Comparing Cross-Survey Micro Imputation and Macro Projection Techniques: Poverty in Post Revolution Tunisia

Jose Cuesta
Georgetown University*
Gabriel Lara Ibarra
World Bank

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Tunisia was showcased for a long time as an example of poverty reduction achievement and pro-poor growth. Yet, after halving its poverty rates a revolution took the world by surprise early in 2011 and since then nothing is known about its poverty levels. To fill that gap, this analysis develops and compares multiple cross-survey micro imputations (using household budgetary and labor force surveys) with macro poverty projections (based on sector GDP, unemployment and inflation). Results from both techniques are robust: poverty in post revolution Tunisia first increased in 2011 to then decrease in 2012. The magnitude of this swing oscillates between 1 and 2.3 percent points and accrues mostly from urban areas. Methods using readily available macro administrative data provide estimates of poverty levels and trends very close to those provided by analytically more sophisticated and data demanding micro imputation techniques. These findings for Tunisia provide relevant insights in data deprived contexts with serious deficiencies in the frequency and accessibility of welfare statistics.

Keywords: Poverty, cross-survey imputation, macro projections, Tunisia, residuals–based imputation
JEL Classifications: I32, C53

*The views in this study reflect those of the authors and do not necessarily reflect those of the World Bank, its Executive Directors or the countries they represent.

Introduction

At the end of the 2000s, Tunisia concluded a period that saw its poverty rate cut in half. Based on official poverty lines, poverty declined from 32 percent in 2000 to 15.5 percent in 2010.[1] Poverty reduction was recognized as exemplary by local and international observers alike. Growth was targeted to be deliberately pro-poor, with successive economic strategies having a strong commitment to poverty reduction (Bibi 2005, Chemingui and Bchir 2008, Chemingui and Sánchez 2011, World Bank 2004, 2009). This would explain, according to advocates, why poverty reduction trends had been sustained during periods of low economic growth, macroeconomic adjustment, and rapid growth years alike. Along with rapid growth rates, generous universal subsidies (especially on energy, food and transport) also contributed to the successful poverty reduction (Ben Romdhane 2007, World Bank 2013). Unemployment rates went down from 15.7 to 13 percent in the same period. However, it was in this context of socioeconomic progress that a revolution sparked in January 2011, inspiring the wave of "Arab Spring" uprisings across North Africa and the Middle East that took the world by surprise.

It is now widely believed that lack of economic opportunities and widespread corruption shoulder the brunt of the responsibility for the Tunisian revolution (Harrigan and El-Said 2009, Hibou 2006, Kallander 2011, Paciello 2011, World Bank 2014). The constraints in the economy and the accentuated social injustice perception not only prompted the demise of the Ben Ali regime, but also raised important post-revolutionary challenges. By most accounts, Tunisia has completed a successful political transition—culminating in fair elections and broad consensus on a new "social pact". However, the economic overhaul needed to bring about inclusive prosperity will be an enormous undertaking, involving major changes in the regional development strategy, investment incentives and consumption subsidies, to name a few. Such changes—especially on consumption subsidies—threaten to produce a social instability on its own that renders the implementation of reforms more difficult in the first place. This delicate situation of dealing with political and financial pressures in face of high social demands has recently deteriorated, with highly visible terrorists attacks from Islamists (at the Bardo Museum in Tunis and Port El Kantaoui) making Tunisia's policy making even more vulnerable to social tensions. The success of the changes already initiated and the ability of the country to meet its short- and long-term objectives—economic, social, and political—are not yet certain.

In this uncertain context it is fair to ask how poverty has evolved after the revolution. Unfortunately, monitoring the evolution of welfare is limited by the availability of data. Tunisia collects a very thorough and detailed household consumption survey every five years, but the most recent one dates back to 2010. This study aims to fill the gap on how poverty has evolved in Tunisia after the events of

2010. We use data from the 2010 household budgetary survey (*Enquete Nationale de Buget et des Conditions de Vie*, ENBCV) to estimate a consumption model using demographic, economic and asset ownership data as regressors. The results of the estimation are used to predict consumption in other time periods where data is available, and from which poverty rates are projected. In particular, the method is applied to data from the Labor Force Survey 2009 and 2012. Finally, several specifications and residual imputation techniques are tested to provide robustness to the results.

The analysis is complemented with simpler methods to predict the evolution of poverty that are based on a macro-approach. Projections of poverty can be obtained by applying the observed evolution of readily available macro indicators such as growth and employment into the micro data (i.e. household consumption surveys). Comparing such analyses allows shedding light on the benefits and limitations of each methodology to portray a more accurate picture of the evolution of poverty in the absence of household-level data.

The contribution of the paper is twofold. To our knowledge this is not the first paper that compares results from different survey-to-survey imputation methodologies (see Christiansen et al 2012, Mathiassen 2013 and Newhouse et al 2014 for recent attempts), but it is the one that most comprehensively compares and contrast micro-imputation techniques with macro-projection methods in the same exercise, for the same country. Secondly, findings from this exercise help inform feasible approaches to project poverty in contexts where data frequency and access are typically seriously limited. Unfortunately this is a very frequent case. Serajuddin et al (2015) report that for the period 2004–13, 74 countries still lacked the basic data required to monitor poverty over two points in time within that 10-year span. These countries have no data points at all, have only one data point each, or have two data points, but more than five years apart.

The rest of the paper is as follows. Section 2 provides some detail on the methodologies available to perform survey-to-survey imputation, as well as the description of the projection methods based on macro administrative data applied in this study. Section 3 describes data sources used while Section 4 presents and discusses the results obtained. Section 5 concludes.

Survey-to-survey Imputation Methodologies

Survey-to-survey imputation projections

New survey-to-survey imputation techniques, only recently developed, can help overcome the lack of frequent budgetary surveys from which directly estimate poverty incidence. In a nutshell, survey-to-survey imputation techniques consist in developing a consumption (or income) model from household expenditure (income) surveys that can be used to impute a distribution of consumption (income) among households in another survey—labor force, for example—in the same or a different year. Early foundations of this technique stem from the "poverty-mapping" approach by Elbers, Lanjouw, and Lanjouw (2003), which predicted consumption data into the census from a consumption model estimated in a previous household survey. More recent applications of this technique have imputed consumption between household surveys and Demographic and Health Surveys, DHS—as in Stifel and Christiaensen (2007), Ferreira et al. (2011), Christiaensen et al. (2012), and Mathiassen (2013).[2] Closer to the Tunisian case, Mathiassen (2009) in Mozambique, Douidich et al. (2013) in Morocco, and Newhouse et al. (2014) in Sri Lanka have imputed consumption from a household expenditure survey into a more recent labor force survey and subsequently estimated poverty rates.

In Tunisia, as elsewhere, survey-to-survey imputation estimates a consumption model in one survey (call it "survey A"), and then uses its parameters to impute consumption in another survey (call it "survey B"). Critically, all variables included in the model estimated in survey A must also be available in survey B to ensure that observed and imputed poverty rates are comparable. This means that variables that potentially could be relevant in explaining consumption in survey A, but are not present in survey B, will not be included in the consumption model. Also, differences in the definition of the same variable in the two surveys may have consequences in the replicability of the model. Furthermore, differences in sampling design of the surveys involved in the imputation may also have consequences in the quality of the estimates (Newhouse et al. 2014).

