, 2013) for more details. For asymptotic standard errors that account for the dual error structure, also see Fujii and van der Weide (2012, 2013). Note that ignoring this error structure, for example by treating the imputed data as observed data, will lead to underestimation of the standard errors and thereby to overestimation of the poverty estimates.

Remark 3: The poverty line must be measured in the same time *t* prices as the expenditure (or income) variable that was used as the dependent variable in the regression model. In other words, if a model is estimated on 2001 household expenditure data (measured in 2001 prices) and subsequently applied to a 2007 LFS, then the imputed data will represent 2007 expenditure measured in 2001 prices. As a result, this imputed expenditure would have to be compared to the 2001 poverty line in order to obtain an estimate of 2007 poverty (see also Remark 1).

Remark 4: The approach has the best chance of identifying trends in poverty if the changes over time can be traced back to changes in the observed independent variables (e.g. changes in education levels, employment characteristics, and housing conditions) as opposed to changes driven by exogenous shocks that are not well captured by the observed data.

Remark 5: The approach adopted is implicitly an evaluation of the between-survey comparability of expenditure data, comparability of HES and LFS, and of temporal price adjustments adopted.

Remark 6: Finally, while endogeneity (reverse causality) will generally bias estimates of the model parameters, it does not necessarily bias the imputed values. In fact, endogeneity may benefit the statistical precision of the imputed data since a non-zero correlation between the independent variables and the error term implies that the error term is now not entirely unpredictable.

4. Data

We use two sets of surveys, the Household Expenditure Surveys (HESs) and the Labor Force Surveys (LFFs). The HESs are the surveys that contain our variable of interest (household expenditure). Hence they are used to construct and estimate the model that we rely on for imputation. The LFSs denote the surveys that are used to estimate poverty, based on imputed data, for time periods that are not covered by the HESs.

Strictly speaking, the HESs in Morocco include two different surveys; the 2000-2001 National Survey on Consumption and Expenditure (NSCE) and the 2006-2007 National Living Standards Survey (NLSS). Both samples measure household expenditure, are nationally and regionally representative as well as representative of urban and rural areas. **The 2000-2001 NSCE** covered 15,000 households and was administered between November 2000 and October 2001 with multiple objectives in mind. It was designed to measure household expenditure and to provide the necessary information to weigh the living standard index constructed for Morocco and other national accounts aggregates. It was also designed to measure household consumption, nutrition, poverty and inequality. The questionnaires included sections on socio-economic characteristics, habitat, energy, economic activities, education, health, transfers, subjective indicators of wellbeing, expenditure, durable goods, anthropometrics, nutrition and also a module administered to the community to measure access to services. **The 2006-2007 NLSS** covered 7,200 households and was administered between December 2006 and November 2007. The survey focused on household expenditure and revenues and was principally administered to measure poverty, inequality and other dimensions of living standards. The questionnaire included modules on socio-demographic characteristics, social mobility, habitat, expenditures, revenues, credits, transfers, education, health, employment, durable goods and poverty perceptions. The **Labor Force Surveys (LFSs)** of Morocco is a household survey covering all residents on the national territory. The sample size is 60,000 households, 40,000 urban and 20,000 rural, and contains information on all household members, approximately 270,000 individuals each year. This sample is divided into four equal independent sub-samples of 15,000 households each interviewed quarterly. Each sub-sample is representative at the national and regional level and by urban and rural areas. Since 2007, interviews are conducted all year long by means of a computerized system where data input occurs with smart phones, and where data input verification is carried out both automatically using specialized software and by supervisors in real time. This allows interviewers to correct most data input errors during the interview.

Since the introduction of the computerized system, half of the sample is renewed every year and, within each year, every quarter. Therefore, every year half of the households are re-interviewed which makes the survey a quarterly panel survey with one time lag of one year. It should be noted that the introduction of the computerized system in 2007 creates a potential discontinuity between the LFSs surveys before and after 2007. It is believed that the computerized administration has further improved the accuracy of the survey. We find however that the main labor force statistics are comparable over time.

All surveys in Morocco are based on a master sample based on the latest population census and all surveys use the same stratification structure. Based on the population census, the country is divided into sampling districts each including a fixed number of neighboring households. Each sampling district belongs to one exclusive stratified area. For urban areas, strata include the region, province, city size (large, medium and small) and type of housing ("lux", "modern", "old medina", "new medina" and "clandestine"). For rural areas, the strata are regions and provinces. These are the stratas that apply to all surveys administered in Morocco and that are defined and updated with population censuses.

For all surveys, the first stage of sampling consists of creating the Primary Sampling Units (PSUs) by joining neighboring sampling districts so that each PSU contains an approximately equal number of households. Neighboring PSUs are then joined in groups of five to create the sampling areas. Based on sampling theory, 20% of PSUs are sufficient to survey a country so that only one in five PSUs within each sampling area is selected. This procedure represents the first stage of the sampling process, applies to all surveys administered in Morocco and results in the set of PSUs to be used for selecting the households to interview.

In Morocco, sampling methods can differ across surveys depending on whether sampling is two stages or three stages. The 2001 NCSE followed a two- stages sampling while the 2007 NLSS and the quarterly LFSs followed a three stages sampling process. For the 2001 NCSE and in the first stage, 1,250 PSUs (710 urban and 540 rural) of approximately 300 households each were extracted from the initial set of PSUs based on the 1994 population census. In the second stage, twelve households per PSUs were extracted with a systematic extraction method.[7] For the 2007 NLSS and the quarterly LFSs, 1,848 PSUs (1,124 urban and 724 rural) of approximately 600 household each were selected from the initial set of PSUs based on the 2004 population sample. In a second stage, PSUs were first subdivided into the Secondary Sample Units (SSUs) representing about 50 households each and six of the twelve SSUs were then extracted randomly from each PSUs. In a third stage, households to interview were selected with systematic extraction from each SSU.

5. Empirical model

To build a model that is both flexible and parsimonious and in line with the samples stratification, we divide the data into urban and rural areas, and model each area separately. The labor markets, sector decomposition, returns to education, living conditions, the availability and use of infrastructure and the price of transport tend to be different between urban and rural areas which may be expected to lead to different models. In what follows, it can be seen for example that employment in agriculture matters in rural (both statistically and economically highly significant) but not in urban Morocco. The reverse holds

[7] This method implies first defining the pace of extraction by dividing the number of households in each PSU by the number of households needed for the sample. Then a number is randomly extracted between 1 and the pace number. And finally household are extracted starting with the extracted number and using the pace number to identify each successive household.

true for employment in the financial sector. Further geographic heterogeneity is captured by interacting selected independent variables with region dummy variables, in addition to region fixed effects.

We will work with both the 2001 and the 2007 HESs data. While we allow the models to be different, by building models that best fit the data for any given year, the models we identified are found to be almost identical (in the sense that they include nearly the same set of explanatory variables).