In this paper, the analysis uses as survey "A" data from the 2010 round of the ENBCV. Information at the household and individual levels is then used to estimate an ordinary least square (OLS) household consumption model. The estimated OLS equation is of the form:

$$ln(y) = X^{'}\beta + \varepsilon \tag{1}$$

where y captures total household (per capita) expenditures; X is a set of controls for socioeconomic and demographic features, location, and access to basic services of the household; and ε is an error term. More specifically, X includes[3]:

- **Sociodemographic variables**: Household size and its square; dependency rate; household head characteristics such as age in logarithm form and its square, gender, and marital status; education (primary, secondary, or university as highest level attended); and education of members of the household other than its head;

- **Labor characteristics**: Employment status (unemployed or otherwise); sector of work (agriculture or otherwise) of the household head and other members of the household; [4]

- **Access to basic services**: Such as tap water and electricity;
- **Asset/durables ownership**: Car, motorcycle, and/or bicycle; television and/or radio; washing machine, refrigerator, freezer, dishwasher, or oven and
- **Location variables**: Rural areas and regional controls.

The dependent variable of the model is the logarithm of annual household consumption per capita. Household consumption includes monetary expenditures for the consumption of food and non-food items (clothing, hygiene and care, leisure); housing investment expenditures; expenditures on transport; own consumption of food; gifts in kind and in-kind benefits received; imputed rent of owner-occupied household or household which enjoys free housing. Consumption does not include capital expenditures, durable goods expenditures, or exceptional ceremony expenditures (INS et al, 2012).[5] Household consumption was divided by the number of household members to obtain a per capita measure without accounting for any age or gender based scaling.

Before applying the cross-survey (or survey to survey) imputation, it was confirmed that the common variables in both the ENBCV and the National Labor Force Surveys (*Enquete Nationale sur la Population and l'Emploi,* ENPE) surveys were consistent in terms of their definitions. Sample design was also comparable across surveys, as both used the 2004 census as a sampling framework. The ENBCV 2010 contains information on 11,281 households across seven regions, while the sampling frame was stratified by the governorate and living area (large cities, medium and small towns, and non-communal areas). The surveys used in the imputation exercise are only one and two years apart, imputing consumption from the ENBCV 2010 into ENPE 2009 and ENPE 2012. Underlying the imputation exercise, it is assumed that the consumption model in 2010 is appropriate to explain consumption in 2012. The short period of time, two years, between imputations support this assumption, but the fact that a revolution took place between both years may question the validity of this assumption. In fact, abrupt changes in the returns to poverty determinants will not be captured by the cross-survey imputation. While this is a cause of concern, it is believed that changes in returns might have been more likely a challenge for imputation in 2011 than in 2012. This is the case because the largest economic changes following the revolution—in terms of GDP and unemployment—took place in 2011, while they returned to pre-revolution levels in 2012. Hence, the comparability of returns between 2010 and 2012 should arguably be a closer fit than returns in 2010 and 2011

The consumption model described in (1) is used to impute expenditures across households based on the values of their explanatory variables. Poverty rates and their standard errors are estimated based on these imputed expenditures. However, consumption models used in cross-survey imputation typically have limitations in their prediction capacity, thus they are unable to fully account for all of the consumer's behavior. A strategy developed to account for consumption behavior not captured directly in the consumption model consists of imputing the estimated residuals of the consumption model in survey A[6] into survey B (see, for example, Ferreira et al. [2011] and Douidich et al. [2013]). These analyses impute the "average residual" of households pertaining to each decile of a distribution of wealth in survey A into the households pertaining to the respective wealth deciles defined by the same set of assets in survey B.[7] This strategy is believed to be more precise than a random inclusion of residuals as it minimizes the chance that residuals obtained in households of low socioeconomic status in survey A may end up allocated to a household of a very different socioeconomic extraction in survey B. How much is, however, an empirical matter.

Dang, Lanjouw, and Serajuddin (2014) provide another alternative to simulate the final consumption imputation. Their approach estimates a clustered random effects[8] consumption model using survey A information. Next, it applies the estimated coefficients from that regression in survey A to individuals in survey B to obtain a predicted consumption. Finally, they randomly allocate both the clustered random effects and error terms of the regression in survey A to each individual in survey B. This process is bootstrapped and the projected poverty rate is obtained from the average of all repetitions. By separating two sources of error terms—one related to imputation-specific limitations and the other to design limitations—their estimates can potentially control better for survey data and design limitations, thus estimating more precisely the standard errors of imputed consumption estimates.

The incipient empirical body of work on cross-survey imputation has not yet concluded which of the alternative methods is superior and under what circumstances. Issues such as simplicity of the empirical strategy, comparability of surveys, treatment of residuals, consumption modeling, and data quality and accessibility, among others, should all play a role in the selection of the most appropriate imputation methodology. Rather than choosing a single cross-survey imputation approach among the presented alternatives, the current analysis produces multiple survey-to-survey imputation sets of results using all the described approaches and compare them to draw relevant lessons.

First, residuals from survey A are randomly allocated to survey B, regardless of the characteristics and location of the households in each survey. Results under this method are reported under the scenario called "random residuals imputation." Second, following Ferreira, Gignoux, and Aran (2011) method, residuals from survey A are more precisely imputed in survey B by randomly allocating residuals within predefined groups in both surveys. As reported above, Ferreira, Gignoux, and Aran (2011) use deciles of a generated wealth index (and defined by ownership of durable goods, housing characteristics, and access to utilities) to allocate residuals between surveys.[9] It is only possible to conduct this allocation of residuals among surveys when the same assets can be identified in both surveys. This method produces estimates of poverty under the scenario called "wealth index deciles imputation." An extension of this methodology is also attempted by further dividing asset-based deciles by urban and rural populations, effectively separating deciles of wealth between urban and rural households. This is captured in the scenario "wealth index deciles and urban-rural imputation." A final method follows the Dang, Lanjouw, and Serajuddin (2014) survey-to-survey imputation method described above, consisting of imputing cluster random effects and errors across surveys. Results are presented under the scenario described as "DLS imputation."

Figure 1 below summarizes the steps leading to each of the four imputation methods used in this analysis.

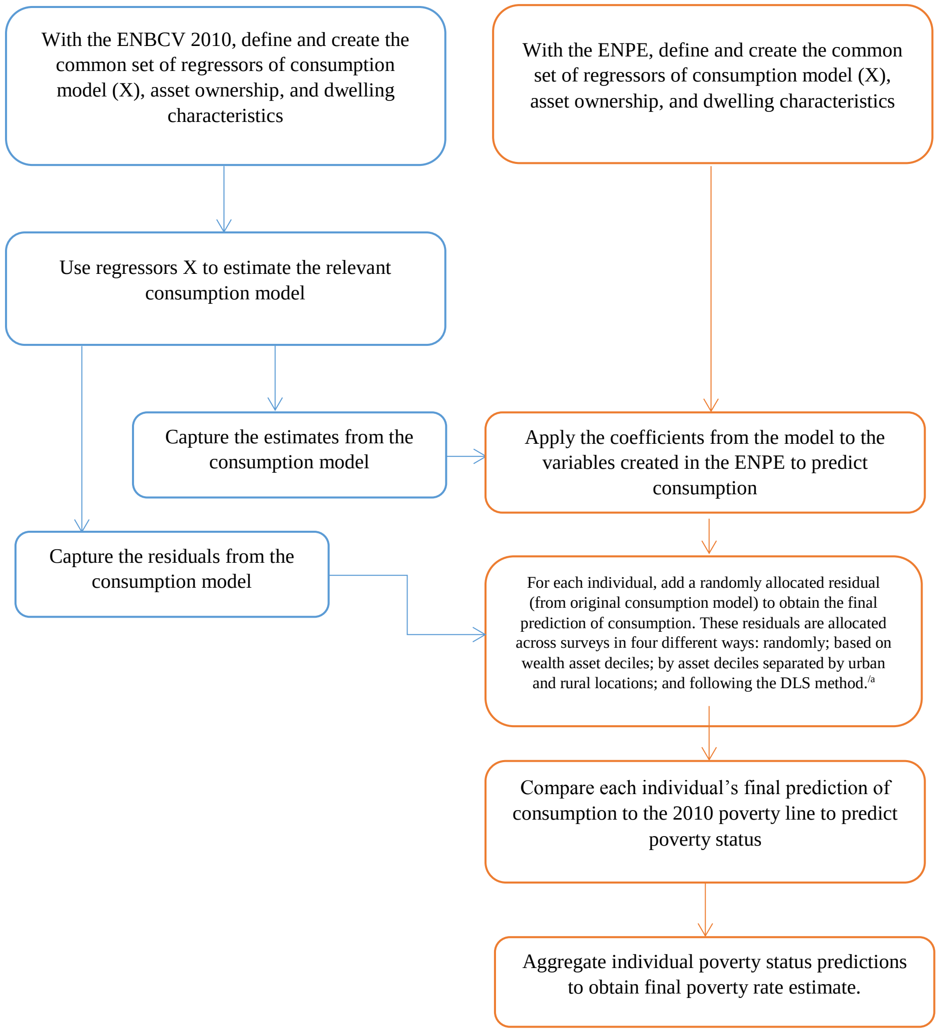
Macro-based projections

Complementary to the analysis above, we obtain projections of the national poverty rates using readily available macroeconomic data. This technique uses information on GDP growth, sector composition, unemployment, and CPI as inputs within a partial equilibrium model. Other determinants should be expected to affect poverty. However, they cannot be easily traced back in household surveys; do not change dramatically in the short run; or are hard to measure. For example, changes in human capital accumulation are unlikely to have changed dramatically in a one- or two-year span, leading to skill changes to not be considered in the analysis. Other factors such as social transfers or subsidies cannot be traced back in the household survey with precision to improve the accuracy of projections.

For changes considered in the exercise—GDP, unemployment, and CPI—the analysis imputes the observed changes in those variables in 2011 and 2012 back into the original distribution of households' consumption obtained from ENCBV 2010. So, the predicted distributions of consumption for 2011 and 2012 result from "shocking" the observed consumption distribution in 2010 with the changes in macro variables observed in 2011 and 2012. Those resulting distributions of consumption post-revolution are then used to estimate the proportion of households under CPI-updated poverty lines for the years 2011 and 2012, respectively. This simple methodology projects poverty rates for such years.

Figure 2 presents the steps to construct the simulation scenarios. In its simplest version of the projection exercise, *simulation 1 (GDP only)*, the GDP growth observed in 2009, 2011, and 2012 are successively imputed to each household in the 2010 ENBCV. Under simulation 1, per worker consumption of each household is adjusted by the officially reported GDP growth for the projected years. The underlying assumption is that there is a perfect pass through between income and

Figure 1
Major Phases of Survey-to-Survey Imputation



Note. ENBCV refers to the Household Consumption Survey. ENPE refers to the Labor Force Survey. a. This step (along with subsequent steps) is typically bootstrapped. DLS model refers to the Dang, Lanjouw, and Serajuddin (2014) cluster random effects model that includes asset ownership and dwelling characteristics.

consumption growth in any given year. The poverty line is then adjusted based on each year's CPI, as reported by the INS. The resulting new distribution of consumption is compared with the updated poverty line, and those households below the new poverty line are classified as poor.

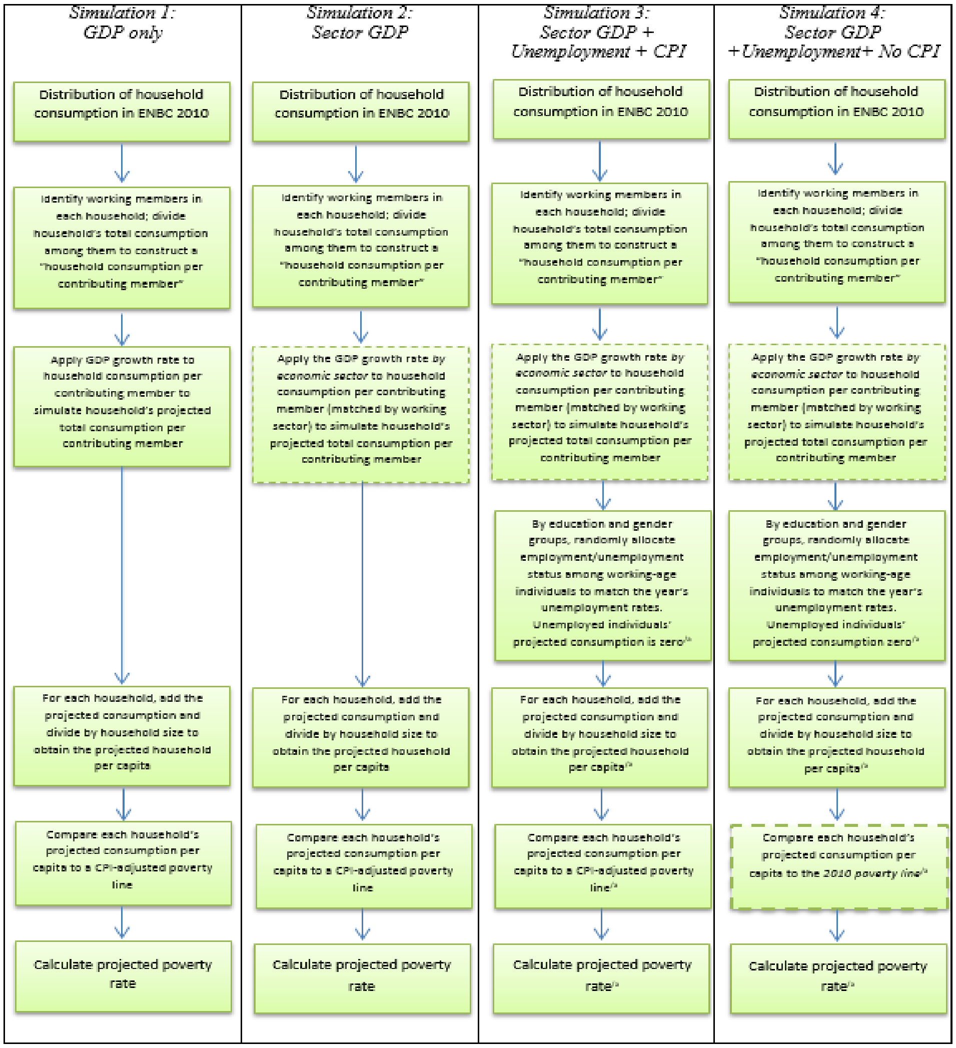
A first alternative projection scenario includes sector-specific GDP growth. Under *simulation 2 (sector GDP)*, the mechanics of simulation 1 are repeated, but now workers in each of the three broad sectors of the economy (agriculture, manufactures, and services) are imputed their sector-specific growth rate. The main assumption in this simulation is that sector-specific growth rates are a good approximation for describing the growth experienced across all activities comprising the three sectors of the economy.

A third and more sophisticated projection, *simulation 3 (sector GDP, unemployment)* explicitly includes the observed unemployment rates in 2011 and 2012. In Tunisia, official data on unemployment rates is disaggregated in four educational attainment levels: unable to read, individuals with primary education, secondary education, and tertiary education. Unfortunately, the Tunisian Statistical Office (INS) reports disaggregate unemployment rates for 2011 and 2012, but not for later years thus limiting the set of possible projections to 2011 and 2012. Also, unemployment rates by education level could only be further disaggregated by gender, but not age, which would have provided a higher-resolution simulation. The annual changes in unemployment observed in each year are imputed back randomly across the distribution of households in ENBCV 2010 to match the projected year's unemployment rate. If unemployment increased in the projected year with respect to 2010, a random sample of working individuals is assumed to have lost their job and considered unemployed so that unemployment rates in the simulated distribution matched the observed rates. Individuals who are assigned unemployment status in the simulation are imputed no consumption per capita from labor. The final estimates are obtained by bootstrapping methods. That is, the described simulation procedure is replicated 100 times (with random draws affecting different individuals in each replication) and a projected poverty rate is obtained from the average poverty rate of all replications.