As an experiment, a second set of models is obtained by adding a handful of variables on durable asset ownership and housing conditions that are available in the HES but not in the LFS. Because these are not LFS variables, we cannot consider these models for imputation into the LFS. We can however use them to impute consumption poverty into the HES, and subsequently assess how imputed poverty data compares to observed poverty data. The purpose of this exercise is to verify whether adding these variables to the model significantly improves the statistical precision of the imputed data. Other studies have found that durable asset ownership and housing conditions are particularly powerful predictors of poverty (see e.g. Christiaensen *et al.*, 2012). If the same holds true for Morocco, then an argument can be made for adding these variables to future rounds of the LFS.

Table 1 shows selected descriptive statistics for the four regression models (urban versus rural plus 2001 versus 2007). A number of characteristics are apparent: (a) the models provide good in-sample fits of the data judging by the high adjusted R-squared, (b) the urban models fit the data better than the rural models, which is typical for these type of regression models, and (c) as expected, adding the five durable assets and housing variables significantly improves the in-sample fit. Whether this also translates into better out-of-sample fits is examined in the next section.

Table 1 – Summary Statistics, Urban and Rural Models 2001 and 2007

	2001		2007	
Statistic	Urban	Rural	Urban	Rural
R2	0.59	0.43	0.58	0.42
R2 (assets)	0.64	0.48	0.63	0.48
# vars	52 (57)	45 (50)	58 (63)	51 (56)
Obs	7888	6355	4266	2796

Source: HESs (2001, 2007); the numbers in between brackets denote the number of independent variables in the models where additional “asset” variables have been included

5.1 Urban model

Table 2 presents the urban models for Morocco (for both years; with and without additional variables). The _IcuX* variables denote interactions between selected independent variables and regional dummy variables.

The estimates of the model coefficients are found to be largely coherent: (a) per capita expenditure decreases with household size with a declining marginal effect, (b) the `returns to education' are all positive with higher returns for higher education levels (i.e. tertiary > secondary > primary education coefficient), (c) unemployment enters negatively, while waged-, self-employment and being an employer all enter the regression positively, (d) public sector employment too enters positively, while employment in the BTP sector (construction) is associated with lower standard of living, which is consistent with the BTP being a low-wage sector, (e) employment in the financial sector is clearly beneficial, but only in 2007, it was not yet significant in 2001, (f) size of the house as measured by the number of rooms per capita is strongly positively associated with total household expenditure, although the marginal effect declines for larger houses as expected, (g) similarly, households equipped with electricity, sewage, in-house clean drinking water (as well as the added durable assets and housing variables) are found to have higher total expenditure on average, (h) the significance of the interactions with the region dummy variables shows that the significance of the above mentioned variables is stronger for some areas than for others.

Table 2 – Urban Model

	Without Additional Assets				**With Additional Assets**			
Variable	**2001**		**2007**		**2001**		**2007**	
Domain U2	-0.233	***	-0.132		-0.178	***	-0.122	
Domain U3	-0.041		-0.160	**	-0.031		-0.070	
Domain U4	-0.103	**	-0.191	**	-0.043		-0.145	*
Domain U5	0.000		-0.108		0.127	***	-0.026	
Hhld size	-0.090	***	-0.113	***	-0.140	***	-0.169	***
Hhld size^2	0.002	***	0.005	***	0.005	***	0.008	***
Log age (head)	0.082	***	0.108	***	0.070	***	0.082	***
Married (head)	0.096	***	0.140	***	0.070	***	0.114	***
Primary (head)	0.101	***	0.071	***	0.069	***	0.037	*
Secondary (head)	0.231	***	0.187	***	0.149	***	0.114	***
Tertiary (head)	0.489	***	0.439	***	0.382	***	0.352	***
Employed (head)	-0.055		-0.191	*	-0.043		-0.193	**
Unemployed (head)	-0.196	***	-0.308	***	-0.144	***	-0.300	***
Selfemployed (head)	0.098	***	0.191	***	0.159	***	0.265	***
Employer (head)	0.296	***	0.403	***	0.226	***	0.353	***
Employer (count)	0.385	**	0.749	***	0.394	***	0.721	***
Public (count)	0.315	***	0.300	***	0.249	***	0.240	***
BTP (head)	-0.097	***	-0.127	***	-0.077	***	-0.091	***
Finance (head)			0.135	*			0.160	**
Finance (count)			0.580	***			0.447	**
Waged (count)	0.222	***	0.253	***	0.264	***	0.339	***
Primary 1 (count)	0.122	***	0.145	***	0.039		0.106	***
Primary 2 (count)	0.420	***	0.369	***	0.266	***	0.234	***
Secondary (count)	0.639	***	0.485	***	0.412	***	0.355	***
Tertiary (count)	0.684	***	0.795	***	0.470	***	0.636	***

Rooms per cap	0.602	***	0.679	***	0.410	***	0.488	***
Rooms per cap^2	-0.059	***	-0.071	***	-0.034	***	-0.047	***
Electricity	0.183	***	0.154	***	0.084	***	0.052	
Sewage	0.065	***	0.131	***	0.057	***	0.079	*
Drinking water	0.145	***	0.067		0.087	***	0.031	
Flush toilet					0.058	*	0.074	
Kitchen					0.075	***	0.027	
Douche					0.228	***	0.225	***
Tv					0.145	***	0.112	***
Parabole					0.227	***	0.209	***
U2 x unemp (hd)	-0.104		0.141		-0.052		0.182	
U3 x unemp (hd)	-0.157		0.159		-0.090		0.144	
U4 x unemp (hd)	0.086		0.298	**	0.076		0.270	*
U5 x unemp (hd)	-0.137		0.085		-0.084		0.111	
U2 x waged (count)	-0.144	*	-0.258	**	-0.118		-0.223	**
U3 x waged (count)	-0.057		-0.040		-0.087		-0.097	
U4 x waged (count)	-0.068		-0.315	***	-0.060		-0.273	***
U5 x waged (count)	0.116		0.033		0.106		-0.008	
U2 x public (hd)	-0.037		0.043		-0.066		-0.009	
U3 x public (hd)	0.009		-0.015		0.031		-0.036	
U4 x public (hd)	-0.135	**	-0.054		-0.108	**	-0.054	
U5 x public (hd)	-0.149	**	-0.161	***	-0.094		-0.140	**
U2 x drinkwater	0.035		-0.038		0.028		-0.066	
U3 x drinkwater	0.047		0.242	***	0.041		0.221	***
U4 x drinkwater	-0.047		0.173	**	-0.079	**	0.111	
U5 x drinkwater	0.142	***	0.248	***	0.087	**	0.174	**
U2 x sewage			0.035				0.082	
U3 x sewage			-0.246	***			-0.245	***
U4 x sewage			0.014				0.022	
U5 x sewage			-0.186	**			-0.160	*
U2 x roompc	0.241	***	-0.027		0.146	**	-0.063	
U3 x roompc	0.077		0.136		0.086	*	0.048	
U4 x roompc	0.441	***	0.159		0.278	***	0.085	
U5 x roompc	0.331	***	0.080		0.136	*	0.018	
U2 x roompc^2	-0.057	***	0.021		-0.021		0.032	
U3 x roompc^2	-0.001		-0.041	*	-0.009		-0.012	
U4 x roompc^2	-0.143	***	-0.065	**	-0.087	***	-0.036	
U5 x roompc^2	-0.071	**	0.004		0.010		0.013	
Constant	8.095	***	8.187	***	8.261	***	8.427	***
adj-R2	0.591		0.579		0.619		0.619	
Obs	7888		4266		7888		4266	

Source: HESs (2001, 2007)

5.2 Rural model

Table 3 presents the rural models for Morocco (for both years; with and without additional variables). As with the urban model, the _IruX* variables denote interactions between selected independent variables and regional dummy variables.

Also here we find that the estimated model coefficients are largely coherent. For the variables that are shared by the rural and urban models, the signs of the coefficients generally match. Let us highlight some aspects that differentiate the rural model from the urban model: (a) employment in agriculture, transport and commerce all enter the regression positively (sectors that are found to be less significant in urban Morocco), (b) returns to education are lower in rural compared to urban Morocco, as is to be expected.

Table 3 – Rural Model

	Without Additional Assets				With Additional Assets			
	2001		2007		2001		2007	
Domain R2	0.269	***	0.010		0.319	***	0.105	
Domain R3	0.060		-0.143		0.127	*	-0.073	
Domain R4	0.224	***	-0.086		0.239	***	0.008	
Hhld size	-0.092	***	-0.162	***	-0.115	***	-0.197	***
Hhld size^2	0.003	***	0.007	***	0.004	***	0.008	***
Married (head)	0.109	***	0.181	***	0.088	***	0.147	***
Primary (head)	0.066	***	0.055	**	0.054	***	0.029	
Secondary (head)	0.147	**	0.236	***	0.079		0.219	***
Tertiary (head)	0.449	***	0.271	**	0.405	***	0.133	
Unemployed (count)	-0.420	***	0.422	*	-0.389	**	0.468	**
Selfemployed (count)	0.122	***	-0.137	*	0.156	***	-0.112	
Employer (count)	1.841	***	1.519	***	1.614	***	1.329	***
Agriculture (count)	0.170	***	0.212	***	0.182	***	0.253	***
Transport (count)	0.704	***	0.829	***	0.550	***	0.587	***
Commerce (count)	0.604	***	0.556	***	0.449	***	0.483	***
Public (head)	0.354	***	0.283	***	0.276	***	0.184	**
Waged (head)	-0.115	***	-0.166	***	-0.104	***	-0.146	***
Waged (count)	0.365	***	0.393	***	0.301	***	0.418	***
Primary 1 (count)	0.170	***	0.167	***	0.092	***	0.094	**
Primary 2 (count)	0.542	***	0.480	***	0.371	***	0.322	***
Secondary (count)	0.849	***	0.599	***	0.695	***	0.348	***
Tertiary (count)	1.145	***	0.723	***	0.950	***	0.631	***
Rooms per cap	0.533	***	0.286	***	0.418	***	0.162	**
Rooms per cap^2	-0.070	***	-0.016		-0.051	***	-0.002	
Electricity	0.206	***	0.236	***	0.087	***	0.054	**
Sewage	0.041		0.493		-0.006		0.418	
Drinking water	0.063	***	0.079		0.046	**	0.063	

Flush toilet					0.129	***	0.096	***
Kitchen					0.029	**	0.047	*
Douche					0.140	***	0.230	***
Tv					0.163	***	0.153	***
Parabole					0.156	***	0.227	***
R2 x hhld size	-0.024	***	-0.006		-0.024	***	-0.004	
R3 x hhld size	0.004		0.019	*	0.002		0.026	**
R4 x hhld size	-0.006		0.012		-0.001		0.013	
R2 x unemp (count)	-0.055		-0.490		-0.122		-0.547	*
R3 x unemp (count)	0.487	**	-0.848	***	0.493	**	-0.946	***
R4 x unemp (count)	0.075		-1.146	***	0.026		-1.066	***
R2 x waged (count)	-0.279	***	-0.173		-0.245	**	-0.199	
R3 x waged (count)	-0.018		-0.369	***	0.055		-0.411	***
R4 x waged (count)	-0.501	***	-0.392	***	-0.435	***	-0.451	***
R2 x public (hd)	-0.181		-0.020		-0.123		-0.021	
R3 x public (hd)	-0.159		-0.156		-0.123		-0.045	
R4 x public (hd)	-0.098		-0.384	***	-0.070		-0.283	**
R2 x drinkwater			-0.044				-0.070	
R3 x drinkwater			0.275	***			0.233	**
R4 x drinkwater			0.091				0.041	
R2 x sewage			-0.588				-0.515	
R3 x sewage			-0.504				-0.507	
R4 x sewage			-0.441				-0.431	
R2 x roompc	-0.205	**	0.048		-0.224	***	0.010	
R3 x roompc	0.224	***	0.358	***	0.124		0.280	**
R4 x roompc	0.171	**	0.370	***	0.168	**	0.306	***
R2 x roompc^2	0.041	*	-0.009		0.048	**	-0.003	
R3 x roompc^2	-0.031		-0.087	**	-0.001		-0.064	*
R4 x roompc^2	-0.028	*	-0.065	**	-0.028	*	-0.051	*
Constant	8.168	***	8.737	***	8.199	***	8.786	***
adj-R2	0.429		0.404		0.478		0.469	
Obs	6355		2796		6355		2796	

Source: HESs (2001, 2007)

6. Validation tests

Before imputing expenditure poverty into all available years of the LFS, this section considers two different tests of the methodology proposed. Both tests use only 2001 and 2007 data, so that imputation-based estimates can be compared to official estimates based on observed data. The first test is within HESs samples, while the second test is cross-surveys using HESs and LFSs.

In the first test, we conduct cross-imputations using only the HESs, by estimating the expenditure model in 2001 and then imputing expenditure poverty in 2007 and vice-versa. This means that we do not have to worry about comparability between HESs and LFSs. It also allows us to test whether the additional durable assets and housing variables (that are not available in the LFS) yield better out-of-sample estimates.

The findings are reported in Table 4. The official poverty estimates are listed in the first column, which shows that poverty has almost halved over the six years' period from 15.3 to 8.9 percent. Our imputation-based estimates of poverty are able to capture this trend remarkably well. What is equally very encouraging is that the 2001 and 2007 models yield almost identical poverty estimates, despite the six years' gap, which suggests that the assumption of a time-invariant model is not an unreasonable assumption in the case of Morocco. Finally, what this first test also shows is that the extended model (with assets) does not yield an improvement in poverty estimates. In all estimations with the exception of the 2001 model, the model with assets overshoots more than the model without assets, despite its better in-sample fit.