A final projection, *simulation 4 (sector GDP, unemployment, and no CPI adjustment)* is conducted to better understand the effect that poverty line adjustments have on projected poverty estimates. This simulation simply replicates simulation 3, except for the CPI adjustment of poverty lines. Instead, the original poverty line in 2010 is used to determine whether or not a household in 2011 and 2012 is poor, after sector-specific growth and unemployment rates are imputed. Once again, the allocation of observed sector GDP growth and unemployment rates into 2010 ENCBV households is replicated 100 times and all of these poverty rates are averaged out to report the final poverty projection for this scenario.

In these simulations, we assume that the growth in the economy, or the sectoral-specific growth, translates into earnings of workers. Thus, our simulations will increase the consumption of households that have at least one worker. This approach affects 86 percent of individuals in 2010 (as they all live in a household with at least one working member). We do not pursue adjusting the consumption for individuals

Figure 2
Diagrammatic Representation of Poverty Simulations



Note. ^{a} These steps are bootstrapped 100 times account for the random allocation process of employment status.

without a working member for two reasons. First, the majority of government transfers to individuals are universal subsidies which did not change–as a government policy—during the period of analysis. Secondly, the survey collects good information on consumption of households, but not on income transfers. Thus, assigning an increase would require strong assumptions as to define which households would benefit from these. We recognize these are shortcomings of the methodology.

Data

Data availability determines the extent to which imputation and projections methods are applied to the Tunisian context. In effect there are no official poverty estimates in Tunisia after 2010. The last ENBCV collected, processed, and with results officially released dates back to that year. The new ENBCV finalized data collection in early 2016, but results could be expected to be released by 2017. In the absence of updated evidence, poverty is expected to have increased immediately after the January 2011 revolution, as the economy plunged into recession with a growth rate of -1.9 percent (World Bank 2015). It becomes harder to predict poverty trends thereafter, as the economy recovered in 2012 with a 3.6 percent growth rate in that year, and then slowed to 2.6 percent in 2013.[10] According to INS official figures, unemployment increased in 2011 to 18 percent, up from 13 percent in 2010. Since then, unemployment has declined to 16.9 percent, 15.8 percent and 15.1 percent,[11] respectively, in 2012, 2013 and 2014, but still above pre-revolution levels. The Consumer Price Index (CPI) has strengthened progressively, going up 3.5 percent, 5.1 percent, 5.8 percent and 4.9 percent, respectively, between 2011 and 2014, and making the satisfaction of basic needs more expensive (Tunisia Central Bank 2015).

As a result data availability, ENBCV 2010 constitutes our benchmark survey. This survey, “survey A”, is the most recent survey from which official poverty incidence is estimated from households’ consumption. ENPEs constitute “survey B.” They have been collected every year since 2005. However, INS has only made available the entire ENPE 2009, 2010, and 2012. So, for the purpose of this exercise, the different imputation methods are applied to those surveys. The definitions of all variables of the consumption model are confirmed to be comparable. This turns out to be the case for the 2010 and 2012 ENPEs, but not for the 2009 ENPE. In that year, the ENPE did not include the occupation of individuals. This means that the extended of “full” consumption model estimated in the ENBCV 2010 cannot be replicated in 2009. Two options are presented to overcome this problem. One is to retain the extended model for 2010, the “full model,” and apply it only to ENPE 2012. This models includes as regressors: household size and its squared, age of the household head and its squared, the dependency rate, an indicator variable for whether the head is married, male, unemployed or works independently, as an employer or an employee, and whether she works in agriculture or the public sector, an indicator for her educational attainment, an indicator variable for the region of residency, and the number of household members (besides the head) that are unemployed, independent workers, employers, employees, the number of members in each educational level, and a rural location dummy.

Predictions are obtained using a model that can be compared for more years. This predictive model is actually a more parsimonious version of the full model described above. The regressors excluded from the predictive model are the number of children in the household and household head and members' labor occupation. This model, labeled "comparable model," is applied to both the ENPE 2009 and 2012.

The use of this rich array of methods–four residual imputation techniques, four projection scenarios and two full and comparable consumption models–provides a wide range of poverty estimates from survey-to-survey imputation that take into account best international practices while customizing their application to the specific circumstances of Tunisia. At the same time, those sets of results also underscore the limitations of imputed poverty estimates, which are proportional to the capacity of the consumption model to reproduce observed poverty estimates.

Results

The main objective of this study is to obtain a reliable prediction on the evolution of poverty in Tunisia after 2010. We abstract from testing several models and choosing a "preferred" one. This is so because we do not have observed poverty rates after 2010 upon which compare the fit of the predicted rates. Instead, we use the results from a set of predictive models based on the 2010 ENBCV data to compare predicted poverty rates vis-à-vis the observed poverty rate in 2010. In addition, we also "backcast" 2005 poverty rates applying our alternative predictive models to 2005 data and comparing the resulting estimates with the observed 2005 poverty rate.

The objective of this strategy is to assess the fit of the different predictive models to previous data and, having concluded that they are a reasonably good fit, project poverty rates into subsequent years. We do this recognizing that all estimated models have limitations and advantages, and thus a conservative approach would be to analyze whether a consistent story, a reliable trend, can be inferred from the group of individual results. This is appropriate in contexts where household surveys are not frequently collected and long spans between surveys make a proper validation of predictions of alternative models an infeasible strategy. This is precisely the context that characterizes Tunisia and the Middle East and North Africa region and, more generally, developing countries severely data deprived. Although unable to provide a proper validation of forecasting quality, inferences on the *backcasting* fit of the different predictive models provide meaningful evidence on the performance of our set of models.

Indeed, we present results from the estimation of two types of models across a range of error imputation techniques. The models used in the imputation projections fit well the observed data and they are able to provide a reasonable approximation to the observed poverty rates in 2010. The first model, the "full" model, is used to predict into the ENPE 2012 data. The results from the OLS estimation are presented in Table 1. The R^2 squared of the full model using the entire sample is 0.535. The model is able to explain less of the variation when it is estimated separately by urban and rural locations. The urban model has an R^2 of 0.499 while the rural one has 0.385 Table 2 presents the results from the OLS estimation of the “comparable” model. These estimates were used to calculate the imputations into ENPE 2009 and the ENPE 2012. The comparable model is found to explain a non-negligible share of the variation of the consumption. The R^2 of this model is 0.513.