Table 4 – Validation Tests Results, within HESs

		No Assets		**With Assets**	
Year	Official Poverty Estimates	2001 Model	2007 Model	2001 Model	2007 Model
2001	15.3	16.0	15.9	16.2	17.1
	(0.5445)	(0.30)	(0.54)	(0.30)	(0.56)
2007	8.9	9.6	9.9	8.8	10.1
	(0.6089)	(0.27)	(0.34)	(0.28)	(0.45)

Source: HESs (2001, 2007). Bootstrapped standard errors in parentheses (500 repetitions).

With the second test we impute into the LFS, but still only for the HES years, so that also in this case we are able to compare our estimates to the official poverty estimates. If anything, the imputation-based estimates match the "true" poverty rates even more closely. One possible explanation for this finding is that the LFS is considerably larger than the HES (although note that the "true" estimates are obtained using the HES). It is striking how accurately we are able to estimate poverty in 2007 based on a model estimated using 2001 consumption data, and vice versa.

Table 5 – Validation Tests Results, cross-survey

Year	**Official Poverty Estimates**	**2001 Model**	**2007 Model**
2001	15.3	15.2	15.1
	(0.5445)	(0.27)	(0.51)
2007	8.9	8.4	8.6
	(0.6089)	(0.19)	(0.28)

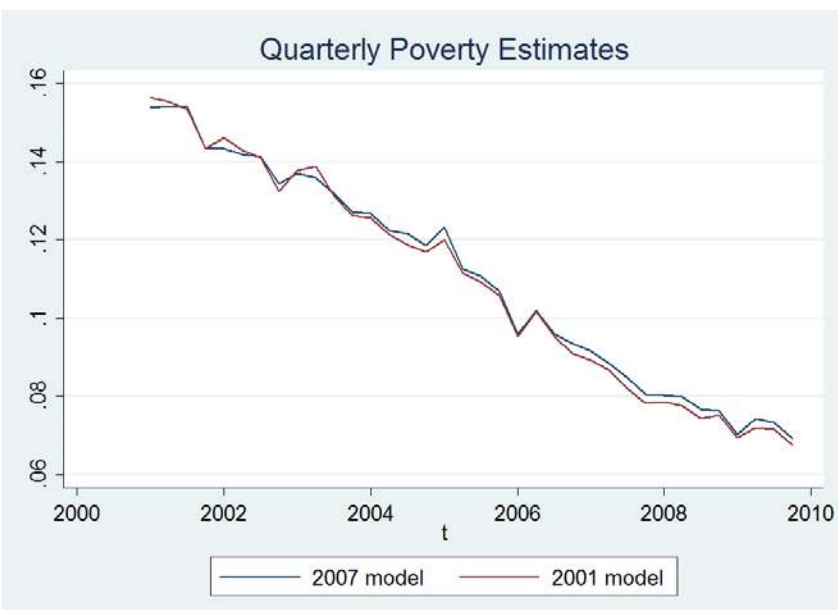
Source: HESs (2001, 2007). Bootstrapped standard errors in parentheses (500 repetitions).

Note that the standard errors (SEs) associated with the imputation-based estimators are smaller than the SEs for the survey direct estimates. This can be attributed to: (1) under the null hypothesis that we identified the correct model, imputation-based estimators tend to be more efficient than survey direct estimates since they exploit information in the form of model structure and data on covariates that is not utilized by the survey direct estimates (see Fujii and van der Weide, 2013); and (2) the LFS is larger than the HES in terms of number of households, such that the sampling errors will be smaller for LFS-based estimates.

7. Poverty estimations 2001-2010

This section presents our main findings. We use both the 2001 and 2007 household expenditure models to estimate quarterly poverty rates for the period 2001 to 2010 by imputing household expenditure in all rounds of the LFSs. Figure 5 shows the poverty trend at the national level. Notice the consistency between the two different models. The distance between the two curves is at best a small fraction of a percentage point. The two curves closely follow each other, replicating seasonal variations almost identically. There is also no discontinuity before and after 2007 when the new survey and computerized data collection systems were introduced. Interestingly, both imputation-based estimates find that poverty in Morocco has continued its decline beyond the 2007-2008 global financial crisis, which may be explained in part by the positive performance of the agricultural sector.

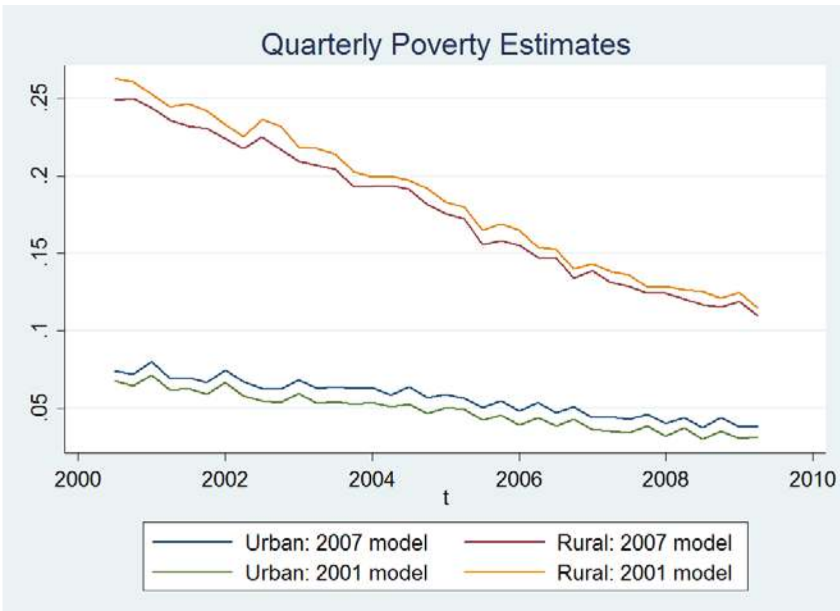
Figure 5 – Quarterly Poverty Estimates 2001-2010



Source: LFSs (2001-2010)

Figure 6 disaggregates the poverty estimates into an urban and a rural trend. This shows the divide between urban and rural standards of living, as is to be expected, but also that this divide is shrinking over time. The difference between the 2001 and 2007 models is now larger in both urban and rural areas as it should be expected given the smaller samples, but the difference is still very small and the trends depicted by the two models are the same for all periods considered. In fact, by separating urban and rural areas, the 2001 and 2007 models are even closer in depicting seasonal variations.

Figure 6 – Quarterly Poverty Estimates 2001-2010, Urban and Rural Areas



Source: LFSs (2001-2010)

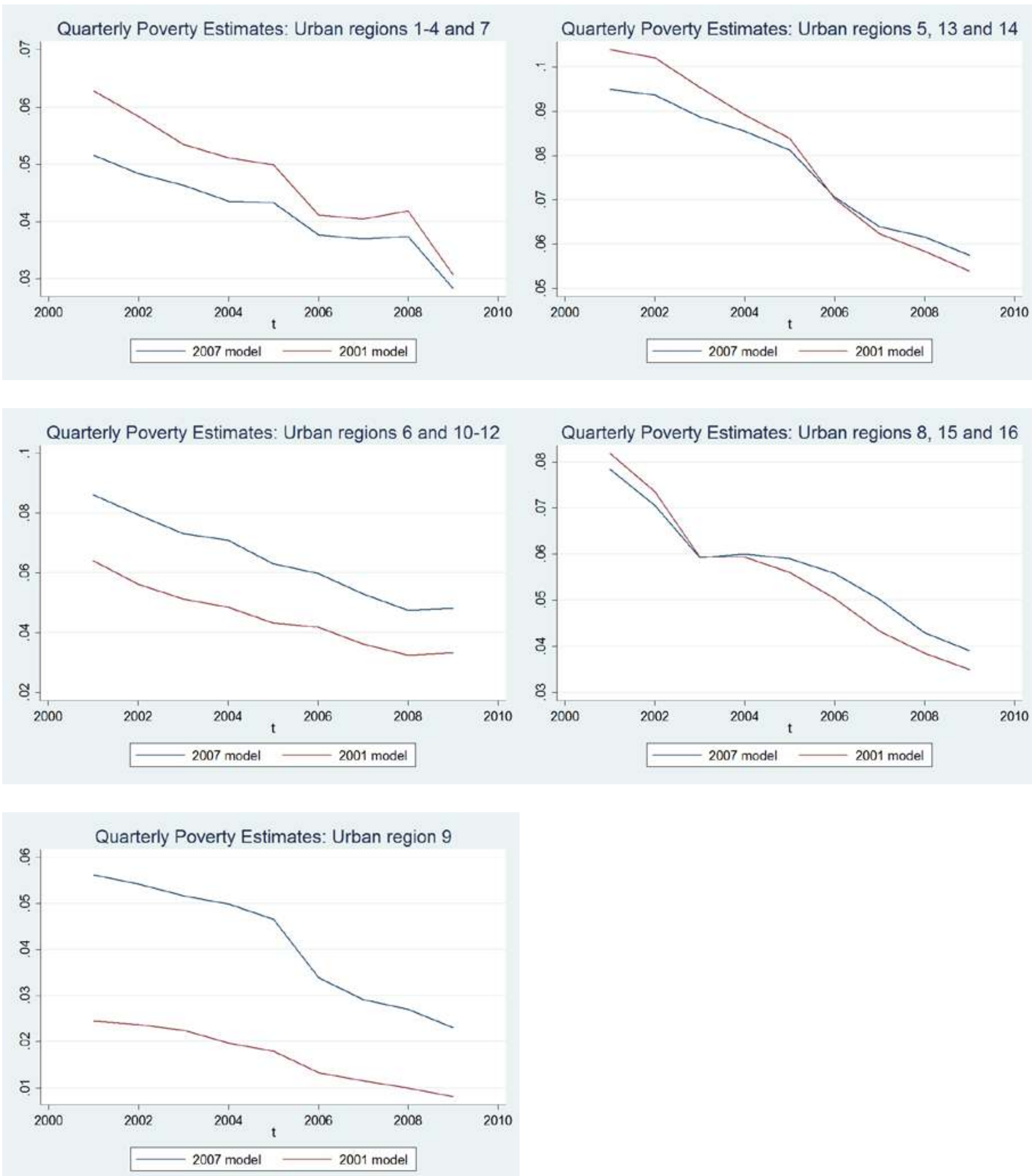
The figures below (Figures 7 and 8) further disaggregate the urban and rural poverty trends into sub-regions. Note that the sub-regions consist of groupings of Morocco's original 16 regions.[8] What is apparent from these estimates is that by this sub-division all sub-regions of Morocco show the same declining trend in poverty. (Results not reported here show that when we disaggregate further, some of Morocco's original 16 regions are found to be more stagnant.) Note that, at this level of disaggregation, we also start to see that the reduction in poverty has been less steep in certain regions as compared to others. We also observe a larger difference between the 2001 and 2007 model estimates, as is to be expected, although the differences remain modest.

Despite these encouraging results, some caution should be applied when considering the imputation-based estimates. Note that while the impact of the recent global financial crisis may have been offset at least party by exceptional agricultural output as a result of good harvests shortly after the crisis, it is conceivable that not all changes brought on by the crisis are well captured by the labor force surveys. For example, while households might have been able to hold on to employment, they might have re-adjusted consumption patterns by shifting to lower quality goods and/or reducing consumption altogether. Also, not all variables that may signal labor market distress, such as changes in contractual arrangements or changes in working time, are used in the consumption model so that these forms of

[8] These groupings were determined by the High Commission for the Plan of Morocco based on population density.

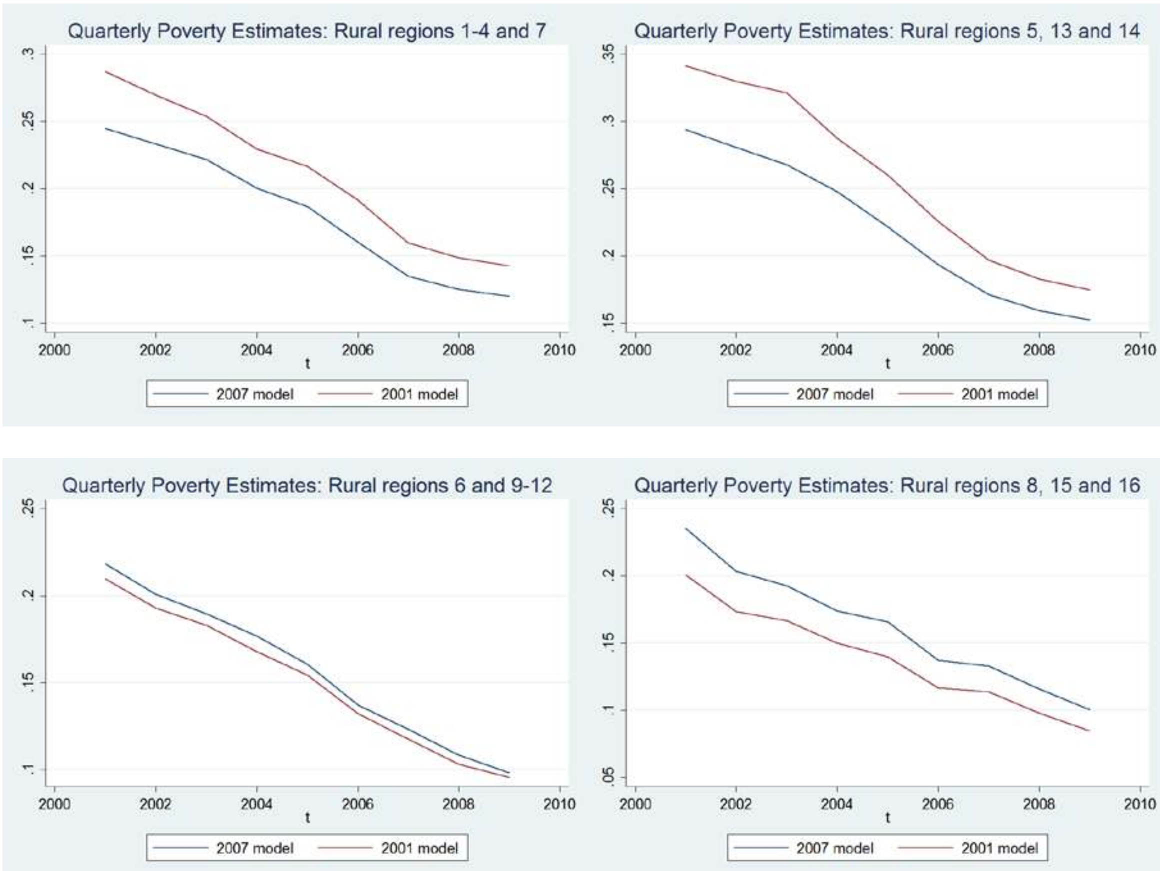
labor market adjustments are not reflected in the imputation-based estimates. In sum, when estimating poverty rates beyond the last available consumption survey, it is important to clarify what is captured and what is not captured by the model, and always validate estimates when a new consumption survey becomes available.