Table 1
"Full" Consumption Model used for Prediction

Dependent variable: Log(annual consumption per capita, *millimes)*			
Controls	National	Rural	Urban
Household size	-0.338***	-0.291***	-0.364***
	(0.011)	(0.016)	(0.015)
Household size squared	0.013***	0.009***	0.016***
	(0.001)	(0.001)	(0.001)
Log of household head age	1.609***	1.249	1.506**
	(0.523)	(0.871)	(0.632)
Log household head age squared	-0.188***	-0.150	-0.172**
	(0.067)	(0.112)	(0.081)
Indicator: household head is married	0.052**	0.082***	0.048*
	(0.024)	(0.032)	(0.029)
Indicator: household head is unemployed	-0.289***	-0.257***	-0.309***
	(0.035)	(0.056)	(0.041)
Indicator : household head is self-employed	0.013	0.081**	-0.025
	(0.017)	(0.036)	(0.020)
Indicator : household head is employer	0.197***	0.273***	0.178***
	(0.021)	(0.043)	(0.027)
Indicator : household head is salaried worker	-0.102***	-0.081***	-0.106***
	(0.014)	(0.030)	(0.016)
Dependency rate	-0.102***	-0.176***	-0.045
	(0.024)	(0.039)	(0.029)
Indicator: household head is male	0.045*	0.082**	0.021

	(0.023)	(0.038)	(0.028)
Indicator: household head's education: *primary*	0.129***	0.095***	0.151***
	(0.015)	(0.024)	(0.019)
Indicator: household head's education: *secondary*	0.314***	0.218***	0.350***
	(0.018)	(0.032)	(0.021)
Indicator: household head's education: *university*	0.615***	0.545***	0.636***
	(0.024)	(0.066)	(0.027)
Region indicator: Northeast	-0.162***	-0.072	-0.194***
	(0.022)	(0.066)	(0.025)
Region indicator: Northwest	-0.352***	-0.321***	-0.329***
	(0.027)	(0.063)	(0.037)
Region indicator: Center east	0.027	0.045	0.034
	(0.025)	(0.070)	(0.025)
Region indicator: Center west	-0.337***	-0.296***	-0.325***
	(0.028)	(0.063)	(0.036)
Region indicator: Southeast	-0.073**	-0.103	-0.039
	(0.034)	(0.076)	(0.030)
Region indicator: Southwest	-0.244***	-0.183***	-0.251***
	(0.031)	(0.070)	(0.034)
Number of household members who are unemployed+	-0.048***	-0.058***	-0.045***
	(0.008)	(0.013)	(0.011)
Number of household members who are self-employed	0.123***	0.110***	0.129***
	(0.017)	(0.024)	(0.022)
Number of household members who are employers	0.245***	0.312***	0.216***
	(0.033)	(0.052)	(0.036)
Number of household members who are employees	0.074***	0.087***	0.072***

	(0.008)	(0.014)	(0.008)
Number of household members who attended *primary*+	0.052***	0.073***	0.038***
	(0.005)	(0.009)	(0.008)
Number of household members who attended *secondary*+	0.120***	0.147***	0.112***
	(0.007)	(0.012)	(0.008)
Number of household members who attended *university*+	0.179***	0.210***	0.174***
	(0.009)	(0.016)	(0.011)
Indicator: household head works in agriculture	-0.038**	-0.075***	-0.081***
	(0.019)	(0.025)	(0.026)
Indicator : household head works in the public sector	0.103***	0.131***	0.095***
	(0.014)	(0.029)	(0.016)
Indicator : Rural location	-0.186***		
	(0.019)		
Constant	12.054***	12.472***	12.295***
	(1.012)	(1.680)	(1.236)
Observations	11,280	4,020	7,260
R-squared	0.535	0.385	0.499

Note. Authors' calculations using the ENBCV 2010. Standard errors in parenthesis. + Includes all household members but the household head. Indicators refer to a binary variable taking the value 1 when the criteria is met and 0 otherwise. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table 2
Consumption Model Used for Prediction

Dependent variable: Log(annual consupmtion per capita, *millimes)*	
Household size	-0.324***
	(0.010)
Household size squared	0.014***
	(0.001)
Log of household head age	0.327
	(0.558)
Log household head age squared	-0.010
	(0.071)
Indicator: household head is male	0.018
	(0.024)
Indicator: household head is married	0.049**
	(0.022)
Indicator: household head is unemployed	-0.262***
	(0.033)
Dependency rate	-0.188***
	(0.024)
Indicator: household head's education: *primary*	0.120***
	(0.014)
Indicator: household head's education: *secondary*	0.326***
	(0.017)
Indicator: household head's education: *university*	0.655***
	(0.022)
Indicator: household head works in agriculture	-0.014
	(0.016)
Region indicator: Northeast	-0.153***
	(0.025)
Region indicator: Northwest	-0.349***
	(0.028)
Region indicator: Center east	0.041*
	(0.024)
Region indicator: Center west	-0.345***
	(0.033)
Region indicator: Southeast	-0.085***
	(0.031)
Region indicator: Southwest	-0.249***
	(0.031)

Table 2
Consumption Model Used for Prediction

Dependent variable: Log(annual consupmtion per capita, *millimes)*	
No. of household members who are unemployed+	-0.079***
	(0.008)
No. of household members who attended *primary*+	0.061***
	(0.006)
No. of household members who attended *secondary*+	0.125***
	(0.007)
No. of household members who attended *university*+	0.189***
	(0.010)
Indicator: Rural location	-0.201***
	(0.021)
Constant	14.347***
	(1.095)
Observations	11,280
R-squared	0.513

Authors' calculations using the ENBCV 2010. Standard errors in parenthesis. + Includes all household members but the household head. Indicators refer to a binary variable taking the value 1 when the criteria is met and 0 otherwise. $***p < 0.01, **p < 0.05, *p < 0.1$.

Table 3 presents the predicted national poverty rates for the two years for which there is household survey. The table shows that the estimated consumption model provide a reasonable approximation to the observed poverty rates in 2010. Looking at the right panel in Table 3, "ENBCV 2010 predicted," the consumption model estimated in ENBCV 2010 yields a national poverty estimate of 16.8 percent using the random residuals method—compared to the observed official poverty rate of 15.5 percent. Poverty estimates using wealth deciles for imputing residuals predict a rate of 17.8 percent—and only a slightly lower poverty estimate of 17.7 percent when urban and rural populations are separated. Using models that are comparable for all years confirm the results obtained from the full model. Estimates under the comparable model suggest that the Dang, Lanjouw, and Serajuddin (DLS, 2014) method of imputation, with a predicted rate of 16.1 percent, provides a closer estimate of poverty to the official rate in 2010. Generally, all models seem to provide a close prediction of the true distribution of consumption. Annex 1 confirms the reassuringly reasonable match between the *actual* poverty and distributive statistics before the year 2011, i.e. for the years before the crisis when micro data is available, and the *predicted* statistics across the several imputation models. Furthermore, Figure 3 shows the 5th and 95th percentiles of the predicted consumption distribution for each imputation method as well as the observed consumption distribution. With the exception of the wealth-decile residuals, the models are able to predict consumption distributions that follow the actual consumption distribution. The wealth-decile residual imputation models provide a good fit for the relatively rich and poor individuals, but tend to consistently underestimate the consumption of individuals in the middle of the distribution. Lastly, the predictive models are also used to predict the poverty rates for 2005 as a means to test their predictive capabilities, as discussed above. The models are able to predict the fall in poverty between 2005 and 2010, though the change is estimated to be smaller. The location-specific wealth decile predictive model (Table 3 row 3) yields the closest estimates to the official rate in 2005, whereas the DLS imputation method (Table 3 row 6) yields the second closest estimate though is it an overestimation.