Figure 7 – Quarterly Poverty Estimates 2001-2010 by Urban Regional Group



Source: LFSs (2001-2010)

Figure 8 – Quarterly Poverty Estimates 2001-2010 by Rural Regional Group



Source: LFSs (2001-2010)

8. Extensions and applications

The newly obtained time-series of poverty, possibly disaggregated by sub-region, opens the door to a number of different extensions and applications.

The first obvious application is the possibility to *update poverty statistics in real time.* The Direction of Statistics in Morocco is able to publish labor force statistics within thirty days from data collection thanks to the computer assisted system in place. This means that the Observatory for Living Standards Conditions in Morocco, which is responsible for poverty statistics, would be able to publish poverty estimates within a few weeks from obtaining the data from the Direction of Statistics. Moreover, this could be done every quarter of the year with relatively little effort.

Note that while we focus on the head-count poverty rate as the measure of choice, the exact same methodology can be applied to *estimate other welfare measures* including the poverty gap, the severity of poverty, and the Gini inequality index. All that is required is that the welfare measure can be expressed as a function of household expenditure (or income), and by consequence as a function of the model error and idiosyncratic errors when relying on imputed household expenditure. An estimate of average welfare is obtained by evaluating the expected value of the welfare function, which involves taking expectations over the error terms. The corresponding standard errors are obtained by evaluating the variance of the welfare function, where again the model error and idiosyncratic errors denote the random variables. While this can in principle be done analytically, for general non-linear welfare functions (i.e. non-linear functions of the error terms) the evaluation of the expected value and variance can pose a challenge. A practical alternative is to estimate average welfare along with the corresponding standard error by means of simulation (see Fujii and van der Weide 2012, 2013).

Another possibility relates to the use of the *estimated poverty series as a dependent or independent variable in cross-sections models*. This application is also explored in Elbers et al. (2005). The latter paper considers the use of small area estimates of poverty and inequality obtained by combining household income survey with population census data in regression analysis. The difference with our approach is that the household incomes are imputed into a second survey (the LFS) instead of a population census, which introduces sampling error as an additional source of error (in addition to model error). Provided that this dual error structure is accounted for, the results of Elbers et al. (2005) should directly carry over; they show how the imputation-based poverty estimates can be used as both dependent and independent variables, and how accurate standard errors of the regression coefficients can be obtained. It is important to note however that the imputed household consumption data cannot be treated as if it were observed data; for example, counting the percentage of households with imputed consumption below the poverty line would provide a biased estimate of poverty (as it ignores the error term that separates observed consumption from predicted consumption).

Exploring the time variation in estimated poverty rates, possibly disaggregated by sub-regions, can also be a powerful instrument to *understand the causes of poverty using the newly obtained panel data*. Suppose for example that the researcher has (as for Morocco) 48 points in time and also representative data for 20 regions. This would amount to a panel of 960 observations that can be used to study the determinants of poverty when combined with regional quarterly macro and micro data. Such a wealth of poverty points is rare in poverty studies and could substantially expand the poverty work that is routinely undertaken in country poverty assessments.

Another possible application is poverty *forecasting*. Using the most recent LFSs, Morocco today can count on 12 years of quarterly statistics for a total of 48 points in time. This time series can be used to produce poverty forecasts for the future using dynamic panel data models. Note that one will have to account for the fact that one is dealing with imputed data and not observed data in order to obtain consistent estimates of the parameters of the panel data model.

It is also possible to use the imputation-based poverty estimates for *simulations of policy reforms and economic shocks*. For example, one could simulate how an increase in the unemployment rate or an increase in female labor force participation might affect the poverty rate.

There are a number of technical questions that could be explored with further work. One such question is what level of disaggregation can be handled satisfactorily. Similarly, what time-gaps between estimation and application of the model can be handled; as the LFSs move further away from the last administered household consumption survey, the assumption that the consumption model has not changed over time becomes increasingly optimistic, in which case the imputation-based poverty estimates are expected to become less reliable. Other empirical questions include: Are upward and downward trends captured equally well? Can other moments of the income distribution, such as average income and inequality, be captured equally well? And, can we generally say something about the conditions under which the approach is expected to do well or not so well? Further empirical work is needed to answer these questions.

Finally, in order to strengthen the validation of the proposed approach some alternative tests could be explored. For example, instead of imputing household expenditure one could consider a model for a dependent variable that is readily available in the LFS (such as education, employment or durable assets). This has the important advantage that imputed data can be compared to actual observed data for all available rounds of the LFS.

9. Concluding remarks

The paper has shown that Labor Force Surveys (LFSs) can be used effectively to estimate poverty when Household Expenditure Surveys (HESs) are not available. We have used cross-survey imputation methods to estimate poverty rates for Morocco and obtained a quarterly series for the period 2001-2010.

Results are very encouraging. We constructed first a consumption model based on the 2001 HCS data and a second model based on the 2007 HCS data. We then used the 2001 model to estimate poverty with the 2001 and 2007 HCS data and, vice-versa, used the 2007 model to estimate poverty for both the 2001 and 2007 years. The imputation-based poverty estimates are found to be close to the official poverty estimates, regardless of which model is used. Next, we used the 2001 and 2007 consumption models to estimate poverty with the LFSs for the period 2001-2010; also here we obtained almost overlapping quarterly poverty trends, even when we disaggregated by urban and rural areas.

This exercise provided several new insights for the study of poverty in Morocco. The imputation methodology adopted has implicitly validated the quality and comparability of the 2001 and 2007 HESs and the quality and consistency of the LFSs used. The decline in poverty depicted by the estimated quarterly poverty rates has shown that Morocco has been able to withstand domestic and global shocks, a finding that would not have been possible with the 2001 and 2007 HESs alone. Disaggregated poverty estimates at the regional level show that the poverty trends in Morocco have not been homogeneous across regions, a finding that was not visible when only two points in time were considered. As a byproduct of this work, the High Commission for the Plan of Morocco can now estimate poverty rates every quarter and within weeks of the administration of the LFSs.

The potential for extensions and applications of this work is large. Section 8 has discussed various avenues for future extensions and applications and suggested a number of options, including the use of the estimated quarterly poverty series for further cross-section and panel econometric work, forecasting and simulation of policy reforms and economic shocks. These are all possible extensions of the work presented in this paper that can substantially increase the toolkit of the welfare economist.

References

Christiaensen, L, Lanjouw, P., Luoto, J and Stifel, D. (2012) Small area estimation-based prediction methods to track poverty: validation and applications, Journal of Economic Inequality, 10, 267-297

Deaton, A. (2008): Price trends in India and their implications for measuring poverty. Econ. Polit.Weekly, 7, 3729–3748

Deaton, A., Kozel, V. (2005) Data and dogma: the great Indian poverty debate. World Bank Research Observer, 20 (2), 177–199

Douidich, M. and Ezzrari, A. (2008) Dynamique de la pauvreté au Maroc 1985-2007, Haut Commissariat au Plan, Morocco

Elbers, C., Lanjouw, J.O., Lanjouw, P. (2002) Micro-level estimation of welfare. Policy Research Working Paper 2911. World Bank, Washington DC (2002)

Elbers, C., Lanjouw, J.O., Lanjouw, P. (2003) Micro-level estimation of poverty and inequality. Econometrica, 71(1), 355–364

Elbers, C., Lanjouw, J.O. and Lanjouw, P. (2005) Imputed Welfare Estimates in Regression Analysis, Journal of Economic geography, 5, pp.101-118

Fujii, T. and R. van der Weide (2012), Two-Sample Cross-Tabulation, mimeo, The World Bank

Fujii, T. and R. van der Weide (2013), Cost-effective estimation of the population mean using prediction estimators, mimeo, The World Bank

HCP (2000-2010) National Accounts, Haut Commissariat au Plan, Maroc

Grosse, Melanie, Klasen, Stephan and Spatz, Julius, (2009), Matching Household Surveys with DHS Data to Create Nationally Representative Time Series of Poverty: An Application to Bolivia, No 21, Courant Research Centre: Poverty, Equity and Growth - Discussion Papers, Courant Research Centre PEG.

Kijima, Y., Lanjouw, P. (2003): Poverty in India during the 1990s: a regional perspective. Policy Research Department Working Paper 3141. World Bank, Washington DC

Rubin, D. (1978) Multiple Imputations in Sample Surveys - A Phenomenological Bayesian Approach to Nonresponse. The Proceedings of the Survey Research Methods Section of the American Statistical Association, pp. 20-34. With discussion and reply. Also in Imputation and Editing of Faulty or Missing Survey Data. U.S. Department of Commerce, pp. 1-23.

Rubin, D. (1987). Multiple Imputations. Wiley.

Stifel, D., Christiaensen, L.(2007) Tracking poverty over time in the absence of comparable consumption data. World Bank Econ. Rev. 21(2), 317–341

Tarozzi, A. (2007) Calculating comparable statistics from incomparable surveys, with an application to poverty in India. Journal of Business and Economic Statistics 25(3), 314–336

ANNEX – Regional Poverty (Model 2001)

					National				
Region	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
1	0.029	0.040	0.037	0.021	0.023	0.094	0.059	0.083	0.031
2	0.065	0.055	0.052	0.042	0.043	0.044	0.058	0.062	0.034
3	0.130	0.115	0.123	0.104	0.091	0.091	0.067	0.057	0.081
4	0.187	0.169	0.161	0.151	0.144	0.123	0.107	0.094	0.086
5	0.278	0.269	0.276	0.234	0.199	0.179	0.156	0.150	0.140
6	0.135	0.124	0.121	0.105	0.092	0.094	0.081	0.065	0.065
7	0.216	0.207	0.193	0.169	0.158	0.139	0.116	0.116	0.104
8	0.114	0.104	0.094	0.081	0.068	0.071	0.070	0.056	0.046
9	0.029	0.027	0.025	0.027	0.023	0.018	0.016	0.013	0.011
10	0.091	0.074	0.068	0.072	0.060	0.055	0.047	0.040	0.035
11	0.182	0.175	0.158	0.147	0.141	0.106	0.103	0.097	0.088
12	0.146	0.131	0.133	0.121	0.112	0.103	0.082	0.074	0.078
13	0.181	0.177	0.172	0.158	0.156	0.133	0.111	0.100	0.095
14	0.177	0.166	0.142	0.135	0.122	0.096	0.091	0.082	0.077
15	0.187	0.162	0.146	0.134	0.127	0.102	0.102	0.094	0.086
16	0.133	0.113	0.107	0.103	0.099	0.079	0.067	0.058	0.050
Total	**0.152**	**0.140**	**0.134**	**0.121**	**0.111**	**0.096**	**0.084**	**0.076**	**0.070**

					Urban				
Region	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
1	0.029	0.040	0.037	0.021	0.023	0.066	0.060	0.050	0.039
2	0.059	0.053	0.051	0.036	0.034	0.038	0.054	0.058	0.029
3	0.065	0.054	0.056	0.054	0.049	0.042	0.039	0.037	0.040
4	0.068	0.066	0.061	0.062	0.065	0.047	0.045	0.040	0.032
5	0.120	0.127	0.133	0.118	0.102	0.088	0.075	0.077	0.073
6	0.049	0.047	0.046	0.043	0.040	0.040	0.037	0.033	0.039
7	0.058	0.053	0.046	0.044	0.038	0.034	0.032	0.041	0.027
8	0.078	0.070	0.057	0.059	0.046	0.046	0.042	0.034	0.033
9	0.025	0.024	0.022	0.020	0.018	0.013	0.011	0.010	0.008
10	0.065	0.053	0.047	0.049	0.040	0.036	0.029	0.027	0.025
11	0.072	0.069	0.063	0.049	0.051	0.048	0.049	0.040	0.038
12	0.070	0.062	0.057	0.053	0.049	0.059	0.042	0.044	0.051
13	0.085	0.081	0.074	0.072	0.069	0.068	0.061	0.054	0.044
14	0.112	0.106	0.091	0.088	0.087	0.060	0.055	0.050	0.051
15	0.078	0.063	0.051	0.054	0.053	0.058	0.049	0.053	0.049
16	0.086	0.079	0.063	0.061	0.065	0.051	0.043	0.038	0.032
Total	**0.066**	**0.062**	**0.056**	**0.053**	**0.049**	**0.043**	**0.038**	**0.036**	**0.032**