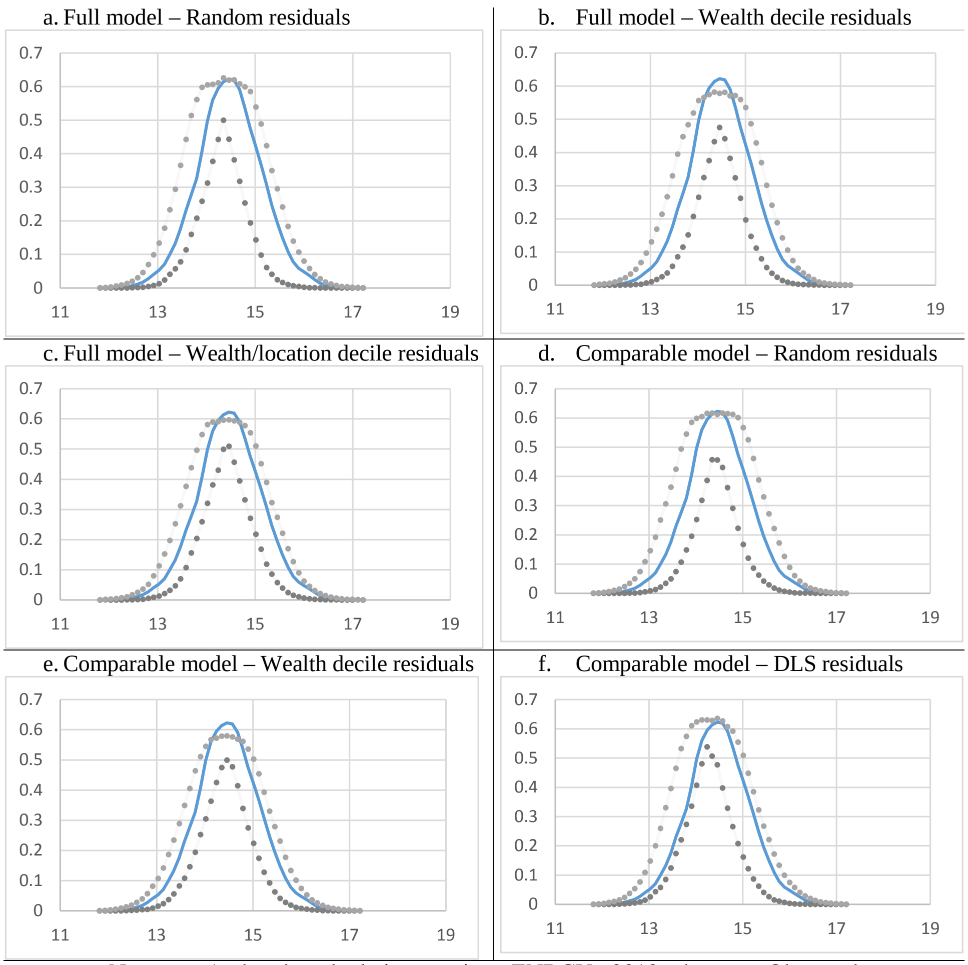
Table 3
Predicted Poverty Rates, by predictive model.

Consumption model	*Survey-to-survey method*	ENBVC 2005 Pred. national pov. rate	ENBCV 2010 Pred. nat. pov. rate
Full model ENPE 2010/12	Random resid.	20.3	16.8
		(0.34)	(0.34)
	Wealth decile	21.4	17.8
		(0.39)	(0.34)
	Wealth decile, u/r	21.8	17.6
		(0.33)	(0.33)
Comp. model ENPE 2009/10/2012	Random resid.	20.4	16.8
		(0.39)	(0.34)
	Wealth decile	21.5	17.7
		(0.32)	(0.36)
	DLS residuals	24.9	16.1
		(0.31)	(0.41)

Note. Authors' calculations using ENBCV and ENPE data. The official poverty rates for 2005 and 2010 were 23.3 and 15.5, respectively. The point estimates are obtained from the average estimates from 100 bootstrap simulations. DLS residuals are based on 200 repetitions. The corresponding standard deviations are shown in parenthesis.

The validation exercises of our predictive models for 2010 and 2005 suggest that there is no conclusive evidence to be able to define a preferred model. There are two points worth highlighting, however. Using 2005 to test the predictive power of these models may be requesting too much of the model. Given the large gap

Figure 3
Observed and predicted consumption distribution, by predictive model



Note. Authors' calculations using ENBCV 2010 data. Observed log(consumption) distribution shown in blue. The 95% interval of predicted log(consumption) shown in shaded lines.

between the time when the model was predicted as the one applying the data to increases the potential for structural changes (say, in the economy) to render the model invalid or limit is applicability. Nonetheless, it is worth pointing out that for 2010 the DLS model predicts a poverty rate within one standard error of the true rate.

Survey-to-survey-imputation projections in Tunisia

Table 4 presents the results of the consumption prediction models as applied to the labor force surveys. When consumption models from the ENBCV 2010 are imputed into the 2010 ENPE (Table 4, column "ENPE 2010 predicted"), results from the different methods all show lower poverty rates than the officially rate. Imputed poverty incidence ranges from 14.3 percent to 14.6 percent of the national population. In other words, the predicted poverty rate—resulting from consumption models—within the 2010 ENBCV *overestimates* the true or observed poverty rate of 15.5 percent, while the predicted poverty rate within the 2010 ENPE *underestimates* the true poverty rate in that year.

With these results in mind, poverty estimates for 2012 resulting from survey-to-survey imputation into that year's ENPE (Table 4, column "ENPE 2012 predicted") are found significantly lower than poverty incidence estimates for 2010. This result is robust to the method used—full or comparable—and the way residuals are allocated—random, by decile, and by urban/rural location. Interestingly, the decrease in poverty rates across methods suggests a range between 1.1 and 2.2 percentage points, when comparing ENPE 2010 and ENPE 2012 distributions, reassuringly close to those reported below (next section) for 2012 following the projection methodology: a reduction in poverty ranging between 1 and 2.3 percentage points.

Results also suggest that much of the change in poverty between 2010 and 2012 typically came from reductions across urban households, with more modest decreases in rural poverty. Comparing the predicted poverty rates in ENPE 2010 and ENPE 2012 suggests that the method of random allocation of residuals renders the largest reductions in poverty, both in urban and rural areas. The other methodologies, allocating residuals based on assets ownership and urban/rural location and DLS, show much more modest decreases in poverty than the random allocation. A simple decomposition exercise—not shown here—indicates that the contribution of urban poverty changes to national poverty reduction between 2010 and 2012—comparing ENPE 2010 and ENPE 2012 predictions—lies between 65 percent and 90 percent of the total change, depending on the simulation method used.

Table 4
Predicted Poverty Rates by Predictive Model

Consumption model	Survey-to-survey method	ENPE 2009 (predicted) National	ENPE 2009 (predicted) Urban	ENPE 2009 (predicted) Rural	ENPE 2010 (predicted) National	ENPE 2010 (predicted) Urban	ENPE 2010 (predicted) Rural	ENPE 2012 (predicted) National	ENPE 2012 (predicted) Urban	ENPE 2012 (predicted) Rural
Full model: Comparable to ENPE 2010, 2012	Random residuals				14.5 (0.10)	12.2 (0.13)	18.8 (0.17)	12.3 (0.11)	10.1 (0.13)	16.9 (0.2)
	Wealth decile				14.6 (0.09)	9.9 (0.12)	23.3 (0.18)	13.1 (0.09)	8.7 (0.12)	22.4 (0.22)
	Wealth decile, u/r				14.5 (0.1)	12.1 (0.12)	18.9 (0.17)	12.9 (0.09)	10.3 (0.12)	18.5 (0.17)
Comparable model: Comparable to ENPE 2009, 2010, 2012	Random residuals	15.0 (0.09)	11.9 (0.12)	21.0 (0.16)	14.5 (0.11)	12.2 (0.13)	18.7 (0.2)	12.7 (0.09)	10.4 (0.11)	17.7 (0.18)
	Wealth decile	15.5 (0.09)	9.7 (0.1)	26.8 (0.17)	14.5 (0.1)	9.5 (0.12)	23.6 (0.21)	13.4 (0.09)	8.6 (0.12)	23.5 (0.22)
	DLS residuals	15.4 (0.01)	12.1 (0.01)	21.8 (0.02)	14.3 (0.01)	11.7 (0.01)	19.2 (0.02)	12.5 (0.01)	9.8 (0.01)	18.2 (0.02)

Note. Authors' calculations using ENBCV and ENPE data.The point estimates are obtained from the average estimates from 100 bootstrap simulations. The corresponding standard deviations are shown in parenthesis.