Rural									
Region	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
1	--	--	--	--	--	0.146	0.057	0.148	0.016
2	0.219	0.112	0.066	0.119	0.159	0.122	0.122	0.130	0.109
3	0.228	0.205	0.221	0.189	0.164	0.176	0.116	0.092	0.157
4	0.265	0.239	0.228	0.213	0.200	0.177	0.152	0.135	0.127
5	0.385	0.366	0.369	0.317	0.270	0.246	0.218	0.207	0.192
6	0.196	0.179	0.171	0.153	0.133	0.138	0.116	0.092	0.088
7	0.314	0.305	0.284	0.250	0.238	0.209	0.174	0.168	0.159
8	0.167	0.155	0.149	0.117	0.105	0.112	0.119	0.095	0.069
9	0.113	0.092	0.096	0.099	0.076	0.076	0.065	0.054	0.042
10	0.218	0.180	0.170	0.169	0.150	0.142	0.127	0.102	0.084
11	0.246	0.236	0.212	0.201	0.192	0.140	0.136	0.131	0.119
12	0.189	0.170	0.174	0.161	0.149	0.130	0.106	0.093	0.094
13	0.290	0.287	0.283	0.267	0.267	0.217	0.178	0.162	0.166
14	0.347	0.331	0.282	0.257	0.216	0.193	0.187	0.170	0.151
15	0.220	0.191	0.174	0.160	0.151	0.117	0.120	0.108	0.099
16	0.200	0.162	0.169	0.160	0.148	0.120	0.102	0.087	0.077
Total	**0.255**	**0.236**	**0.226**	**0.204**	**0.188**	**0.163**	**0.144**	**0.130**	**0.121**

ANNEX – Regional Poverty (Model 2007)

National

Region	2001	2002	2003	2004	2005	2006	2007	2008	2009
1	0.027	0.030	0.035	0.021	0.019	0.071	0.057	0.059	0.025
2	0.054	0.050	0.048	0.038	0.039	0.042	0.051	0.055	0.032
3	0.111	0.103	0.110	0.094	0.082	0.082	0.057	0.052	0.075
4	0.154	0.141	0.137	0.127	0.121	0.103	0.092	0.082	0.074
5	0.236	0.229	0.229	0.198	0.169	0.155	0.138	0.133	0.124
6	0.152	0.143	0.137	0.122	0.107	0.109	0.093	0.076	0.075
7	0.188	0.183	0.171	0.151	0.140	0.118	0.099	0.097	0.088
8	0.133	0.119	0.109	0.093	0.080	0.085	0.082	0.066	0.056
9	0.061	0.057	0.055	0.058	0.051	0.040	0.035	0.031	0.026
10	0.117	0.099	0.092	0.095	0.080	0.074	0.065	0.057	0.051
11	0.196	0.187	0.170	0.158	0.152	0.115	0.112	0.106	0.097
12	0.146	0.133	0.133	0.122	0.111	0.097	0.080	0.071	0.073
13	0.163	0.155	0.148	0.143	0.140	0.120	0.103	0.094	0.090
14	0.156	0.150	0.131	0.128	0.115	0.093	0.087	0.081	0.078
15	0.210	0.182	0.166	0.155	0.145	0.119	0.119	0.109	0.101
16	0.142	0.120	0.115	0.110	0.113	0.088	0.078	0.067	0.056
Total	**0.151**	**0.140**	**0.133**	**0.122**	**0.113**	**0.097**	**0.086**	**0.078**	**0.072**

Urban

Region	2001	2002	2003	2004	2005	2006	2007	2008	2009
1	0.027	0.030	0.035	0.021	0.019	0.062	0.061	0.050	0.035
2	0.050	0.048	0.047	0.034	0.035	0.039	0.050	0.052	0.029
3	0.058	0.052	0.052	0.049	0.045	0.040	0.038	0.038	0.038
4	0.052	0.051	0.052	0.052	0.054	0.043	0.041	0.037	0.030
5	0.108	0.112	0.119	0.105	0.096	0.087	0.074	0.079	0.073
6	0.073	0.073	0.071	0.065	0.059	0.061	0.055	0.048	0.052
7	0.051	0.046	0.040	0.037	0.033	0.030	0.029	0.035	0.024
8	0.083	0.076	0.064	0.069	0.051	0.056	0.050	0.039	0.038
9	0.056	0.054	0.052	0.050	0.046	0.034	0.029	0.027	0.023
10	0.088	0.078	0.072	0.074	0.060	0.055	0.048	0.043	0.042
11	0.094	0.092	0.081	0.071	0.074	0.060	0.059	0.051	0.054
12	0.084	0.075	0.069	0.069	0.061	0.075	0.061	0.059	0.060
13	0.079	0.077	0.071	0.072	0.069	0.068	0.063	0.057	0.049
14	0.102	0.098	0.087	0.086	0.083	0.062	0.058	0.055	0.056
15	0.072	0.056	0.049	0.051	0.054	0.065	0.058	0.062	0.058
16	0.077	0.070	0.059	0.055	0.067	0.053	0.048	0.041	0.034
Total	**0.074**	**0.070**	**0.064**	**0.062**	**0.058**	**0.052**	**0.047**	**0.043**	**0.039**

					Rural				
Region	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
1	--	--	--	--	--	0.088	0.049	0.076	0.008
2	0.164	0.094	0.069	0.099	0.096	0.084	0.066	0.088	0.080
3	0.192	0.180	0.196	0.168	0.146	0.153	0.091	0.077	0.141
4	0.220	0.202	0.195	0.180	0.168	0.146	0.129	0.115	0.107
5	0.323	0.309	0.302	0.265	0.221	0.206	0.187	0.174	0.163
6	0.206	0.193	0.180	0.167	0.145	0.148	0.124	0.099	0.095
7	0.274	0.269	0.252	0.225	0.209	0.177	0.147	0.140	0.133
8	0.205	0.185	0.175	0.132	0.128	0.135	0.137	0.114	0.086
9	0.152	0.126	0.128	0.140	0.103	0.108	0.099	0.076	0.056
10	0.252	0.200	0.187	0.188	0.168	0.161	0.145	0.122	0.095
11	0.254	0.242	0.221	0.206	0.197	0.147	0.144	0.140	0.124
12	0.181	0.166	0.168	0.153	0.140	0.110	0.091	0.078	0.082
13	0.259	0.244	0.235	0.234	0.232	0.187	0.157	0.146	0.146
14	0.300	0.290	0.252	0.236	0.197	0.176	0.164	0.151	0.140
15	0.252	0.220	0.200	0.188	0.175	0.137	0.140	0.125	0.116
16	0.236	0.192	0.196	0.185	0.179	0.139	0.121	0.105	0.090
Total	**0.244**	**0.226**	**0.215**	**0.196**	**0.180**	**0.154**	**0.138**	**0.124**	**0.115**