GDP-based projections

Table 5 and Figure 4 present the average point estimates of poverty incidence under the four projection scenarios. The estimates indicate, first, that poverty rates increased in 2011 and decreased in 2012. According to these results, the poverty impact of the revolution oscillates between 0.9 and 2.2 percentage points, depending on which of the four simulations is considered. When the effect of specific-sector GDP and unemployment are included (simulation 3), the impact is largest with 2.2 percentage points. If, simplistically, only GDP growth is considered (simulation 1), the effect is the smallest, with a 0.9 percentage point increase in poverty incidence.

Table 5
Projected Poverty Rates 2011-12

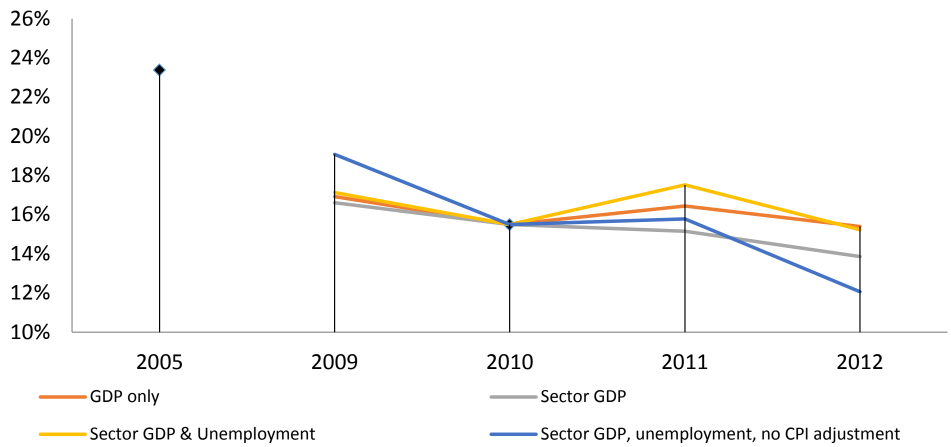
	Official	Simulation			
	(baseline)	S1	S2	S3	S4
2005	23.4				
2009		16.9	16.6	17.1	19.1
				(0.16)	(0.16)
2010	15.5	15.5	15.5	15.5	15.5
2011		16.4	15.2	17.5	15.8
				(0.37)	(0.37)
2012		16.4	15.2	17.5	15.8
				(0.26)	(0.25)

Note. S1: GDP only; S2: Sector GDP; S3: Sector GDP and unemployment; S4: Sector GDP, unemployment, and no. adj. for CPI. Authors' estimates based on ENBCV 2005 and 2010, and INS official data on growth, unemployment, and CPI.

Second, the recovery in 2012 was enough to reverse the increased poverty observed in 2011. Had it not been for the observed increase in prices (as reported in simulation 4), the economic recovery of that year would have brought poverty levels below those observed in 2010. It is indeed the increasing cost of basic needs that counteracted to some extent the positive impact on poverty of (sector-specific) GDP growth and reduction in unemployment observed in 2012. All things considered, sector growth, unemployment and CPI, poverty rates in 2012 were similar to those observed pre-revolution (Figure 4).

Figure 5 reports additional estimates for extreme poverty and compares them with the official and projected poverty rates pre- and post-revolution. Poverty estimates reported in this figure are based on scenario 3 projections that include GDP,

Figure 4
Projected Post-Revolution Poverty Rates in Tunisia



Source: Authors' estimates based on ENCBV 2005 and 2010, and INS official data on growth, unemployment, and CPI.

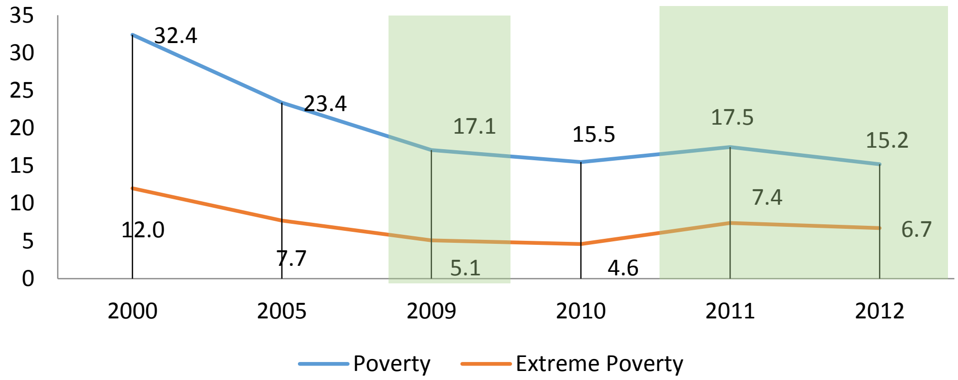
unemployment, and CPI changes over time. Projected extreme poverty trends show similar results to those reported for poverty: a sizable increase in 2011 and a notable decrease in 2012. However, in contrast to poverty trends, the reduction in extreme poverty in 2012 is not sufficient to fully revert increases observed in 2011. This is because of the larger impact that unemployment had on extreme poverty than on poverty in 2011 (and the more limited impact of the employment recovery in 2012 on the larger pool of extreme poor in 2011).

It should be noted that these projected rates are likely an upper bound of the true poverty variation that took place in those years. This is because the effects of consumption subsidies, social transfers, remittances and private transfers, and labor coping strategies (increasing work supply, changing labor status, for example) are not considered in these projections. To the extent that coping strategies were adopted by households and/or government initiated compensation interventions, estimates failing to include them might overestimate poverty impacts.

Conclusions

Effective monitoring of poverty and other welfare indicators are crucial to better understand poverty dynamics and changes in the living conditions of the most vulnerable of the population, especially in a rapidly changing landscape such as Tunisia, both pre and post revolution. However, there is not an available new household survey reporting consumption after 2010. How then can we analyze poverty trends or estimate a poverty rate in the post-revolution period? Thus, to explore how poverty

Figure 5
Official and Projected Poverty Rates: Poverty and Extreme Poverty Trends, 2000–2012



Source: Authors' calculations using ENBCV data and INS estimates of growth, unemployment, and CPI (simulation 3). Note: Shadowed areas indicate Bank's estimated rates. Non-shadowed rates are official estimates.

has evolved after the revolution, this paper applies several imputation techniques to obtain robust estimates of the evolution of poverty post-2010. The study applies survey to survey imputation methodologies using data from the national consumption survey (ENBCV) of 2010 and the Labor Force Surveys (ENPE) of 2009, 2010 and 2012 after estimating a series of benchmark consumption models. Lacking a post revolution ENBCV, the current analysis proposes applying different methodologies that help present a reliable prediction of post-revolution poverty rates for the first time in Tunisia.

This proposed exercise is not meant to select a dominating or superior predicting model to forecast post revolution poverty rates. We, instead, provide a wide set of models, assess their predictive ability, and analyze the variation of predictions they provide. This assessment of alternative methods is particularly relevant in contexts characterized by micro data deprivation, which unfortunately remain far too common in developing countries. In such cases, methods exploiting macro administrative data provide a legitimate alternative. Without the observed or true post revolution poverty rate against which truly validate the two methods, the obvious question to address is whether a very simple projection using macro data readily available provides a largely different estimate from a highly-sophisticated survey-to-survey imputation. In addition, the paper aims to understand what happened to poverty after the revolution in Tunisia. Estimates suggest that the macro-projections are in line with respect to the survey-to-survey imputation results though they tend to understate the expected changes in poverty. Macro-projection estimates suggest that poverty rates increased in 2011 immediately after the revolution and decreased in 2012. During the year of the revolution, poverty increased with the expected change oscillating between 0.9 and 2 percentage points, depending on the assumptions used to project post-revolution poverty rates. The recovery of GDP and employment in 2012 contributed to reversing the poverty increase of the previous year, while the increase in the cost of living limited the favorable impact on poverty of the economic recovery. All in all, estimated poverty rates in 2012 are slightly below 2010 levels. Projected extreme poverty rates for 2010 and 2012 suggest similar trends. These findings accrue from projections of the observed household consumption in 2010 (reported in the ENBCV) that are updated consistently with the macroeconomic developments in 2011 and 2012.

By and large, projections are confirmed when using the alternative methodology, cross-survey imputation. In this approach, a consumption model based on observed 2010 data from the ENBCV is imputed into 2012 household data from the ENPE. Cross-survey imputation results suggest that poverty rates in 2012 were between 1.1 and 2.2 percentage points below the levels estimated in 2010, depending on the assumptions made to impute consumption across surveys. This result is robust to the predictive model used—full or comparable—and the residual imputation method—random, by decile, by location-specific decile, or using clustered random effects. Results also suggest that much of the change in poverty between 2010 and 2012 typically came from reductions across urban households, with more modest decreases in rural poverty.

The similarity of results regardless of method suggests that both survey-to-survey techniques taking into account best international practices and poverty projections from macro data render robust results in Tunisia. At the same time, these very sets of results also underscore the limitations of imputed poverty estimates, which are proportional to the capacity of the consumption model to reproduce observed poverty estimates. In the case of Tunisia, the estimated consumption model clearly provides a *reasonable* approximation to the observed poverty rates in 2010. But it is found that, systematically, the predicted poverty rate—resulting from consumption models—within the 2010 ENBCV *overestimates* the true or observed poverty rate of 15.5 percent, while the predicted poverty rate within the 2010 ENPE *underestimates* the true poverty rate in that year.

It is complex to determine a priori what the factors behind these biases are. What the exercise confirms, however, is that even though the message does not change (poverty increased in 2011 to then decrease thereafter), precise estimates do. In fact, comparing the predicted poverty rates in ENPE 2010 and ENPE 2012 suggests that the method of random allocation of residuals renders the largest reductions in poverty, both in urban and rural areas. The other methodologies, allocating residuals based on assets ownership and urban/rural location and DLS, show much more modest decreases in poverty than the random allocation. Ultimately, in the absence of more frequent and accessible data, specific decision making that may involve the allocation of resources to certain vulnerable and poor groups must acknowledge that this type of poverty monitoring has consequences in terms of precision and measurement bias. More analysis is needed to investigate why, how universal it is, and what consequences may have in other settings. In the meantime, while such analyses are developed, alternative projections based on readily available macro data may still provide relevant insights into poverty levels and trends at a much lower cost in terms of analytics and resources.

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Appendix

Table A1. Observed and predicted poverty and distributional statistics, 2005 and 2010

	2005							2010						
		Predicted, full model			Predicted, comparable				Predicted, full model			Predicted, comparable		
	O	R	W	W U/R	R	W	DLS	O	R	W	W U/R	R	W	DLS
p0	23.3	20.3	21.4	21.8	20.4	21.5	25.0	15.5	16.8	17.8	17.7	16.9	17.8	16.1
p1	6.2	5.3	6.1	6.1	5.3	6.1	6.7	3.8	4.2	4.8	4.7	4.2	4.7	3.8
p2	2.4	2.1	2.5	2.5	2.0	2.5	2.6	1.4	1.6	1.9	1.8	1.6	1.9	1.4
Gini	0.377	0.369	0.401	0.391	0.37	0.405	0.374	0.358	0.366	0.392	0.382	0.366	0.394	0.363
p25	71.7	75.5	73.4	73.9	75.1	72.9	68.5	104.2	99.9	97.7	99.6	99.7	97.3	100.8
p50	109.9	119.3	122.5	120	118.3	122	107.8	158	157.3	159.3	158.5	156.2	158.5	155.8
p75	170.2	187.1	200.6	193.5	186.1	200.9	169.7	242.3	246.8	258.7	253.9	245.5	258.1	242.5

Note. Authors' estimates based on ENCBV 2005 and 2010, and INS official data on growth, unemployment, and CPI. Consumption is expressed in TND (monthly, thousands). O: observed; R: random; W: wealth; W U/R: Wealth U/R; $p0$: headcount rate; $p1$: poverty gap; $p2$: severity of poverty.

Notes

[1]Poverty rates reflect the percentage of the population whose consumption levels are below a minimum threshold required to cover their basic food and non-food needs. In 2010, the poverty line was 757 TDN in big cities, to 733 in small and medium towns, to 571 in non-communal areas. The methodology is based on the Cost of Basic Needs approach and a money-metric approach to measure welfare (*Institut National des Statistiques et al.* 2012)

[2]Tarozzi (2007) imputes consumption using the same type of survey, a budgetary survey, over time.

[3]This final list is the result of an iterative process where additional variables (e.g. allowing for household composition, or a more exhaustive list of access to basic services) and alternative specifications of the variables (e.g., different groupings of educational attainment) were tried in search of a robust model maximizing statistical performance in terms of statistical representativeness of variables and explanatory power. The model used here was found to have the highest predictive power.

[4]Additional information on type of employment (self-employed, salaried worker, private or public employment) was available in the ENBCV 2010, but absent in what we define to be our survey “B” (i.e. the Labor Force Survey) and thus discarded from the final estimations. In contrast, ownership of assets and dwelling characteristics is widely available in the ENBCV 2010. This information is not incorporated into the model, but used to calculate a wealth index for the imputation of errors following Ferreira et al. (2011)’s imputation approach.

[5]Typically, welfare measures based on consumption include an estimate of the flow of services obtained from the durable goods the household possesses. Unfortunately, the ENBCV only captures expenditures incurred during the year before to the survey. There is no information on purchase year, purchase value, or current value for any of the durable goods that may have been purchased before the survey year. Thus, estimation of a value of flow of services for these goods would require strong assumptions. The official measure of consumption expenditure used by the INS did not include any expenditure on durable goods and we follow their approach.

[6]These estimate residuals capture the difference between each individual or household’s observed consumption and its predicted consumption by the model used in survey A.

[7]In Ferreira et al. (2011), deciles are defined over the first principal component of an index composed of household ownership of durable goods (such as refrigerators, televisions, cars, computers, and so forth), on housing characteristics (such as the type of roof materials and floor cover), and on access to utilities (such as water and sanitation). Obviously, it is essential that wealth deciles must be defined in each survey according to the same set of assets, for which these assets must be both present and identically defined in each of the surveys used in the cross-survey imputation.

[8]In this methodology, households are clustered based on the Primary Sampling Unit (PSU) used for the sampling strategy for the survey.

[9]An index is calculated using factor decomposition analysis from a set of commonly available assets in survey A and B. In turn, households are assigned to one of the ten deciles of the resulting index (with deciles calculated separately for each survey).. Finally, the distribution of residuals specific to each decile from survey A are used as the pool of potential residuals in the imputation of households’ consumption in survey B..

[10]Official figures from INS on GDP growth for 2011 to 2014 are -1.0 percent, 4.5 percent, 2.8 percent and 2.7 percent, respectively (INS 2015).

[11]Figures reported online by INS accessed on July 28, 2015 at http://www.ins.tn/indexfr.php. Estimates for 2014 include only three quarters–the second quarter was not reported.